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Documents contributions to forest inventory in the areas of sampling, remote sensing, modeling, information management and analysis for the Forest Inventory and Analysis program of the USDA Forest Service.

KEY WORDS: Sampling, estimation, remote sensing, modeling, information science, policy, analysis

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Preface

The Seventh Annual Forest Inventory and Analysis Symposium was held October 3–6, 2005, in Portland, ME. The symposium featured participation, including 18 presentations, by scientists from 12 foreign countries. In addition, the trend for participation by scientists from outside the formal Forest Inventory and Analysis program continues to increase. The symposium organizers thank all participants and presenters and convey special thanks to those who submitted their papers for these proceedings.

Ronald E. McRoberts
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Forest Inventory: Role in Accountability for Sustainable Forest Management

Lloyd C. Irland[1]

Abstract.—Forest inventory can play several roles in accountability for sustainable forest management. A first dimension is accountability for national performance. The new field of Criteria and Indicators is an expression of this need. A more familiar role for the U.S. Department of Agriculture Forest Service Forest Inventory and Analysis (FIA) program is for assessment and outlook development in States and regions. This essay poses three big challenges for FIA today: sustain and build on the Annual Forest Inventory System, show relevance to nontimber and science user groups, and improve measures of ecological health.

Introduction

I was introduced to Forest Inventory and Analysis (FIA) data by Professor Lee James at Michigan State, who in the mid 1960s thrust a copy of the 1965 Timber Trends Report (USDA Forest Service 1965) into the hands of an eager young forestry student. Since then, I have been a regular FIA data user, and a frequent source of suggestions to the FIA units. While in State Government, I helped coordinate efforts to develop State funding for plot augmentation and other improvements to Maine's FIA efforts. As a writer and consultant, I regularly mine FIA information. The various units have been helpful in supplying unpublished data, going back to the days when it would be furnished on microfiche. Looking back only 15 years, the amount of progress is truly extraordinary.

Interest is growing in taking a global perspective to forest inventory, with national inventories viewed as elements in a global assessment, just as States or provinces are elements in the U.S. and Canadian national timber budgets. Some even aspire to comparisons, by way of the Criteria and Indicators (C&I) process, which show how different nations are doing. Due to unresolved difficulties at national levels (see, e.g., Irland 2007), and inconsistent definitions for data, an international perspective is not promising at the moment.

Accountability

Accountability sounds simple but it is not. Different stakeholders are concerned with different aspects of the forest. To mention accountability immediately raises the question of who is responsible. In the United States, responsibility is spread among levels of Government, agencies, and property owners. For many aspects of the forest resource, when the question is "Who are you going to call?" we do not know the answer.

Different Stakeholders and Perspectives

Timber Sustainability, Growth/Drain
Despite the way the political winds are blowing these days, I am convinced of the continuing relevance of accountability especially when handled in a somewhat more inclusive way and with more neutral terms than in the past (Ince 2000, Irland 2003, Nilsson *et al.* 1999).

Habitat
To my surprise, FIA data and analysis is less used for this question than it should be. Certainly a good start has been made, with national overviews by Flather, Brady, and Knowles (1999), and Noss, Laroe, and Scott (1995).

Health/Ecological Condition/Biodiversity
This huge gap in our monitoring capacity will not be soon filled. In fact, we do not even have a sensible way to proceed

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(EPA 2002, NCSSF 2005, The Irland Group 2001). FIA has to respond in a measured manner, but avoid getting drawn into this black hole of limitless demands for new data. Yet, FIA data does offer ways to depict key changes and to offer diagnostics on overall conditions related to ecological health (e.g., Dahms and Geils 1997; O'Laughlin and Cook 2003; Shaw, Brytten, and Blander 2005; USDA Forest Service and BLM 1996).

Land Use

Land use is an emerging social concern and is an area where FIA has established strengths, as I will note below.

Carbon Budgets

Carbon budgets are an example of a new social concern for which the FIA system happened to be there, ready and waiting, with a rigorous national data set that can respond to this need (see, e.g., Smith, Heath, and Woodbury 2004). As Kyoto-like policies continue to be debated, we will enter dangerous waters here, and will need to be on our guard against misuse or misunderstanding of this information.

Accountability for Interpretation

Interpretation includes many things, including seeing that data and interpretations are presented with clarity, especially where data limitations are being pushed and need to be clearly identified. Somewhere in the forestry profession, we will need Truth Squads who can point out misinterpretations of forest conditions and abuses of FIA data by whatever interest group provides the latest example of selectively edited and partial views of what is happening in the forest. Government is understandably reluctant to speak directly about the bad news. In the future, there will be bad news and we had better get used to it. Data producers such as FIA have an obligation to make the data easy to use and understand, and especially to counsel less familiar users on limitations (see, e.g., Luppold and McWilliams 2004).

Accountability at National Level: Key Points on C&I

In the eagerness to implement C&I, a number of critical points have received limited consideration (Irland 2007). These have no immediate answers, but can no longer be ignored. Some of the problems originate in the definitions of the Criteria themselves. A few major challenges appear evident, based on the 2003 National Report (USDA Forest Service 2004), which represents a national application of the Montreal C&I. Those involved are engaged in detailed discussions on all of these questions.

The Aggregation Problem

In an ecologically diverse Nation of continental scale, averages may mean little. How much total growing stock is standing in the forests is good to know, but how to interpret this statistic in terms of sustainable forest management (SFM) may be ambiguous, and the meaning of the national aggregate may be limited. The 2003 National Report summarizes 22 forest type groups, a highly aggregative way to view the forest. The Nature Conservancy defines 1,505 forest associations, plus almost 1,500 more for woodland and shrubland (Noss and Peters 1995, Stein, Kutner, and Adams 2000). The FIA data system probably could not support disaggregation down to 1,505 forest types, but using only 22 cannot lead to very helpful conclusions about changes in the forest.

Credible Measures of Ecological Health

Credible measures of ecological health are lacking. Unfortunately, this lack of measures is often covered up by improvisations and euphemisms. Those conducting assessments are presently unwilling to use the best local or regional examples when national coverage is lacking. The FIA effort can undoubtedly relate to this problem, but at the same time, its sample design may not offer the best platform for many of the issues.

Improved Ways to Present Data

Improved ways to present data on forest conditions and trends are needed. I think FIA is getting better at this and look forward to further progress. It is not an easy matter to present tables and charts that illuminate without oversimplifying the case.

As the C&I process is currently structured, governments grade themselves. It is time to find a way to empower a truly independent body to conduct period assessments, according to C&I or other criteria. Previous examples include the Heinz Commission's report (2002) and the Millennium Ecosystem Assessment (2005).

The FIA community is a major data provider for analysts working with some of the C&I. The community also has a major responsibility for quality control, providing tough-minded, technically sound reviews of how the data are being used. At times, such comments may not be entirely welcome.

Accountability at Regional Levels: A Few Examples

Type Definitions Can Obscure Realities

In Maine, we were confronted with a severe budworm outbreak from about 1972 to 1985. In the wake of the damage, extensive salvage cutting was conducted. Emerging young stands developed in a variety of patterns. Especially troubling was that in many areas spruce-fir stands were being replaced by dense shrubby stands of early successional hardwoods and species such as pin cherry (*Prunus pensylvanica*) and raspberries (*Rubus idaeus*). These were in patches of varying sizes, some in the hundreds of acres. The 1995 FIA data showed that the area of the spruce-fir type group had fallen markedly since 1982. This figure was widely cited as proof of mismanagement and a deteriorating resource.

Lost in this debate were a few points. First, the type group is much larger than just the spruce-fir types, so the net change number included changes in other softwood types as well. Also, the definition of forest type used in FIA is not entirely transparent. To complicate matters, the forest type algorithm had been changed in the interim. Finally, type change was depicted as a black and white matter—either a stand is or is not spruce-fir. Yet, by depicting type as black and white, realities were obscured. It makes a huge difference whether an acre fell from 75 percent spruce-fir stocking to 50 percent, or from 75 percent to zero. In either case, that acre might be tallied as moving out of the spruce-fir type. Also, uncertainty remains about the extent to which clearcut areas of low spruce-fir stocking will naturally recover softwood stocking over normal stand development.

I was part of an informal probe of this information, in which we screened stocking conditions and change by deciles of spruce-fir stocking. This approach yielded a much richer picture. As a byproduct, we could see that the change in the typing algorithm accounted for a portion of the apparent type change. This example is but one instance in which new processing and computational capabilities enable analysts to probe complex questions in much richer ways.

Better Present Age Class Data/Trends

In dealing with the Maine spruce budworm outbreak in the late 1970s and 1980s, we were frustrated by the difficulty in translating FIA data into age class information that we could use in assessment and modeling. Far too many ad hoc workarounds were necessary. In contrast, a focus on age class seems to have been routine in other regions for some time. Certainly not all stands are even aged, but this is no reason for inadequate attention to age class issues.

Land Use Changes

Sprawl and land use issues are being highlighted as major concerns for the future of American forests. These issues are relevant whatever your specific resource interest might be. The land use change matrices prepared routinely by some of the FIA units are highly informative about the dynamics of land use change. This kind of summary is needed nationwide. Using this data set to shed light on land use change is a perfect example of bringing the FIA capability into important debates on national issues. FIA is one of the only sources of consistent measurement on this point, so the importance of tracking land use can only increase (see, e.g., relevant sections of Wear and Greis 2002).

Measuring Forest Disturbance

The role of disturbance in shaping ecosystems has emerged over recent decades as a powerful source of insights. Using FIA data to track different sources of disturbance, including cutting, can make important contributions. FIA has been engaged in this effort since at least the publications of Gansner *et al.* (1990) at the Northeastern Station. The recent South Carolina report (Conner *et al.* 2004) contains a useful summary placing timber cutting in context of other disturbances. Hopefully, this kind of summary will become a part of the standard presentation in all states.

Regional and State Assessments

The regional scale of assessment that breaks out of the traditional box of State-by-State reporting has been an increasingly important application of the FIA capability (Wear and Greis 2002, USDA Forest Service and BLM 1996, Dahms and Geils 1997). Also, individual States have conducted outstanding assessment work that relies heavily on the FIA information. Examples that come quickly to hand, without prejudice to others, include Oregon (Oregon Department of Forestry 2004), California (California Department of Forestry and Fire Protection 2004), and Maine (Maine Forest Service 2005). A number of States, such as Minnesota and Maryland, have done extraordinary work integrating FIA and other data into massive Geographic Information System (GIS) systems for assessment, monitoring, and at times for analyzing policy or management decisions (Minnesota Department of Natural Resources 2001).

Three Big Challenges for FIA

Sustain and Build on Annual Forest Inventory System

The early years of the Annual Forest Inventory System (AFIS) brought questions in the user community about whether it could be a periodic synthesis of a State's forest position with high statistical accuracy. In the event, the 5-year report produced for Maine has put that concern to bed. It is not only an excellent overview, but it breaks new ground in presentation in a number of ways. Gaining full clarity on the growth/removals balance has not yet been achieved but it appears to be within our grasp.

An additional concern was whether annual funding could be sustained at the State and Federal levels. It is encouraging to hear that FIA has strong support from U.S. Department of Agriculture (USDA) Forest Service senior management. Maine has been able to stay the course. Matters have not gone as well in some other States. Everybody wants something from the FIA but we can't please them all. FIA managers are aware that they must not lose the essentials as they continue adapting to new data needs. More particularly, they will have to resist efforts to get us to address things not well suited to the sample design and analytical system.

Within the United States, the building blocks continue to be the States—if they are unable to follow through with funds and cooperation, the program will not be sustainable. I don't know if anyone has taken an outside look at the current status and funding outlook of the AFIS effort nationally. If not, it might be a good time now that Maine has finished its first 5-year report and others are emerging. We certainly need to have a good handle on progress nationally. I don't think the future financial sustainability of AFIS can be taken for granted. Hopefully, the next two suggestions could help in broadening support in useful ways.

Demonstrate FIA Relevance to Nontimber Issues and Value to Other Science Users

Numerous applications have shown the value of FIA data sets in tracking changes in various proxies for wildlife habitat. Many more nontimber applications are being showcased here. It is extraordinary that many scientists in other disciplines are totally unaware of this information and how to use it. The use of these data offers a major opportunity to advance FIA's contribution to the wider science community, and hopefully generate greater support for the program.

It's time to stop talking of terms such as *timberland*, which presume a resource value for a piece of forest. Terms such as *sawtimber stands*, in addition to using obsolete utilization standards, also presume a timber value for the forest that is often entirely irrelevant to the intended uses of the information. Defining stand size classes in a more neutral manner, not defined by outmoded product definitions, would be useful in any case. Traditional pulp, sawtimber, and related tabulations can be prepared and included in the appendix or otherwise for the timber-oriented audience. Try a thought experiment—how would we describe the forest in a region with no sawmills or pulp mills?

We need to take more advantage of unprecedented processing/sorting/graphics capabilities. Counties are probably obsolete, but there are States (Maine, Minnesota) where their wide range of size (up to a factor of 5 or 6) hinders interpretation. The FIA Survey Units attempt to provide geographic units of sufficient size to assure statistical significance and to capture important regional differences. If only for comparison with past data, I would not abandon them. Also, for certain kinds of geographic comparisons, analysis units of uniform size can be important (see, for an intriguing example, Stein, Kutner, and Adams 2000).

It is now time to integrate the national FIA data set into a suitable version of the ecological units being done on a separate track by the USDA Forest Service—the ecoregion maps by Bailey, Carpenter, and others. Gray (1995) illustrates this approach, using 90 ecologically defined “sections” for Canada. Building reporting around such units could yield important insights. It would demonstrate commitment to the emerging ecosystem paradigm and a willingness to step away from past timber-oriented definitions.

Much as we are gaining from current GIS modes of expression and analysis, we must not forget that better pictures or sophisticated geostatistics yield new views, but not really new data. The traditional dot map is not yet obsolete. The usefulness of displaying plot locations versus geospatially modeled surfaces needs further analysis. New mapping and other visualizing capabilities are doubtless one of the exciting trends in this field. FIA and user groups have done yeoman work building on FIA data sets for biomass and carbon measurement. This spatial initiative is a major success story and is another good answer to the old claim that FIA is a timber only effort.

FIA has made great strides in making its data easy to find. It’s all on the Internet now. Comparable progress in making it easy to understand and apply is needed. New user groups are unfamiliar with much of the system, and have very distinct needs. We need to develop interpretive and how-to products aimed at various science audiences, help them to become familiar with FIA, and to use it more often. We also must address cultural gaps. As an example, I once reviewed a technical journal article assessing ecosystems in New Hampshire. The authors were clearly totally unaware of riches in FIA data sets. When I urged them to look into readily available publications that were highly relevant, they were not too interested in hearing about it. They were comfortable with their dot-map mindset that naturally emerges from people who spend all their time making lists of tiny little spots that host rare plants. Their view was certainly not wrong, but it was incomplete.

We need an academic program training resource analysts to use and improve existing data sets and apply them to a wide range of problems. It would support graduate students’ research, emphasizing mid-career students, and would conduct seminars and training. It would be unselfish, spending resources around the country and not just on campus. Private support for such a venture is needed, and soon.

Build on FIA Strengths to Contribute to Ecological Health Monitoring

The huge hole in our data about trends in ecological condition and ecosystem health hinders our efforts on C&I as well as to our abilities to manage responsibly (see, e.g., EPA 2002; Heinz Center 2002; Irland 2007; The Irland Group 2001; NCSSF 2005). Until substantial progress can be made in filling these gaps, talk of SFM is academic. We need to be certain that real FIA strengths are being employed. It won’t do to just measure more variables on each plot if the plot system poorly fits the matter of concern. Burdening the plot measurements just to satisfy critics is a bad way to respond to emerging needs.

Conclusions

Meeting the three big challenges will necessarily involve FIA with many other sections of the user community and the science community.

FIA is clearly overworked and underresourced. Somehow we must locate leaders who are in a position to help us address the funding issue, and soon. Further, I hope that by adopting my suggestions, we can broaden support in ways that will enable us to sustain the entire program into the future for all the public benefits it will bring.

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A History of U.S. Department of Agriculture Forest Service Forest Survey, 1830–2004

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Abstract.—This article provides a summary of a new report on the history of the Forest Survey (Forest Inventory) in the United States as it evolved within the U.S. Department of Agriculture Forest Service over a period of more than 100 years. It draws on the writings of several authors who have published on various aspects of the Forest Survey program. It reviews nine ground-plot designs used in the Forest Survey and Forest Inventory and Analysis (FIA) programs since 1931. The report also highlights the major events contributing to the current FIA, beginning as far back as 1830.

It is impressive to look at the many contributions of various people working with the Nation's Forest Survey program, as well as the various methodologies that have contributed to understanding and updating the national Forest Survey statistics. It is especially timely that this historical report should occur at the time the Forest Service is celebrating the anniversary of its 100 years of service to the American people.

History of the Forest Survey

The history of the Forest Survey in the United States, as it evolved within the U.S. Department of Agriculture (USDA) Forest Service over a period of more than 100 years, is an interesting story. We have drawn on the writings of several authors who have published on various aspects of the Forest Survey. It is especially timely that this documentation should occur at the time the USDA Forest Service is celebrating the anniversary of its 100 years of service to the American people.

This report is for those readers who wish to understand the evolution and contribution of the Forest Survey program in U.S. forestry. Considerable attention is given to the different plot designs that were used and to an explanation of how the focus and goals of the Forest Survey program changed over time. The report (LaBau *et al.* 2007) documents the various designs and explains how the focus and goals of the Forest Survey demanded changes in plot designs over time. The Forest Survey has always been faced with a variety of conflicting objectives—timber volumes, reproduction success, species composition, tree quality, etc. Statistical efficiency for one objective often compromised the estimate of other attributes. There are many difficulties in estimating growth, mortality, removals, forest type, condition class, and many other multiresource variables that the inventory estimated. The early Forest Surveys were almost exploratory in nature and evolved into increased emphasis on change, condition, quality, and other descriptive characteristics. The changes in design over time attempted to meet the emerging objectives and challenges.

Credit is given to those members of the Forest Survey whose vision and fortitude contributed so much to taking a concept, which began as an effort focused on monitoring the Nation's timber supply and consumption, and expanded that concept to a multiresource and multifunctional program. This program has evolved over the years to meet the changing needs of a Nation that required a broadened forest inventory and monitoring program.

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To the Future

The future of Forest Inventory and Analysis (FIA) program, as in the past, is still timber, but it is so much more. A national information management system has been completed and will serve both internal and external data needs. Work is under way to develop a set of standardized map products such as forest type maps, biomass maps, and a myriad of other spatial products. And, since the mid 1980s FIA and its cooperators have published more than 1,400 papers and articles on nontimber uses of FIA data. Clearly, FIA's client list and program value will continue to grow to meet the needs of monitoring the sustainability of the Nation's forest ecosystems.

In addition to traditional fieldwork, the new FIA continues to conduct surveys of private forest owners to assess their ownership objectives, track wood harvested from America's forests, and conduct utilization studies on active logging operations to provide the factors needed to link the input (trees standing in the forest) with the output (wood products produced by a mill).

Collaborative relationships with universities, industry research organizations, interest groups, and other Federal agencies have been strengthened, allowing FIA to gain increased experience in specialized areas, as well as gain access to creative scientists outside of the USDA Forest Service.

The emphasis of FIA for more than 75 years has been data quality. The new program continues this tradition with a Quality Assurance program that includes documentation of methods, training for data collectors, checks of data quality, peer review of analysis products, and continuous feedback to ensure that the system improves over time. The search will continue for more efficient and more cost effective ways of fulfilling the FIA mission. Good men and women will move forward with a dedication to evaluate forest inventories and forest health, and produce information and analyses that will serve generations well into the future.

Literature Cited

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Separating the Cows From the Trees: Toward Development of National Definitions of Forest and Rangeland

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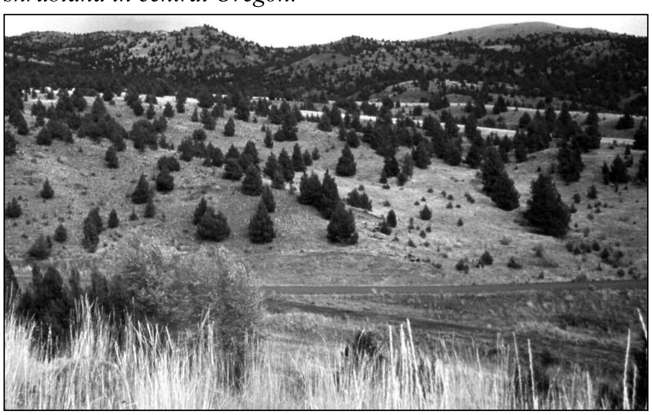
Abstract.—This paper introduces issues surrounding the need for national definitions of forest and rangeland, and it review types of definitions in use, reviews past agreements and their status, and finally gives recommendations as to what should be done next.

The Need for National Definitions

The classification of lands as forest is one of the most important decisions that inventory specialists make in the course of their work. How lands are classified may influence how lands are to be managed and what Agencies are funded. Most of the time, classification is straightforward. Other times it may be difficult. For example, should figure 1 be classified as forest, rangeland, or both?

If lands are classed as forest, the management strategy and funding may be to maintain the lands in tree cover. The U.S.

Figure 1.—*Native juniper* (Juniperus spp.) *invading grass/ shrubland in central Oregon.*



Department of Agriculture (USDA) Forest Service has the lead. If lands are classed as range, then the management strategy and funding may be to maintain grass and shrubs and to remove any trees. The U.S. Natural Resources Conservation Service (NRCS) has the lead on private lands.

The NRCS defines rangeland as "a land cover/use category on which the climax or potential plant cover is composed principally of native grasses, grasslike plants, forbs or shrubs suitable for grazing and browsing, and introduced forage species that are managed like rangeland. This would include areas where introduced hardy and persistent grasses, such as crested wheatgrass, are planted and such practices as deferred grazing, burning, chaining, and rotational grazing are used, with little or no chemicals or fertilizer being applied. Grasslands, savannas, many wetlands, some deserts, and tundra are considered to be rangeland. Certain communities of low forbs and shrubs, such as mesquite, chaparral, mountain shrub, and pinyon-juniper, are also included as rangeland."

The USDA Forest Service defines forest as "land at least 10 percent stocked by forest trees of any size, including land that formerly had such tree cover and that will be naturally or artificially regenerated. Forest land includes transition zones, such as areas between heavily forested and nonforested lands that are at least 10 percent stocked with forest trees and forested areas adjacent to urban or built-up lands. Also included are pinyon juniper and chaparral areas in the West and afforested areas. The minimum area for classification of forest is 1 acre. Roadside, streamside, and shelterbelt strips of timber must have a crown width of at least 120 feet to qualify as forestland. Unimproved roads and trails, streams, and clearings in forest areas are classified as forest if less than 120 feet wide."
The USDA Forest Service Forest Inventory and Analysis (FIA)

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program classifies junipers as trees, while the NRCS National Resource Inventory (NRI) considers them shrubs. The FIA classifies oak and juniper woodlands as forests, while the NRI classifies them as rangeland. According to the Agency definitions, the land shown in figure 1 would be classified as forest by the USDA Forest Service and rangeland by the NRCS. In the United States, at least 50 million acres of such land are in question—roughly an area the size of Nebraska.

The difference between the USDA Forest Service and NRCS is but one example. Sixteen other Federal Agencies have at least one official definition of forest and rangeland, and eight have official definitions of tree.

Because of this overlap, the U.S. Roundtable on Sustainable Forests and the Sustainable Rangelands Roundtable are seeking national definitions for forest and rangelands for mutually exclusive criteria and indicators. To this end, the Federal Geographic Data Committee's (FGDC) Sustainable Forest Data Working Group's created the Forest/Rangeland Definitions Group (FRDG). The objective of the FRDG is to develop standard operational definitions of forests and rangelands, allowing consistent and credible estimates of these areas and of their components, conditions, and products. Ultimately, development of definitions will be done through the FGDC. Membership includes people from the Federal Government, professional societies, and environmental groups.

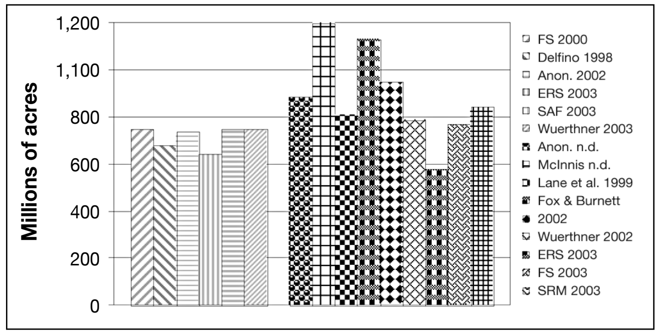
I served as a consultant to the group. This article is based on the final report that I submitted (Lund 2004).

Findings

Forest and Rangeland Estimates

Figure 2 shows recent published estimates of forest and rangeland area in the United States (Lund 2004). Note that the estimates for rangeland vary more widely than those for forest. The reasons for the differences are the sources and perceptions of what constitute forest and rangeland (i.e., the definitions). The estimates of forest are all based on FIA data. Those for rangeland come from a variety of sources using different definitions.

Figure 2.—*Recent published estimates of forest (striped) and rangeland (checkered) area in the United States.*



Source: Lund 2004.

Existing Definitions of Forest, Rangeland, and Tree

In my quest, I found 786 published definitions of forest, 368 definitions of rangeland, and 199 definitions of tree (Lund 2005a, 2005b). Forest and rangeland definitions are grouped into four categories based on cover, use, ecological potential, or administration. Forest definitions are most frequently based on cover, while rangeland definitions are often based on potential or use.

My literature review led me to the following conclusions:

- Estimates of rangeland area vary more widely than those for forestland.
- There is only one party responsible for inventorying the Nation's forests.
- Responsibility for the inventory of rangelands falls to many parties.
- Generally, definitions of forest are more inventory friendly than those of rangeland. That is to say, the definitions are more precise.
- There are accepted national and international definitions of forest but not of rangeland.

Past Attempts at National Standards and Direction

At least six attempts have been made in the past to develop and implement national standards for classification of lands for Federal Agencies. Three were recommendations for standards (Anderson *et al.* 1976, Driscoll *et al.* 1984, and Land Use and Land Cover Common Terminology Workgroup 1985) and three are actual agreements (Anon. 2001, FGDC 1997, and USDA SCS and Forest Service 1977, [National Land Cover Data—NLCD]).

Anderson *et al.* (1976) classed forest as a cover type and rangeland as a land use, so the categories were not mutually exclusive. Driscoll *et al.* (1984) defined forest land but not rangeland. The Land Use and Land Cover Terminology Workgroup (5-WAY) focused on land cover such as treeland, grassland, shrubland, etc., but the recommendations were not implemented.

The USDA SCS Forest Service agreement (1977) combined definitions for a new definition of forest land: "Lands with at least 25 percent tree canopy cover or lands at least 16.7 (10 percent) stocked by forest trees of any size." This definition assumed that a 25 percent tree cover equaled 10 percent stocking. A 16.7 percent stocking is more closely related to 5 percent rather than 10 percent canopy cover. Similarly, a 25 percent canopy cover is more closely related to 68 percent rather than 10 percent stocking (Lund *et al*. 1981).

The FGDC (1997) purposefully did not define forest or rangeland. Instead, it used a similar approach as the 5-WAY based on cover. The NLCD system is also based on cover.

A review of agency definitions in use after the agreements showed that very few agencies fully comply with the past agreements or recommendations. Reasons may include the following:

1. Classification did not meet need.
2. Difficult to break with tradition.
3. Change did not meet need.
4. No advantage.
5. Didn't know about.
6. Didn't have the authority.
7. Fear of being the only one to adopt.
8. Too much trouble.
9. Lack of incentives.
10. Lack of reprisals if direction not followed.

As part of my presentation at this symposium, I tested the audience's perception to see how they define forest and rangeland. The test was in two parts. First, participants wrote down their own definitions of forest and rangeland. Second, I showed a series of images and asked the people to classify the photos according to the definitions they had written. The appendix to this paper contains the results. The bottom line is that none of the participants followed their own direction. Based on past experiences and the test, implementation of Nationwide standards may meet with the same results.

How Do I See the Situation?

We only need standard or common definitions in the following circumstances:

- Comparing estimates from different lands owners.
- Comparing estimates over time.
- Aggregating estimates for upward reporting.

The Forest Situation

- NRCS and FIA present conflicting estimates of forest area on private lands.
- Conflicts could occur between FIA estimates and those of any landowner who uses a different definition of forest.
- FIA has the responsibility for inventory, monitoring, and reporting on forest land at the national and international levels.
- Other agencies and organizations may have their own definitions, as long as their data are not used for national reporting. Therefore, there is no issue with the definition of forest.

The Rangeland Situation

- No single agency is responsible for the inventory and monitoring of rangelands.
- USDA Economic Research Service reports on the Nation's rangelands, but data comes from a variety of sources.
- Many definitions are in use, none of which are inventory friendly.
- As a result, uncertainty exists as to what lands are considered rangelands.
- There appears to be a reporting requirement at the national and international levels.
- The definition of rangeland is an issue at the national level.

Change in area is an indicator of sustainable management for both forest and rangeland activities. We have a good handle on what is considered forest but not is what is considered rangeland. The main definitional issues are what constitute a tree and minimum tree cover.

Where To Go From Here?

The FRDG work is currently on hold until it can do the following:

1. Determine what we really need to create, out of the following options:
   - National definitions that an agency or agencies would use for upward national (and international) reporting.
   - Common definitions that agencies and cooperators would use for comparison and/or upward reporting.
   - FDGC standard definitions that all agencies and cooperators would use regardless of purpose.
   - All of the above.
   - None of the above.

2. Identify national and international reporting requirements. Nationally, the USDA Forest Service periodically reports on forest and rangeland as the result of the Forest and Rangeland Renewable Resources Planning Act (RPA) of 1974. Definitions may overlap. Both the Roundtable on Sustainable Forests and the Sustainable Rangelands Roundtable call for estimates but only for their particular area of interest. At the international level, the United Nations Economic Commission of Europe and the Food and Agriculture Organization periodically conduct the Global Forest Resource Assessment and the Intergovernmental Panel on Climate Change (IPCC) monitors changes in greenhouse emissions (table 1). Of the two, the IPCC has the only reporting requirement for mutually exclusive estimates of forest and rangeland.

3. Identify who has to use definitions, and when and why. Federal agencies are just the tip of the iceberg. Cooperators such as States, counties, municipalities, etc., also must be considered.

4. Determine how adoption of new standards may affect public perceptions of changes.

5. Determine how standards may affect agency funding and programs.

6. Determine what resistance the standard may face and how to mitigate.

7. Identify who will be responsible for what.

8. Construct an inventory-friendly classification system. The system should do the following:
   - Be applicable over all lands.
   - Follow established scientific procedures where appropriate.
   - Be repeatable from place to place (spatial) and from time to time (temporal).
   - Be recognizable on the ground (generally based on cover and current condition).
   - Be unambiguous (i.e., inventory friendly).
   - Include minimum thresholds for area, strip width, vegetation type, height and cover, and any exclusions.

Table 1.—*National and international reporting requirements for forest and rangeland statistics.*

Requirement	Forest	Rangeland	Definition type
Forest and Rangeland Renewable RPA of 1974	Yes	Yes	Definitions may overlap
Roundtable on Sustainable Forests	Yes	No	—
Sustainable Rangelands Roundtable	No	Yes	—
UNECE/FAO's Global Forest Resource Assessment	Yes	No	—
IPCC	Yes	Yes (Grassland)	Mutually exclusive

FAO = Food and Agriculture Organization; IPCC = Intergovernmental Panel on Climate Change; RPA = Resource Planning Act; UNECE = United Nations Economic Commission of Europe.

9. Agree on the following:
   - What we consider a tree.
   - How much tree cover we require to be a forest.
   - A minimum area including strip width.

   The IPCC has six land classes including forest, cropland, grassland (including rangeland), wetland, settlement, and other. Each class is mutually exclusive and all lands are covered (Milne and Jallow 2003). The IPCC classes provide the best base on which to develop any national definitions of forest and rangeland. Box 1 contains a proposed key for classifying lands in the United States based on the IPCC classes.

Box 1.—*A proposed key for land classification based on IPCC classes.*

1. Is the land area > **1 acre and strip width > ___ feet?** Yes—Go to 2. No—Classify with surrounding area.
2. Does the land have tree crown cover > **25 percent?** Yes—Go to 3. No—Go to 4.
3. Are the trees > **6 feet in height?** Yes = **forest land.** No = **nonforest land**—Go to 4.
4. Is the land used for growing crops? Yes = **cropland.** No—Go to 5.
5. Is the land covered or saturated by water for all or part of the year? Yes = **wetland.** No—Go to 6.
6. Is the land dominated by grasses, forbs, or shrubs? Yes = **rangeland.** No—Go to 7.
7. Is the land developed for human activity? Yes = **settlement.** No = **other land.**

IPCC = Intergovernmental Panel on Climate Change.
Source: Lund 2006.

10. Establish a program to encourage agencies to use standards. As indicated above, it is one thing to create standards and another to get people to use them. We need some mechanism to see if people are following direction and, if not, how we can correct the situation.

Following these recommendations, we should be able to separate the cows from the trees.

Appendix

Results of Lund's Great Land Classification Test

Several agencies of the U.S. Government are in the process of developing national definitions of forest and rangeland for upward reporting. Agency and people's perceptions of what is forest and rangeland vary. During my presentation at the 7th Annual Forest Inventory and Analysis (FIA) Symposium in Portland, ME, I tested the audience to see how a group of forest inventory specialists looked at the land. There were two parts to the test—an essay and a multiple-choice test. This article reports on the results. On the average, the FIA audience agreed less then when compared to the results of essentially the same test given to other groups.

Essay

For the first part, participants were asked to write down their mutually exclusive definition of rangeland and forest land. Thirty-one people participated in the test. Only 27, however, provided at least one definition. The results are shown in table A-1. Note that in a couple of instances I could not read parts of definitions. These I noted in the table with XXX.

Multiple Choice

Next, the participants were shown a series of 38 images and were asked to classify each image as to if it was forest, rangeland, or other using the definitions they had written. Not everyone answered all the questions. In addition some people provided two answers for some questions. The latter were not counted. The results are shown in table A-2.

Analysis

The participants agreed on classification on the average of 70.8 percent of the time. Even though the audience was fairly homogeneous in background (all inventory specialists and many FIA employees), a great deal of variety exists as to how they look at the land. This is surprising as the U.S. Department of Agriculture Forest Service has a very specific definition of forest land. It is even more surprising when compared to results for essentially the same test given to other groups over the past 2 years (table A-3).

Table A-1.—*Results of Essay—Definitions.*

Participant	In my opinion... Rangeland is...	In my opinion... Forest land is...	Lund's comment
1	Use.	Cover.	Use for range, cover for forest
2	Less than 10 percent stocked.	More than 10 percent stocked.	Cover definition
3	Used for grazing.	FIA definition.	
4	< 10 percent stocked trees.	> 10 percent stocked trees.	Cover definition
5	Areas between/in forested lands that can be used for grazing.	Lands producing forest products.	Use definition
6	Covered by grazing or browsing species with few than five merchantable trees per acre.	Five or more merchantable size trees per acre and/or covered by regeneration with potential to become merchantable trees.	Cover for range, use for forest
8	This concept is not well known in Europe. My question is how rangeland is divided into forest land, other wooded land, and on the other into forest land and grassland on the basis of IPCC definitions.	I would follow Timber Boreal Forest Resources Assessment 2000 definition or Finnish National definition.	Land use for forest
9	None.	10 percent canopy cover of tree, w/ potential for tree establishment.	Potential or use
10	None.	Covered by a certain amount of trees (crown cover).	Cover class
11	Not forest, but has significant evidence of browsing by domesticated animals.	10 percent cover, has a forest understory or the potential to develop one (usually due to wild animals), not used for anything other than forestry, at least one acre or 120-foot strip.	Use class
12	Land, not defined as forest land, that has vegetation used for grazing XXX. Be good to use 'grassland' vs. rangeland so get away from use definition.	Land =/> 10 percent (5, 10, 25 percent?) stocked w/ trees at least 1 acre in size.	Use for range, cover for forest
13	Critters eat it and not enough trees.	Land with enough tree cover—let the user define 'enough.' I use the 10 percent.	Cover class
14	< 10 percent tree cover.	> 10 percent tree cover (need exception to handle certain situations such as clearcuts and recently planted stands).	Cover for range, use for forest
15	Agriculture area.	Depends on the source of the data. For us the definition is linked with XXX XXX (tree crown cover, XXX, width).	Use for range, cover for forest
16	Lands with primarily grass or shrubs and with plants defined as trees as < 25 percent of cover.	Lands with primarily trees, > 25 percent cover.	Cover class
17	An area dominated by grasslands and predominate used for gazing.	An area dominated by tree cover > 20 percent; trees > 2 m tall and > 1 ha in size.	Cover class
18	< 25 percent tree w/ domestic livestock.	25 percent tree cover potential/probable.	Use class
19	Land uses—a place which raises cows; land provides other functions as well but mainly for cow.	There are trees, crown cover of 10 percent on the 0.1-ha size area—management use for forest products.	Use class
20	Rangeland is land inhabited by people trying to eat cows.	Forest land is land inhabited by bears trying to eat people.	Use class (sort of)
21	Barren land that has natural vegetation by no trees.	Tree land.	Cover class

FIA = Forest Inventory and Analysis; IPCC = Intergovernmental Panel on Climate Change.

Table A-1.—*Results of Essay—Definitions (continued).*

Participant	In my opinion... Rangeland is...	Forest land is...	Lund's comment
22	Produces at least a minimal amount of forage, nonagricultural, nonurban, and below a threshold of forest tree stocking.	Land that meets a minimum size and stocking of trees or the immediate potential to achieve stocking of trees.	Use class
24	Land not in below definition (see forest definition) that is grazed.	Wild land stocked more than 50 percent with trees, or more than 10 percent with shrubs.	Use for range, cover for forest
25	Land use or land cover? Land cover: grassland w/ < 10 percent tree. Land use: grazed. What is a tree?	Land cover =/> 10 forest cover. Land use: not grazed.	Both use and cover
26	Not forest, not developed.	"Undisturbed" understory.	Cover class
28	Not forested, having cover of grass or grazeable shrubs.	10 percent cover of trees, any plant with potential to produce a wood product.	Use class
29	A land use where livestock can be grazed.	> 10 percent canopy cover w/tree species; or the potential to achieve this w/o major change in land use.	Use class
30	I'll know it when I see it.	At least 1 acre, 120 feet wide…of trees…	Cover class

Table A-2.—*Results of the classification test. Numbers are the percent of participants classifying the image as forest, range, or other.*

No.	Image	Forest	Range	Other	High	Comment
1	"Jungle"	100	0	0	100	
2	Oasis	31	31	38	38	Issue is if participants considered palms as trees.
3	Tundra	15	37	48	48	Amount of tree cover is issue.
4	Alpine	68	13	19	68	No live trees—so class not based upon cover.
5	Golf course	0	9	91	91	Image shows elk grazing on course.
6	Mature black spruce stand	100	0	0	100	The trees are less than 1 m in height at maturity. By some definitions this should not have been classed as forest.
7	Desert	28	28	44	44	
8	Pinyon-Juniper (P-J)	84	13	3	84	
9	Mesquite	27	53	20	53	
10	Trees with grass	94	3	3	94	
11	Scattered trees with shrubs	12	61	27	61	
12	Scattered trees on peat bog	50	7	43	50	Amount of tree cover is the issue.
13	Trees and shrubs	57	37	6	57	
14	Open stand	69	21	10	69	
15	Coppice site	93	7	0	93	Those calling the area forest assume a land use, not cover. Note in table 1, most participants defined forest in terms of cover.
16	Canyon walls	56	9	36	56	
17	Degraded land	3	3	94	94	
18	Invading leafy spurge	27	60	13	60	Leafy spurge is not native.
19	Invading native juniper	62	31	7	62	
20	Invading houses	0	0	100	100	

Table A-2.—*Results of the classification test. Numbers are the percent of participants classifying the image as forest, range, or other (continued).*

No.	Image	Forest	Range	Other	High	Comment
21	Chained P-J area	29	61	10	61	Those calling the area rangeland assume a land use, not land cover.
22	Recent clearcuts	94	0	6	94	Those calling the area forest assume a land use, not land cover. Note in table one that most participants wrote a cover definition.
23	Older clearcut	91	9	0	91	
24	Pasture	0	70	30	70	Potential is forest
25	Las Vegas	0	0	100	100	
26	Change in water table	24	30	46	46	Trees are dead.
27	Wetland	3	13	84	84	
28	Riparian	52	25	23	52	Strip width is the issue.
29	Highway	0	3	97	97	Width of the highway is the issue.
30	Back road	3	39	58	58	Same.
31	Isolated stand	63	22	15	63	Size of the stand and distance from another stand is the issue.
32	Area between stands	17	53	30	53	
33	Bare area	0	19	81	81	
34	Plowed and sown area	23	16	61	61	Some people must have put down answers after the use of the land was revealed. This is an afforestation project but one could not tell from the image alone.
35	Seeded area	23	47	30	47	
36	Re-establishing native cedar	77	13	10	77	
37	Young plantation	90	0	10	90	
38	National forest	19	44	38	44	
Total		**1,584**	**887**	**1,331**	**2,691**	
Average		41.7	23.3	35.0	70.8	

Table A-3.—*Comparison of FIA results with results from other groups (percent of participants classifying images as forest, range, or other).*

Group	Number of participants	Forest	Range	Other	Average percent agreement
Board of Directors, Society for Range Management 2003	15	23.0	52.0	25.0	80.0
Forest Rangeland Definitions Group 2003	21	30.0	42.0	29.0	72.0
Mapping and Remote Sensing Specialists EROS Data Center 2004	24	28.5	42.9	26.6	75.5
FIA Seventh Annual Symposium 2005	31	41.7	23.3	35.0	70.8

FIA = Forest Inventory and Analysis.

The Society for Range Management, Forest Rangeland Definitions Group, and EROS Data Center folks tended to classify more lands as range while the FIA tended to classify more lands as forest. As noted in table 3, however, on the average there was less agreement within the FIA classifications than there were with the other three groups tested.

As in the earlier tests, while many participants wrote their own definitions, most did not apply them when classifying images. Images 4, 16, 22, and 24 are good examples. These images contained no live trees, but many of the FIA participants who wrote a cover definition, classified the lands as forest anyway.

The bottom line is that it is easy to write a definition, but it is another thing to follow it. National definitions will meet with the same results.

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Society of American Foresters—An Advocacy for Forest Inventory

John W. Moser, Jr.[1]

Abstract.—The Society of American Foresters (SAF) represents all segments of the forestry profession in the United States, including public and private practitioners, researchers, administrators, educators, and students. Its mission is to advance the science, education, technology, and practice of forestry. SAF's science and education program and its policy program have been long-term advocates for forest inventory with a specific focus on the U.S. Department of Agriculture Forest Service's Forest Inventory and Analysis program. This address, delivered at the 2005 FIA Science Symposium, presents and discusses aspects of SAF's advocacy.

It is a pleasure to join you in another exceptional Forest Inventory and Analysis (FIA) Science Symposium. I would like to extend a warm welcome to all, especially to our international colleagues; you are certainly a notable addition to this year's symposium. I am looking forward to your contributions, renewing past acquaintances, and putting faces with names that I only know through your work. At this time of year, there is no better place to be than on the Maine Coast—it is "The Place" for fall forestry meetings. Two weeks ago, the Sustainable Forestry Initiative Annual Conference was here. Next month, the Northeast Mensurationists will meet a few miles up the coast. And, I fondly recall attending the Society of American Foresters' (SAF's) National Convention here several Octobers ago. To commemorate the occasion, Bill Banzhaf and I planted a young oak tree in a park just down the hill to the west of us. I am looking forward to seeing if that tree is alive and well.

The FIA program traces its roots to the 1928 McSweeney-McNary Forest Research Act. Regarding the signing of that bill, articles in the Journal of Forestry stated, "the passage of that bill marked 1928 as a red letter year in the history of forestry for this country"… by establishing … a comprehensive inventory. . . for the renewable resources of the forest (Anon. 1928, Frayer and Furnival 1999). In the spirit of that lofty acclaim, I titled my comments for this symposium "The Society of American Foresters—An Advocacy for Forest Inventory." It just seemed fitting when SAF's present FIA Position Statement proclaims that "the FIA program is the crucial source of information for assessing the sustainability of the Nation's forests." On the chance that you are not acquainted with SAF, I will briefly introduce you. It represents all segments of the forestry profession in the United States, including public and private practitioners, researchers, administrators, educators, and students. Its mission is to advance the science, education, technology, and practice of forestry; to enhance the competency of its members; to establish professional excellence; and to ensure the continued health and use of forest ecosystems to benefit society.

SAF's science, education, and policy programs have been long-term advocates for forest inventory with a specific focus on the U.S. Department of Agriculture Forest Service's FIA program. SAF's membership and the organizations they represent unquestionably believe that a current and accurate forest ecosystem inventory is prerequisite to substantive discussions of sustainability, national forest policy, carbon sequestration, changes in growth and productivity, changes in land use and demographics, ecosystem health, and economic opportunities in the forest industries sector (Van Deusen *et al.* 1999).

I believe that when SAF established the Forest Science and Technology Board and Working Groups in 1971, it forged a substantial advocacy with the FIA program. The goal of this new science structure was to improve SAF's effectiveness in the development, dissemination, and uses of forest sciences.

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It was anticipated that Working Groups would partner with other organizations to form viable and active communities of scientific and professional interest. Starting in 1974, The Forest Inventory Working Group began an immensely successful periodic series of national and international inventory conferences in which the FIA program and other national and international partners had a very large presence. Their first conference, held in Fort Collins, CO, focused on inventory design and analysis. FIA employees—past, present, and some who would ultimately join FIA in leadership roles—were very much in evidence as speakers; George Furnival, Mel Metcalf, Ken Ware, Joe Barnard, and Ed Frayer just to name a few. You may also find it interesting that three other speakers at that conference are speakers at this symposium; while mingling with the group see if you can guess their identities.

The last in that series of forest inventory conferences was titled "Integrated Tools for Natural Resources Inventories in the 21st Century." It was held in Boise, ID, during 1998. Many of you, I am sure, recall participating in that broadly focused inventory conference. The leading cosponsors included SAF, FIA, the International Union of Forest Research Organizations, and a host of other public and private organizations.

It is my opinion that from 1974 to 1998, SAF's Forest Inventory Working Group exceeded all expectations in forming viable and active communities of scientific and professional interest in forest inventory. Lately, however, I have been disappointed that SAF's advocacy of forest inventory conferences has not been as evident as it has been in the past—particularly when I consider the pace at which new scientific and technological methodology is being applied to natural resource inventories, and the increased importance that monitoring of ecosystems contributes to local, national, and international policies.

To the credit of the FIA program, however, it has continued development and dissemination of forest inventory science and technology. They were the major contributor to the three half-day FIA sessions at SAF's 2003 National Convention in Buffalo, NY. The FIA Science Symposia that began in 1999 and is now beginning its seventh consecutive program spotlight evolving science and technology in the FIA program. It has been observed by some that these programs are too FIA concentric. In looking at program content and structure for this and last year's symposia, I do sense a widening of the spheres. Should these symposia be further broadened to fill the void created by the absence of "Boise-type" inventory conferences? The breath and participation in this conference portrays a strong positive indication to me. That begs another question—who should take the lead? I am reluctant to say, Ron, that you and Greg should get on with that task; never mind that it will drastically impact your primary FIA employment responsibilities. Or is there perhaps an opportunity to revitalize the joint the FIA/SAF Inventory Working Group joint conference sponsorships?

In the mission to advance the science, technology, and practice of forestry, SAF's policy staff has been a vigorous advocate for the FIA program by building support and educating Congress and their staff on informational needs to assess the status, trends, and sustainability of this Nation's greatest renewable natural resource—its forests. During the early 1990s SAF members were among high-level leaders representing environmental organizations, industry, professional societies, academia, and State and Federal agencies that met to express concerns that the FIA program was not receiving adequate funding to meet its mission of "maintaining a comprehensive inventory of the status and trends of the country's diverse forest ecosystems, their use, and their health." It was noted that creeping cycle lengths—some as long as 20 years—created uncertainty about our Nation's forest resources.

That group formed the core of the First Blue Ribbon Panel on FIA. They made the following recommendations:

- Implement a uniform approach on all ownerships.
- Increase consistency and compatibility among FIA units.
- Enhance coordination between FIA and public agencies.
- Improve and expand information on ecosystems and noncommodity values.
- Produce the most current resource data possible.

In October 1992, a subset of the Blue Ribbon Panel met with USDA Forest Service Chief Dale Robertson to reach an agreement for implementing the Panel's recommendations in the short-term and within current budgets. Unfortunately, before achieving positive results, Chief Robertson was replaced by Jack Ward Thomas. Again, the Blue Ribbon panel members presented their case for increased funding to the new Chief. Concurrently, other Panel members conducted briefings for key congressional staff with the objective of conveying the national importance of FIA and the overwhelming constituent support for improving the program.

In the year following the release of the First Blue Ribbon Panel's report, the USDA Forest Service published "A Blueprint for Forest Inventory and Analysis Research and Vision for the Future." That report proposed research directions, guiding principles, and goals to advance the program. In spite of sustained efforts, FIA advocacy groups concluded that there had been inadequate progress fulfilling the First Blue Ribbon Panel's recommendations. To illustrate, in 1991 the Federal appropriation for the FIA field program was $14.2 million; in 1997 that appropriation was $14.9 million. In the same interval, the average inventory cycle length increased from 10 to more than 12 years.

In 1998, a second Blue Ribbon Panel representing an even broader constituency convened to assess the FIA programs' progress since 1992. There were some regional successes; however, the Panel concluded that the lack of major program improvement was leading to the loss of ecological and economic benefits to society by hindering our ability to monitor forest health and sustainability. FIA's usefulness was still being threatened due to increased cycle lengths and funding shortfalls. Briefly stated, the Panel made the following key recommendations:

- Elevate the priority of the program within the USDA.
- Initiate annual inventories across all regions and ownerships.
- Fulfill the mandate of reporting on all forest lands.
- Concentrate on core ecological and timber data.
- Develop a strategic plan to carry out the program's mission.

I view 1998 as a turning point for FIA. The Second Blue Ribbon Panel Report signaled an urgent sense of frustration. Panel participants, such as the SAF, the American Forest and Paper Association, and the National Association of State Foresters kicked their advocacy and presence on Capitol Hill up a notch. Discussions with members of Congress regarding the future of FIA provided interesting responses. One member said, "It gives us an accurate picture of the extent and condition of our forests. We must continue to increase it's funding over the next few years to annualize inventories." Another responded, "I think the 'Foreign Intelligence Agency' is truly important; now more than ever." As you can well see, advocacy and education go hand in hand. "FIA" does not have the same connotation to all.

Overwhelming advocacy by the FIA user community, however, led Congress to include legislation in the 1998 Farm Bill, to implement an annual forest inventory and monitoring program that covers all forest lands in a consistent and timely fashion. The passage of that act demonstrated Congress' commitment to an improved FIA program. In response, the USDA Forest Service developed a strategic plan that strongly responded to Congress' intent, and to the recommendations of the Second Blue Ribbon Panel.

In April 1999, a crucial hearing was held in the U. S. House of Representatives' Agriculture Subcommittee on Forestry. The committee chair specified two prime objectives for the hearing:

- Establish FIA as a clear priority for the USDA Forest Service.
- Establish a structure and funding proposal for FIA that would fulfill the Farm Bill's mandate for a national annualized forest inventory.

The five panelists, all members of SAF, representing the State Foresters, industry, academia, and the USDA Forest Service provided strong and convincing testimony for both programmatic and financial support.

The entire December 1999 issue of SAF's flagship publication, *Journal of Forestry*, was devoted to "Forest Inventory and Analysis—Moving to an Annual National System." A "Perspective" in that issue by Bob Goodlatte, Chair of the House of Representatives' Hearing Committee, and Jim Garner, Virginia State Forester, explained that, "The improved FIA is the cornerstone of ecologically and biologically sustainable forest practices in the 21st century. Congress has provided the framework. Willing partners are in place to help with the transition. The future is waiting." (Goodlatte and Garner 1999.)

In February of 2000, the National Association of State Foresters and the USDA Forest Service entered into a Memorandum of Understanding (MOU) to fully implement the less costly alternative FIA program as proposed in the USDA Forest Service's finalized Strategic Plan. This MOU was certainly a step in the right direction as it clearly documented State agency partners' cooperation and commitment toward the realization of the mandate set forth by Congress in 1998.

In December 2000, SAF's Council adopted a Position Statement on FIA. It stated unequivocally that broad consensus indicates that there has never been a greater need for timely, comprehensive, and reliable inventory data on the Nation's public and private forests. Moreover, the lack of full funding for the program is the primary impediment to successful implementation. A reconvening of the Second Blue Ribbon Panel occurred in 2001 to assess progress and make recommendations for moving the program forward. That Panel commended the FIA program for their accomplishments in developing the strategic plan and the implementation of the annualized inventory in 27 states. It was, however, noted that significant lag time occurs between plot data collection and analysis and this postpones data availability to the public. In addition, some States are taking longer than 1 year to measure a panel; this delay could undermine the preeminent purpose of the annual system as envisioned in the 1998 Farm Bill. The Panel unanimously agreed that full funding support by Congress and the Administration is essential to achieving the goals of a national annualized forest inventory.

While there have been no further calls since 2001 to reconvene the Blue Ribbon Panel, constituents still consistently identify funding priorities as a concern. From the enactment of the 1998 Farm Bill through the most recent fiscal year, appropriated funding has increased from $29.8 million in 1999 to $60.9 million in 2005. While not at the envisioned "full funding level," the FIA program has made substantial progress toward the annualized national inventory. Beginning in 1998, FIA raised the program's accountability with the publication of a "Fiscal Year Business Report" that clearly documents program changes, significant contributions, funding sources, expenditures, and long-term strategic directions. Those reports are clearly an asset in advocating program support.

When I reflect on the evolution of the FIA program over my professional career, I have to look no further than in my own backyard. Indiana's first FIA inventory was completed in 1950. When I arrived in Indiana in 1964 we were anxiously awaiting the first remeasurement, which occurred in 1967. The second remeasurement interval was a bit longer, taking place in 1986. When the third remeasurement occurred in 1998, we were getting close to the national average cycle length. But I refer to the next remeasurement benchmark as a "Blue Ribbon Panel Year." It was 2003 and we had just completed the fifth panel in our 20 percent annualized FIA inventory. And to top that off, this morning Chris Woodall gave me a copy of "Indiana's Forests 1999–2003", one of the first 5-year state reports from the new annualized FIA. This "issues-driven" approach defines a new paradigm for the future of FIA reporting. It can only add to the legacy of a program with the responsibility to census this Nation's forests.

Earlier, I cited Goodlatte and Garner's perspective for FIA: "The future is waiting." I believe that we are getting close.

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Tree Communities of Lowland Warm-Temperate Old-Growth and Neighboring Shelterbelt Forests in the Shikoku Region of Southwestern Japan

Shigeo Kuramoto[1], Shigenori Oshioka[2], Takahisa Hirayama[2], Kaori Sato[3], and Yasumasa Hirata[4]

Abstract.—We characterized the tree species composition of a 30 ha old-growth and neighboring shelterbelt (reserved buffer strips among conifer plantations) in warm-temperate forests in the Shikoku region of southwestern Japan. Using a two-way indicator species analysis of data from 28 plots, we identified four structural groups in terms of relative basal area. These structural groups were interior and edge types of a greater than 30 ha old-growth, middle-sized (5- to 15-ha) shelterbelt type, and small-sized shelterbelt (less than 5 ha) type, respectively. Canonical correspondence analysis also showed differentiation of the four structural types along edge-interior gradient and remnant-size gradient.

Introduction

Warm-temperate old-growth forests in southwestern Japan, especially in lowland areas, were often converted into coniferous plantations, farmland, and other land uses (Ito *et al.* 2003, Miyawaki 1982, Nakagawa and Ito 1997). Only a few large old-growth remnant forests remain. Most natural forests remnants are shelterbelts that reserve buffer strips among conifer plantations or clear-cut areas. Natural forests remnants are important to forest restoration and maintaining biodiversity. First, they preserve many plants and animals. Second, they potentially contribute vegetation recovery as seed sources for adjacent clear-cut or thinned area of plantation forests (Ito *et al.* 2003; Sakai *et al.* 2006). The capacity for maintaining species diversity is strongly influenced by the size and shape of the forest, which many former studies reported as *fragmentation effects* and *edge effects.* (Murcia 1995). Many studies reported the effects of edges facing open sites, such as clear-cut and agricultural lands. The actual role of natural forest adjacent to conifer plantations as the seed source, however, has been little studied (Ito *et al.* 2003). Tree community structure of natural forest remnants is important as an indicator of the edge effects of forest remnants themselves, as well as a determinant of the role of seed source. In this study, we focused on the species composition of trees in natural forest remnants adjacent to conifer plantations in relation to the size of the remnant and other landscape and site environmental attributes.

Study Area and Methods

Study Area

The field survey was conducted in Asizuri peninsula, located on Shikoku Island in southwestern Japan (133 °E, 32 °N). The area is situated in a lowland (approximately 20 to 400 m above sea level), warm-temperate region where the natural vegetation is evergreen broadleaved forest dominated by *Fagaceae*, *Lauraceae*, and *Camelliaceae* species (Miyawaki 1982). Annual mean temperature and precipitation is 17.9 °C and 2,421 mm, respectively.

In the approximate center of peninsula, a wide (greater than 30 ha) undisturbed old-growth forest remains,

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surrounded by conifer plantations consisting of Japanese cedar (*Cryptomeria japonica* D. Don.; Japanese cypress (*Chamaecyparis obutusa* Sieb. et Zucc.), or their mixture; secondary evergreen broadleaved forests; and farmlands. Approximately 20 ha of undisturbed old-growth forest was reserved as the national Sadayama Forest Reserve (SFR) (Kochi National Forest Office 1995). Among compartments of plantations surrounding a wide old-growth forest, including the FSR, reserved buffer strips of evergreen broadleaved forests known as shelterbelts remained. Most conifer plantations were formed in the 1960s and 1970s in the Ashizuri area. Hence, edge formation mainly occurred 30 to 40 years ago.

Tree Census

We settled eight transects in interior and five onsets of plots in the edge of the SFR representing the tree community structure of large-sized old-growth forests in the region. These were designated LOG. We also settled 10 plots in seven randomly selected shelterbelts of different landscape and site environmental attributes representing the tree community structure of shelterbelts. The selected shelterbelts differed in area size from 1.9 to 15 ha. The altitude of all plots ranged from 240 to 340 m above sea level with the exception of two shelterbelts that were approximately 50 m above sea level.

The interior transects of the SFR were 10- m wide and 100-m long rectangles placed in the center part of the reserve more than 60 m from the forest edge to avoid the edge effect (Murcia 1995), and arranged parallel with each other along the topographic gradient from the hilltop to the valley to represent microtopography-mediated variation in species composition of trees (Enoki 2003, Kuramoto and Okuda 2005, Sakai *et al.* 1996). The edge plots of the SFR were placed at five randomly selected points on three edge lines of different direction. Three were places on the South-facing edge line adjoining conifer plantations, while one each was place on the West-facing and North-facing lines.... In each point of edge plots, two 10- by 20-m plots (subplots) were continuously placed along the line from the SFR border toward 20 m inside.

In the case of shelterbelt plots, we set up a 20-m^2 plot in each narrow shelterbelt less than 20-m wide (less than 5 ha) because it covered the entire part of shelterbelt and represented its community structure of trees. In wider shelterbelts, such as those greater than 5 ha, we set up two 20-m^2 plots, placed in the center and near the edge line of the shelterbelt, respectively.

In each plots in the LOG and neighboring shelterbelts, all living trees more than 5-cm diameter at breast height (d.b.h.) were recorded with identification of species and d.b.h. measurement.

Data Analyses

The relative basal area of each tree species was calculated for tree census data of each plot. We used each of the eight interior transects in the LOG and each of the ten plots in shelterbelts as one plot data in following analyses. For five onsets of plots in the edge of the LOG, we separately used each of two plots in a point in the following analyses because the extent of edge effect in warm-temperate forest edge is little known. Hence, we used 28 plots of data (8 of interior transects and 10 edge plots in the LOG, and 10 plots in shelterbelts, as reflecting the area size of the forest) in analyses. Two-way indicator species analysis (TWINSPAN) (Hill 1979) was used to classify the tree communities of LOG and shelterbelts, using PC-ORD (McCune and Mefford 1999). To explore the site environmental and landscape attributes relating tree community structure, canonical correspondence analysis (CCA) was done using CANOCO version 4.02 (ter Braak and Smilauer 1999). Site environmental and landscape attributes considered in the analysis—such as stand age (SAG), altitude (ALT), inclination (STE), area size (PAS), width and length of forest (WD and LEN), edge age (EAG), distance from the edge (DFE), and distance from large remnant forest (DFL)—were estimated for each forest from inventory maps of national forest, field observations, and Geographic Information System data (Y. Hirata [unpublished]).

Results

Classification of Tree Community

In 28 plots surveyed, 60 tree species were recorded. In all the plots, *Castanopsis sieboldii* was dominant. Based on TWINSPAN, four structural groups (G1–G4) were recognized. Each division of groups corresponded with remnant-size difference, interior-edge contrast, and altitudal contrast of plots (fig. 1). For example, the first division corresponded with remnant-size contrast in which small-sized remnants (Group4; shelterbelts less than 5 ha) were separated from others. Within small-sized remnants, those located in exceptionally low altitude (Group4B) were separated from others (Group4A) in the next division. In the other side of first division, middle-sized remnants (Group3; 5- to 15-ha shelterbelts) were separated from the large-sized remnant (LOG). Furthermore, the large-sized remnant (LOG) was divided into interior and edge types (Group1 and Group2, respectively). Of edge plots in the LOG, inside plots of onset of plots (10 to 20 m away from the border) were included in interior type (Group1). The division of the four groups, including two subgroups, and principal tree species were follows (table 1):

- Group 1. Interior of LOG. *Quercus acuta, Machilus thunbergii* were dominant next to *C. sieboldii*.
- Group 2. Edge of LOG. Instead of *C. sieboldii*, *Q. acuta* was dominant. This group was characterized by the abundance of *Cinnamonum japonicum* and *Neolitsea sericea* with the decrease of species that were abundant in the interior.
- Group 3. Mid-sized shelterbelt. *C. sieboldii* represented more than 50 percent of tree species. This group was characterized by sparseness of LOG species from the interior and edge, and occurrence of *Diospyros morrisiana* and *Rapanaea nerrifolia*.
- Group 4. Small-sized shelterbelt. Without *C. sieboldii,* this group had no dominant species. This group was characterized by high species richness and the occurrence of *Daphniphyllum teijsmanii*, *Q. phyliaeoides*, and deciduous species.

Figure 1.—*TWINSPAN dendrogram of 28 plots in a greater than 30 ha old-growth forest and neighboring shelterbelts. Eigenvalues and indicator species with contribution scores in parentheses for each division are shown. Letters in the terminal boxes of the dendrogram represent a structural group of tree communities.*

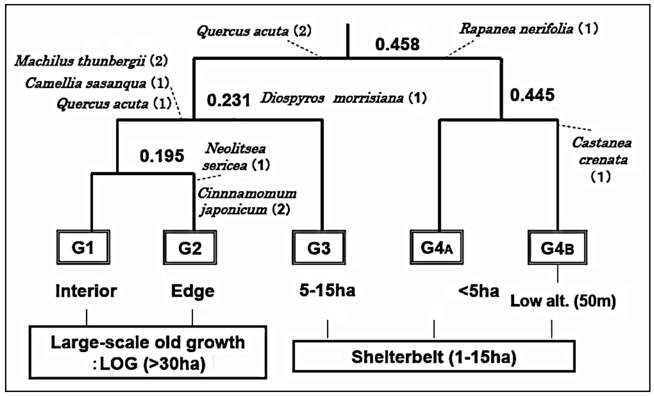


Table 1.—*Vegetation groups classified by TWINSPAN and relative basal area of tree species for each group.*

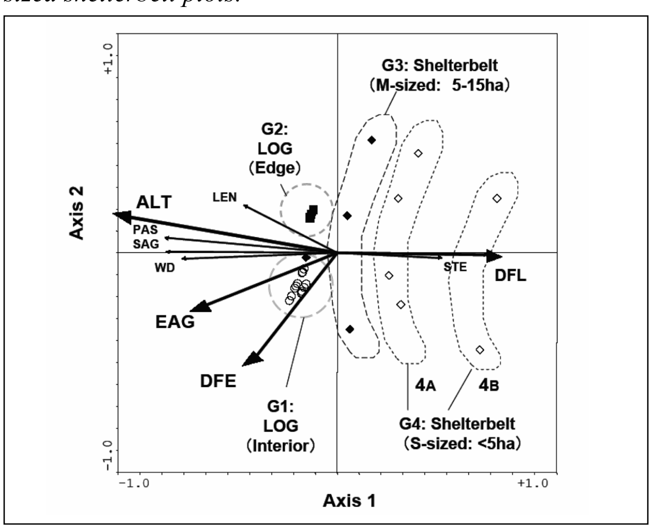
Group	G1	G2	G3	G4	Total
No. of plots	14	4	4	6	28
No. of species	26	23	22	36	60
Dominant among all type					
Castanopsis sieboldii 1	31.1	17.7	58.3	21.9	31.0
Interior (LOG) species					
Quercus acuta 1	27.1	27.3	3.5	0.1	20.0
Machilus thunbergii 2	11.5	9.1	1.2	2.7	8.7
Others (4 species)	12.6	1.0	0.2	0.3	8.4
Edge (LOG) species					
Camellia japonica 3	5.5	7.9	3.0	1.4	4.7
Cinnamonum japonicum 2	2.2	20.4	0.3	0.1	2.8
Others (2 species)	0.0	9.6	0.9	0.6	0.8
Shelterbelt species					
*Chamaecyparis obtusa**	–	–	26.9	18.0	5.8
Daphniphyllum teijsmanii	–	0.5	–	5.9	1.1
Prunus jamasakura	–	–	–	4.0	0.7
Quercus philyaeoides 1	–	–	–	3.0	0.6
Castanea crenata 1	–	–	–	2.0	0.4
Diospyros morrisiana	–	–	1.3	1.4	0.4
Rapanaea nerrifolia	–	–	–	1.2	0.2
Others (3 species)	–	–	1.1	2.8	0.6
Others (3 species)	5.7	1.2	0.9	4.2	4.7
total	95.7	94.7	97.5	69.7	91.1

1: Fagaceae, 2: Lauraceae, 3: Camelliaceae, *: planted conifer
Underlined species are "Indicator species" of TWINSPAN
Values are percent basal area

Ordination: Environmental Attributes and Tree Communities

In CCA ordination, the first three axes explained 67.3 percent of species-environment relations. The first axis, with a correlation of 0.977 between species and environmental factors, explained 32.2 percent of the total variation and 15.1 percent of species variation. The second axis showed a 0.853 correlation between species and environmental factors, and explained 22.4 percent of the total variation and 10.5 percent of species variation. In the ordination diagram (fig. 2), each structural group of four TWINSPAN classifications was separated along two axes. Along the first axis, LOG groups (G1and G2) were separated from shelterbelt groups (G3 and G4). In LOG groups, interior group (G1) was separated from edge group (G2) along the second axis. On both of two axes, distance from the edge (DFE) and edge age (EAG) showed the first and second highest *t*-value, respectively. Stand age (SAG), area size (PAS), and altitude (ALT) also showed high *t*-value on the second axis.

Figure 2.—*CCA ordination diagram with correlation vectors of environmental and landscape variables showing the ordination scores of 33 plots in a greater than 30 ha old-growth forest and neighboring shelterbelts. Size of arrow and letter of each correlation vector represent intensity of contribution. Enclosed aggregations of plots show each structural group of tree community classified by TWINSPAN. Open circle, solid square, solid diamond, and open diamond show interior of old-growth forest, edge of old-growth forest, mid-sized shelterbelt plots, and small-sized shelterbelt plots.*



CCA = canonical correspondence analysis.

Discussions

Effects of Remnant Size on Tree Communities

Studies have reported that species richness changes with patch size of warm-temperate broadleaved forests (Hattori and Ishida 2000) and tropical rainforests (Laurance *et al*. 1998). In these studies, positive correlation of species richness to area size of forests was detected. In our results, however, the number of tree species was not significantly different between old-growth forest and shelterbelts, with the exception of a 1.5 times higher number in small shelterbelts, in our results. Fukamachi *et al.* (1996) reported the negative relationship between patch size and tree species richness per unit area basis in cool-temperate regions of Japan. Large patches include higher microtopographic and elevational variation (Fukamachi *et al.* 1996, Hattori and Ishida 2000). Change of tree species composition in large forest patches was basically influenced by microtopography and elevation, although the change was gradual. Infrequent species, which contribute to species richness, were actually rare on the basis of each unit's area. If the total area was considered, species richness might be increased. Furthermore, the effects of area size of forests on plant species diversity may be different among strata and life forms as well as forest types.

Most former studies focused on species richness, while detailed change of species was given less attention. Our results documented the drastic change of species of trees from LOG to shelterbelts along with patch-size gradient. In tropical rainforests, which have extra-high species richness, forest fragmentation resulted increase of tree mortality (Laurance *et al.* 1998), indicating that in smaller patches tree mortality was higher. A marked increase in wind-induced tree mortality in edges with decreased area of fragments was reported in a boreal conifer forest (Esseen 1994). Most shelterbelts were situated along the ridge. Our data suggested that tree mortality was higher in shelterbelts.

Species richness was also correlated with tree density (Fukamachi *et al.* 1996). In small-sized shelterbelts (G4), tree density was 3 times that in interior of LOG plots (G1), and 1.5 times that in edge of LOG plots (G2) and mid-sized shelterbelts (G3) (Kuramoto and Okuda 2005). Mean d.b.h. of trees decreased from large patches to smaller patches in the plots we surveyed. In conifer plantations, breakage of canopy closure caused by thinning or selective cutting induced an increase of light availability and density of understory trees (Kiyono 1990, Suzuki *et al*. 2005). Kiyono (1990) pointed out that deciduous tree species only could establish themselves after cutting events such as thinning, while evergreen tree species could establish themselves even under closed canopy in conifer plantations. Therefore, it was implied that species richness increased in shelterbelts by accelerated establishment of deciduous broadleaved tree species and light-demanding evergreen tree species, compensating for the decrease of old-growth evergreen species induced by edge effect.

Impact of Edge Formation on Principal Canopy Tree Species and Their Response

Several evergreen broadleaved tree species that are common in interior LOG plots apparently decreased in edge of LOG plots and shelterbelts in our results. Of principal species in LOG plots, response to forest fragmentation and edge formation were different among species. *C. sieboldii* was dominant throughout different size of remnants, while *Q. acuta* and *M. thunbergii* were almost extinct in shelterbelts. Sprouting ability, photoinhibition, and potential distribution were suggested as reasons for these different responses. *C. sieboldii* was dominant in the lower part of the warm-temperate forest zone, compared with *Q. acuta,* which was dominant in the upper part. *M. thunbergii* was mainly distributed in the upper slope of LOG plots, where large-sized trees were grown. Most shelterbelts were positioned on the ridge, which suggested low suitability as a growth site for *M. thunbergii*. When the size of forest remnants was small, the edge effect was strong and the impact of direct cutting probably increased. Sprouting ability is important because it compensates for high mortality and other impacts of cutting. *C. sieboldii* had superior sprouting ability (Miura and Yamamoto 2003) over other LOG species. Rapid increase of light availability in shelterbelts and edge plots may cause photoinhibition of shade-tolerant species (Kitao *et al.* 2000). Tree species that occurred in shelterbelts were quite infrequent in LOG. Many of these species were deciduous broadleaved species, which required the light increase by the canopy opening of adjacent part and reserved belts, as reported of understory development in conifer plantations (Kiyono 1990, Suzuki *et al*. 2005). Evergreen broadleaved species typical in shelterbelts, such as *D. teijsmanii*, *D. morrisiana*, and *R. nerrifolia*, were supposed to be as light demanding as deciduous trees. These species seldom grow over 20 or 30 m high. In shelterbelts, low canopy height induced by high wind stress and low nutrient and water availability, enabled these species not to be suppressed by other canopy tree species.

These facts implied that the function of shelterbelts as the seed source to adjacent conifer plantations were potentially different from LOG at the point of species composition, although species richness was not so different.

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Development of a National Forest Inventory for Carbon Accounting Purposes in New Zealand's Planted Kyoto Forests

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Abstract.—This article discusses the development of a monitoring system to estimate carbon sequestration in New Zealand's planted Kyoto forests, those forests that have been planted since January 1, 1990, on land that previously did not contain forest. The system must meet the Intergovernmental Panel on Climate Change good practice guidance and must be seen to be unbiased, transparent, and verifiable. At the same time, the system should meet a wider set of objectives for international forest reporting and forest health. The core of the system is to be a network of some 400 permanent sample points, established objectively on a 4- by 4-km grid coincident with an area of Kyoto forest. Each sample point is a cluster of four 0.04-ha circular plots installed in a design similar to that employed in the United States Forest Inventory and Analysis program. Sufficient data are collected at each point to enable the carbon density in each of the required reporting pools to be calculated or modelled. At a subset of points, integrated with an existing system implemented on an 8-km square grid over New Zealand's indigenous forest and shrubland, assessments of soil carbon and plant biodiversity are made. The intention is that the inventory will have a 3-year measurement cycle, with one-third of the points remeasured each year.

Introduction

New Zealand is committed to estimate greenhouse gas (GHG) emissions by sources and removals by sinks for reporting to the Conference of Parties of the United Nations Framework Convention on Climate Change. In accordance with Article 3.3 of the Kyoto Protocol, New Zealand has agreed to report, in a transparent and verifiable manner, GHG emissions by sources and removals by sinks associated with direct human-induced land use change and forestry activities, limited to afforestation, reforestation, and deforestation since 1990. Net carbon stock changes on land subject to afforestation (A), reforestation (R), and deforestation (D) must be estimated each year over the defined commitment period, the first of which is from January 1, 2008, to December 31, 2012, from information on land area (ha) and its corresponding carbon density (tC/ha) for each of five carbon pools.

Large-scale plantings of introduced tree species in New Zealand commenced in the 1920s. As of April 2004, the total area of exotic plantations in New Zealand was 1.82 million ha (MAF 2005). In addition, New Zealand contains approximately 6.25 million hectares of indigenous forests (i.e., natural forests containing tree species that are either indigenous or endemic to New Zealand) and 2.65 million hectares of shrublands, containing both indigenous and exotic species. Radiata pine (*Pinus radiata*) is the most common plantation species, with approximately 89 percent of the total plantation area comprised of this species. Other plantation species include Douglas fir (*Pseudotsuga menziesii*) and eucalypts (*Eucalyptus* spp.). A significant

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proportion of these exotic forests were planted since January 1, 1990, on land that previously did not contain forest. These forests are referred to as Kyoto-compliant forests. Between 1990 and 2004, it is estimated that approximately 600,000 ha of such forests have been established (MAF 2005).

New Zealand does not currently have a plot-based national forest inventory covering all of its forests. A plot-based system covering the indigenous forest and shrubland is in the fourth year of a 5-year implementation program. Information on the area and the amount of growing stock in exotic plantations by age class, species, and region is compiled in the National Exotic Forest Description (NEFD). The data presented in the NEFD are obtained from surveys that are sent out annually to owners and managers of larger forests (at least 1,000 ha in size), or biennially to owners and managers whose forests are between 40 and 999 ha. The response rate for these surveys is generally very high. For example, in the 2003 NEFD some 1,400 survey forms were mailed out to all owners of forests at least 40 ha in size; a 90 percent response rate was received, with a 99 percent response for owners with more than 1,000 ha. (MAF 2005). Since 1992, new planting that is not captured by these surveys of forest owners has been imputed from nursery surveys. Forest nurseries provide accurate estimates of the number of planting stock sold. Using assumed stocking rates and a number of other factors (e.g., restocking, blanking, and field wastage) the area of new forest planting is calculated. The total area of afforestation that has been imputed using data from nursery surveys is estimated to be around 180,000 ha.

The data that are provided to the NEFD by large owners are considered to be very reliable. The data provided by many smaller owners or managers are of unknown quality, however, and, in general, their net stocked areas are thought to be overestimated. Much of the Kyoto-compliant afforestation that has occurred since 1990 is thought to have been carried out by these small-scale owners and may not be well represented by the NEFD. Therefore, to provide the necessary data to allow carbon stocks and stock changes to be estimated in accordance with the recently adopted good practice guidance for Land Use, Land-Use Change and Forestry (IPCC 2003), a means to inventory forests specifically designed for carbon monitoring is required.

This article will outline the development of New Zealand's proposed approach for an inventory of its planted Kyoto forests and describes some of the experiences gained from a pilot study that was conducted in the Nelson and Marlborough regions of the South Island.

Estimation of Forest Area

To meet its requirements under the United Nations Framework Convention on Climate Change and the Kyoto Protocol, New Zealand must determine the area of forest land. Under the Marrakesh Accords, countries must choose a definition of forest land from a predefined range of parameters describing minimum area, crown cover, and height at maturity *in situ*. New Zealand has provisionally adopted the following thresholds for the definition of forest land: a minimum area of 1 ha, crown cover of 30 percent, and a potential height *in situ* of 5 m. The exact approach for determining the area of Kyoto forest land is still to be finalized; however it is likely to be complete coverage mapping based on remote imagery, most probably acquired from satellites with some high-resolution aerial imagery. The recently completed Land Cover Database 2 (LCDB2) is based on a complete national coverage of Landsat 7 Enhanced Thematic Mapper Plus satellite imagery and has a target spatial resolution of 1 ha. It is recognised that the use of satellite imagery to determine the area of forest land is not without its problems, particularly in detecting changes in the area of forest land to a high degree of precision. It is envisaged that high-spatial resolution aerial photography will be used to provide past land use detail that is not provided by existing satellite imagery. For future land use and land use change mapping, high-spatial resolution satellite imagery may also be used.

Development of a Plot-Based Inventory System

At the national scale, New Zealand's woody vegetation can be thought of as being stratified into the following classes:

1. Indigenous high forest.
2. Shrubland (or other wooded land [OWL]).
3. Pre-Kyoto exotic forest.
4. Kyoto-compliant exotic forest.

The forest inventory approach adopted by the New Zealand Carbon Accounting System is to use a national grid-based network of permanent plots to provide a statistically valid, unbiased estimate of carbon stored in planted forests. Currently, a network of plots is being installed on an 8- by 8-km grid in indigenous forests and shrublands (Coomes *et al.* 2002, Payton *et al.* 2004). For Kyoto-compliant forests, a set of nested grids, coincident with the 8-km grid used to sample carbon stocks and plant biodiversity in indigenous forests and in shrublands, are placed over forests. This design is simple and robust to changes over time, permitting more complex statistical sampling designs and analyses to be imposed over the basic sample frame in the future, when necessary.

There are three proposed phases to the data collection.

Phase 1. Information on stand age, stocking, and management regime (e.g., thinning, pruning, forest health) is obtained for sample points on a 2-km grid[7] across the planted forest estate. This information is used (1) to determine the proportion of the planted forests that comply with the Kyoto Protocol definitions, and (2) for double sampling with regression estimation to improve the precision of estimates of carbon.

Phase 2. Data to estimate carbon stocks and forest health are obtained from sample points on a 4-km grid[7].

Phase 3. Additional soil carbon and plant biodiversity data are collected from sample points on an 8-km grid[7] (i.e., at approximately one-quarter of the phase 2 sample points). Protocols for soil carbon measurement are described in Davis *et al.* (2004), while those for assessing plant biodiversity are described in Payton *et al.* (2004).

Data in phase 1 of the system are collected via discussions with landowners or forestry consultants, while data in phases 2 and 3 are collected through a network of fixed-area plots. To minimize costs, it is proposed to visit only those points that have a high probability of sampling Kyoto forest.

Size of the Plot Network

The location of sample sites in planted Kyoto-compliant forests is determined by placing a 4- by 4-km grid over those LCDB2 classes thought to have a high likelihood of containing such forest (additional verification is done using recent fine-scale aerial photography). Assuming that the area of Kyoto-compliant post-1990 afforestation is 640,000 ha[8] (MAF 2005), then a 4- by 4-km grid is expected to yield on average 400 intersections (sample points). A subset of 100 of these points will be on the 8-km grid that is coincident with that used for the Indigenous Forest and Shrublands Carbon Monitoring System (Payton *et al.* 2004).

Using existing data from research monitoring plots, Goulding (2003) estimated that the coefficient of variation for stem volume in first rotation stands planted since 1990 (i.e., maximum age of 13) was 50 percent. By the end of the Kyoto Protocol Commitment Period 1 (CP1) trees planted since 1990 will range in age from 1 year up to 22.5 years and Goulding (2003) estimated that for stands aged between 4 and 23 years the coefficient of variation for stem volume increases to approximately 65 percent. Using these data and the assumption that the coefficient of variation for total carbon stocks is similar to that for stem volume, a network of 400 sites would produce an estimate of carbon stocks

[7] Nested grids that are coincident with the 8-km grid used to sample carbon stocks and plant biodiversity in indigenous forests and in shrublands.

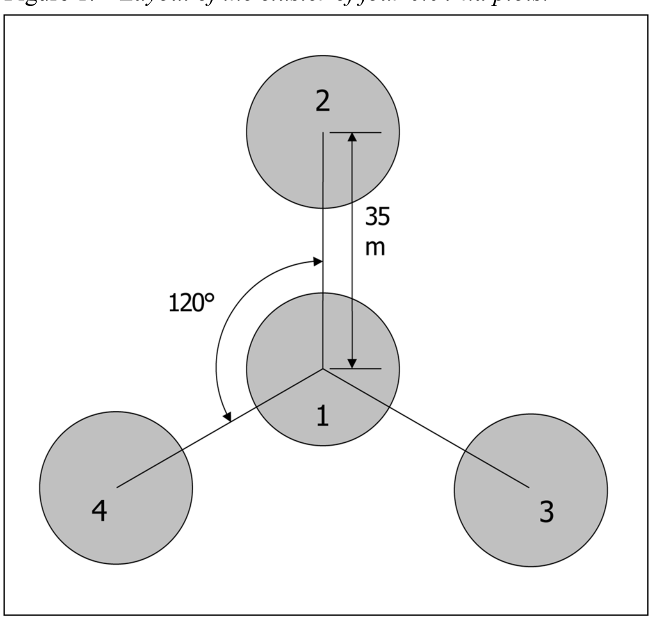
[8] The total area of post-1990 afforestation is approximately 670,000 ha; however, a proportion of this will not be Kyoto compliant as it occurred on land that already contained at least 30 percent canopy cover of a species capable of reaching 5 m in height.

that has probable limits of error (the ratio of the 95 percent confidence interval to the mean) of approximately 6 to 7 percent. Because these plots will be permanent, estimates of the change in carbon stocks over time will have a greater degree of precision associated with them than if they were computed from independent sets of temporary plots.

Plot Design

Much of the work that led to the final choice of plot design is described by Moore *et al.* (2004a), who examined the effect of plot size on the variability of the estimates of standing volume and carbon stocks as well as the within-site and between-site variation in these quantities. It was found that increasing the plot area above 0.04 ha did not further decrease between-plot variance, while that variance was unrelated to distance between plots within a stand over the range of distances examined (48 to 118 m). As a consequence of the study, it was recommended that each sample point consists of a cluster of four 0.04-ha circular subplots. The central subplot would be coincident with the intersection of the sample point; the centres of three other subplots located 35 m away and arranged at 120 degrees apart (fig. 1). This arrangement is similar to that adopted by the United States Forest Inventory and Analysis (FIA) (Bechtold *et al.* 2005, Scott 1993). The choice of 35 m as the separation distance between subplots was based on the need to increase the likelihood of obtaining differences in carbon density between subplots within a cluster, while at the same time trying to minimise the likelihood that subplots fall outside the target population.

Figure 1.—*Layout of the cluster of four 0.04-ha plots.*

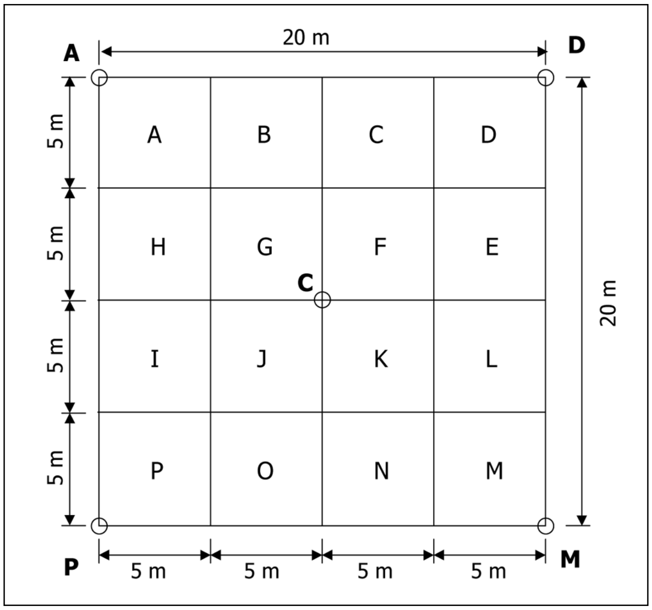


In New Zealand, many of the Kyoto-compliant forests are small (< 50 ha) and, therefore, it is likely that a number of subplots will straddle the boundary between planted forest and adjacent nonforest land-cover classes. Unlike the case of a single plot that straddles multiple conditions (where techniques such as the "mirage method" can be used to correct for the part of the plot which falls outside the target population), it is not possible to rotate subplots into a single uniform condition (i.e., planted forest) as this will generate a bias by altering the selection probabilities of trees, especially those near the edge (Williams *et al.* 1996).

To overcome this problem, New Zealand will adopt the same approach recommended for the FIA (Hahn *et al.* 1995, Scott *et al.* 1995). When a subplot straddles two or more conditions, field crews record the two azimuths where the condition-class boundary crosses the subplot perimeter. This is called the "fixed-radius, mapped plot" design. The plot level estimators (e.g., basal area, volume, stand density) are computed on the basis of the revised plot area and procedures for estimating means and variances are given in Van Deusen (2004).

For those sites that lie on the 8-km grid (i.e., phase 3), an additional 20-m square plot is installed at the center of the cluster for the purposes of recording plant species composition (plant biodiversity) by height tier. The plot is subdivided into 16 5- by 5-m subplots (fig. 2), with 24- by 0.75-m^2 circular subplots established to measure understory/seedling vegetation. The emphasis is on ensuring that biodiversity data collected from planted forest stands are compatible with equivalent data sets obtained from the inventory of indigenous forests and shrublands (Payton *et al.* 2004).

Figure 2.—*Layout of the 0.04-ha (20- by 20-m) square plot used for plant biodiversity measurement.*



Vegetation Measurements

The key purpose of the inventory is to collect sufficient information to allow the average carbon density (i.e., tonnes of carbon per hectare) of New Zealand's Kyoto-compliant planted forests to be estimated. The good practice guidance for Land Use, Land-Use Change and Forestry inventories (IPCC 2003) recognises five carbon pools that need to be reported on: (1) above-ground live, (2) below-ground live, (3) dead wood, (4) litter, and (5) soil. In the current New Zealand Carbon Accounting System, pools (1) and (3) are estimated directly from field measurements, while the remaining three pools are modelled. Soil modelling (pool 5) requires soil data collected from a proportion of the plots. The approach for measuring pools (1) and (3) is briefly described in the following section.

For measurement purposes the above-ground live carbon pool is subdivided into four subpools. These are assessed using either height and diameter measurements (trees and tree ferns, saplings and seedlings) or height and cover measurements (shrubs, ground cover).

- Trees are defined as woody stems > 25 mm diameter at breast height (d.b.h.) (1.4 m).
- Saplings are woody stems > 1.4 m tall, but < 25 mm d.b.h.
- Seedlings are woody stems < 1.4 m tall.
- Shrubs are plants > 0.3 m high that lack the monopodial form typical of trees, saplings, and seedlings. For the purpose of estimating carbon they may be woody (e.g., gorse) or nonwoody (e.g., pampas).
- Ground cover refers to vegetation (woody or nonwoody) < 0.3 m high.

The d.b.h. of each standing tree on the plot is measured and its bearing and horizontal distance from the plot center recorded. A subsample of up to 16 trees per species spanning the range of d.b.h. values is selected for measurement of total height, green crown height, and pruned height.

Dead wood includes standing and fallen dead stems, thinned trees, broken tops, stumps, etc., (including remnants of previous land covers) that have a diameter ≥ 10 cm. In intensively managed plantations, most dead wood originates from thinning operations. Therefore, the dead wood is assessed using the same protocols as for standing trees, but with a suitable allowance made for decay. Immediately following an operation, particularly one in which the felled trees are not extracted but left *in situ* (i.e., precommercial thinning or "thinning to waste"), the amount of dead wood may be substantial, but this decays rapidly.

Remeasurement Frequency

The growth rates of New Zealand's exotic forests are often higher than those for forests in areas such as the United States and Scandinavia, as is the intensity of management. (In New Zealand there can be up to three green-branch pruning lifts and two thinning operations before a stand is 10 years old.) Therefore, it is proposed that the remeasurement interval should be 3 years. (Note: the current standard remeasurement interval for permanent sample plots in New Zealand is 1 to 3 years.) If the interval is longer, changes to stand structure and levels of growing stock could be significant and difficult to estimate.

It is proposed that the system be an annualised inventory (Van Deusen *et al.* 1999), with one-third of plots measured each year. Under the annual approach some new data are available each year. It will be important for New Zealand to have current data on a regular basis to assess its national carbon balance leading up to and during CP1. In addition, the continuity of work should make it easier to retain experienced people and reduce the need to recruit and train new people, and the costs of conducting the inventory will be spread over the measurement cycle.

During the first year of implementation of the inventory, estimates of carbon stocks will only be able to be estimated from the current year's measurements. In subsequent years, however, data will be available from multiple years. While the simplest way to calculate annual estimates of carbon stocks is to use only the data from those plots measured in the current year, their precision will be lower because of the reduced sample size (i.e., only one-third of plots are measured in any one year). The approach for producing estimates of carbon stocks and stock changes using data from multiple years has not been decided on. It is likely, however, that New Zealand will use an imputation approach with appropriate growth models used to update information from plots measured in previous years.

Testing of the Approach in a Pilot Study

A pilot study was carried out within the Marlborough, Nelson, and Tasman Districts of the South Island to address many of the issues relating to estimation of the carbon pools and fluxes in Kyoto-compliant planted forest lands, and to make recommendations for a national inventory based on precision, cost, and effort (Moore *et al.* 2005). A total of 32 sites were sampled in August and September 2004—23 on the 4-km grid (phase 2), and 9 on the 8-km grid (phase 3), which is also used for the inventory of indigenous forests and shrublands. At each site a standard series of measurements was made as described in the relevant field manual. From these measurements, the amount of carbon (t/ha) in pools (1) through (4) was predicted for each plot using the C_Change model (Beets *et al.* 1999), and for pools (1), (2), and (3) using a series of allometric equations in order to provide a comparison with values from the model. The change in carbon stocks in pools (1) through (4) during the first Commitment Period of the Kyoto Protocol was also predicted using a combination of the C_Change model and appropriate growth models.

Results

In general, field teams had little difficulty with the measurement protocols. Some problems arose, however, with the measurement of coarse woody debris and the assessment of crown transparency. There were also some issues with the identification of forest land from LCDB2, with 4 of the 32 sites actually occurring on nonforest land (mainly pasture). Because the planted Kyoto forest estate consisted of many small blocks that were dispersed, plots that straddled boundary conditions were reasonably common; this straddling occurred at 14 of the 32 sites.

Both methods of calculating carbon stocks, the allometric and modelling approaches, produced similar estimates of the amount of carbon in the various pools, indicating that the carbon calculation protocols are robust. These estimates were specific to the region over which the pilot study was conducted and should not be considered representative of all Kyoto-compliant forests in New Zealand. Analysis of sampling precision for the pilot supported earlier suggestions that the carbon stock could be estimated nationally using this design to within ± 7 percent of the mean.

From data collected on plant biodiversity, it was found that radiata pine stands contained an average of 25 ± 2.5 (n = 23) plant species per plot, with no suggestion of differences between Kyoto-compliant and non-Kyoto-compliant stands. Forty percent of the plant species in the radiata pine plots were New Zealand natives. As with the overall plant species diversity, native plant biodiversity varied widely between the radiata pine stands that were sampled (0 to 78 percent) and did not appear related to stand type.

As a result of the pilot study a number of refinements have been made to the field procedures, but the basic design of the inventory is unchanged. The national implementation of the inventory was due to commence in winter 2005, which would have permitted a full cycle of measurement to be completed before the start of the first Kyoto Protocol Commitment Period in 2008. A number of issues over access to private land, however, have delayed the national implementation. If these issues can be overcome before December 2006, then plots will be established over a 2-year time span, but will be remeasured on a 3-year cycle. If access to private land is not forthcoming, then the inventory may have to be redesigned to allow estimates of carbon stocks to be obtained from airborne remote sensing (e.g., high-resolution laser image detection and ranging coupled with color infrared aerial photography).

Discussion and Conclusions

The New Zealand Carbon Accounting System has been designed to provide national estimates at a "reasonable" level of precision compared to cost. Sampling on a 4-km square grid across Kyoto compliant forests should result in some 400 sample sites. Employing clusters of 4- by 0.04-ha plots should result in an estimate of the national Kyoto compliant forest carbon stock per hectare to within ± 7 percent. Indications are that an estimate of the change in stocks over the commitment period may be obtained with more precise confidence limits, given that it will be derived from remeasurements of permanent sample plots (Moore *et al.* 2004b). It is also a very "basic" design that can stand alone or be used to provide information for more complex inventory methods that may answer specific questions. It has the potential sometime in the future to be statistically integrated with remotely sensed images in a combined system that will provide more detailed, spatially explicit information or results at a subnational or regional level more precisely than from plots alone. While the design of the inventory itself is relatively simple, the statistical techniques required to analyse the data, particularly determining the precision of carbon estimates, are more complex. To obtain estimates of the carbon stocks and change with their variances, analysis of the data has to account for clusters of mapped plots, missing plots, rolling estimators/imputation, and the use of double sampling with regression estimators. It is therefore important that New Zealand maintains strong links with scientists in other countries who are involved with national forest inventories, particularly those in the United States due to the similarities in the systems, to keep abreast of advances in methodological and analytical approaches.

The system also has the potential to contribute to a range of national and international reporting requirements should the measurement procedures be extended beyond the minimum set required to estimate carbon stock. These include internationally derived requirements associated with sustainable forest management (e.g., New Zealand is a participant in the Montreal Process) and conservation of biological diversity (e.g., the Convention on Biological Diversity). Within New Zealand, the system could contribute data for the National Exotic Forest Description, Ministry of Agriculture and Forestry, and for Environmental Performance Indicators, Ministry for the Environment.

It is anticipated that over time the plot-based inventory will be extended to all planted forests, which will provide the data to enable full carbon accounting of all forest lands

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Current and Emerging Operational Uses of Remote Sensing in Swedish Forestry

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Abstract.—Satellite remote sensing is being used operationally by Swedish authorities in applications involving, for example, change detection of clear felled areas, use of *k*-Nearest Neighbour estimates of forest parameters, and post-stratification (in combination with National Forest Inventory plots). For forest management planning of estates, aerial photointerpretation in combination with stand-wise field surveys is used. Automated analysis of digital aerial photos is a promising technique for tree species classification; laser scanning is being applied to assess tree height, stem volume, and tree size distribution; and low-frequency radar is being used for stem volume estimation. Obtaining timely photos of single stands from small unmanned aircraft is also an increasingly realistic option.

Introduction

Sweden has 22.9 million ha of forest land, which is managed for the production of timber and pulpwood. Half of this area is owned by a few large companies and the other half is divided into more than 200,000 private estates. Information about this forest resource is needed at three levels: (1) the authorities need overviews that encompass all forest owners; (2) the individual forest owners need more detailed information for management planning of each estate; and (3) timely information is needed about individual stands where cuttings are planned or have just been carried out. New remote sensing methods are now being introduced and tested at all of these three levels. The aim of this article is to provide an overview of this recent development in Sweden in the field of remote-sensing-aided forest resource assessment. Because much of the forestry related remote sensing research in Sweden is done at the Remote Sensing Laboratory at the Swedish University of Agricultural Sciences (SLU), a second aim is also to provide an overview of the lab's recent relevant research and to provide references to studies where more details about each topic can be found.

Satellite-Data-Aided National Forest Monitoring

Moderate resolution optical satellite imagery from Landsat or SPOT has been operationally utilized by both the Swedish Forest Agency and the Swedish National Forest Inventory (NFI) during recent years. Since 1999, the Forest Agency has annually obtained satellite images for all forest land in Sweden. The primary application is for verification of cutting permits; since 2003, cut areas have also been delineated. This verification is done by the local foresters at about 100 district offices, using tailormade Geographic Information System and image processing applications created by the Forest Agency and the Swedish National Land Survey. The change detection is based on relative calibrated imagery using forest pixel values as a spectral reference. In support of this application, the SPOT satellites have been programmed to cover all of Sweden annually during recent summers. As a side benefit, the resulting image database is useful for many other applications, such as estimates of forest parameters by combining image data with NFI sample plots.

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The Swedish NFI

The NFI design is based on an annual systematic sample of field plots across Sweden (Ranneby *et al.* 1987, Ståhl 2004). The aim is to allow reliable summary statistics for 31 counties or parts of counties, using 5-year averages of field plot data. Plots are located in square-shaped clusters that consist of either 6 or 12 temporary plots of 7-m radius or 8 permanent plots of 10-m radius. In total, about 5,300 permanent and 3,500 temporary plots are inventoried across Sweden every year. Permanent plots are reinventoried every 5 to 10 years. The plots have been positioned with the Global Positioning System since 1996, which further enables their use in combination with satellite image pixels.

The Munin Production Line

An automated production line has been developed for combining NFI plot data with Landsat satellite data. In a first step, the NFI plots are used for preprocessing of the satellite data. The local geometrical errors between the satellite data and each field plot are modeled and the most likely pixel values given this modeling are selected (Hagner and Reese [in press]). Furthermore, the correspondence between NFI plot data and the image data is also used for parameterization of a slope correction and for reducing haze differences within the individual satellite scenes (Hagner and Olsson 2004).

The first use of the Munin production line was for a nationwide classification of forest land into seven different forest classes. This work was done by SLU from 2002 to 2003 under contract with the Swedish National Land Survey and it was used as input to national and European land cover databases. In total, 50 Landsat Enhanced Thematic Mapper Plus (ETM+) scenes and 34,000 NFI plots were used. The forest classification was based on "calibrated" maximum likelihood algorithm which made use of prior probabilities. The classification of each Landsat scene was iterated until the frequency for each forest class corresponded to the frequency according to the NFI plots within the scene (Hagner and Reese [in press]).

The *k*-NN Product

The Landsat ETM+ images and the NFI plots used for the previously mentioned land cover classification were also used in production of a nationwide forest parameter database using a version of the Finnish *k*-Nearest Neighbors (*k*-NN) method (Reese *et al.* 2003, Tomppo 1993). The first "*k*-NN Sweden" database was produced with images from around 2000, and is available as a raster product with estimates of total stem volume, stem volume for different tree species, stand age, and mean tree height for each pixel. Estimates were made for all pixels defined as forestland according to the 1:100 000 topographic map. With the production line in place, generating such a database for all forest land in Sweden takes about 1 man-year including all data handling and quality checking. There is also a version of the *k*-NN product that has been generalized, using a segmentation software developed in house (Hagner 1990) to represent approximate stands.

While the pixel-level accuracy for the *k*-NN product can be quite poor, the accuracy for aggregated areas is still acceptable for many applications. Typically, the estimation accuracy for stem volume is on the order of 60 percent at pixel level, 40 percent at stand level, and 15 percent when aggregated over a 100-ha area (Fazakas *et al.* 1999, Reese *et al.* 2002, Reese *et al.* 2003). Because the relationship between optical satellite data and stem volume is poor for closed canopies, the *k*-NN product underestimates stands with high volume. In addition, standing volume in sparse areas or young forest may be overestimated.

The *k*-nn database has been used by forest authorities, environmental authorities, and the tax agency to obtain an overview of forest resources for large areas (Nilsson *et al.* 2004). It is also used in many research projects, such as species habitat modeling, as a baseline for landscape scenarios, and together with change images for analysis of storm-damaged areas. During 2006, a new version of the nationwide *k*-nn database, using SPOT images from the summer of 2005, is being produced.

Post-Stratification of NFI Estimates

Post-stratification of NFI plot estimates is presently being introduced as an operational routine. Tests show that the standard errors for estimates of total stem volume; stem volume for pine, spruce, and deciduous trees; as well as tree biomass can be reduced by 10 to 30 percent at a county level by using post-stratification based on Landsat ETM+ products compared to only using field data for the estimation (Nilsson *et al.* 2003, Nilsson *et al*. 2005). Post-stratification has proven to be a straightforward and efficient method for combining satellite data and NFI data. Most problems that might lead to biased estimates are avoided, which might not be the case using other methods.

Forest Management Planning Using Airborne Sensors

In Sweden, the forest management planning of estates is the responsibility of the land owner. In this section, remote sensing techniques that could provide stand-wise estimates useful for planning purposes are discussed. Estimation results for the most important variable, stem volume, are also summarized in table 1.

Optical satellite data with 5- to 30-m resolution pixels have been used operationally for updating of stand boundaries and could also be used for other tasks such as locating stands where shrub cleaning is needed, provided that a smooth supply of data is available. Satellite data, however, are generally not considered accurate enough for capturing basic data necessary for forest management planning. Instead, various combinations of aerial photointerpretation and field work have been used. Traditionally, the photos have been used mainly for defining homogeneous stands; however, especially for large forest holdings, photogrammetric instruments have been used as well, for measurements of tree heights and manually aided estimation of stem volumes. Aerial photography is the only terrestrial remote sensing data source in Sweden that is regularly acquired with government subsidies. During recent years, scanned digital orthophotos have become the most widely used data source for everyday work in the forest sector. In 2004, the Swedish National Land Survey acquired a Z/I Digital Mapping Camera. The experiences so far has been that the radiometric quality of these images is much better than that of scanned aerial photos.

Automated Interpretation of Aerial Photos

In our research with automated interpretation of aerial photos, we have implemented a version of the template matching method developed by Richard Pollock in Canada (Pollock 1996). This method is based on the generation of synthetic tree templates that are rendered with the appropriate illumination and view angle for each position in the image. The template trees are then compared with potential trees in the image using correlation techniques. Using template matching, studies carried out in a coniferous forest area in southern Sweden, approximately two-thirds of the trees could be found and positioned (Erikson and Olofsson 2005, Olofsson 2002). By using the digital photo pixel values associated with trees detected by template matching, we have, in early tests, separated tree species for spruce, pine, and deciduous trees for 90 percent of all detected trees (Olofsson *et al.* 2006).

Table 1.—*Stem volume estimation accuracies on stand level for different remote sensing sensors, validated at the same test site; all estimates except the photogrammetric measurements are made with regression techniques.*

Sensor or sensors used	References	RMSE (%)
SPOT HRVIR, SPOT HRG, or Landsat ETM+ satellite data	Fransson *et al.* 2004; Magnusson and Fransson 2005a.	23–31
Interpretation of aerial photos in photogrammetric instrument	Magnusson and Fransson 2005b.	18–24
CARABAS VHF SAR	Magnusson and Fransson 2004.	19
Combination of CARABAS and SPOT HRVIR	Magnusson and Fransson 2004.	16
Laser scanner	Fransson *et al.* 2004.	12

Laser Scanning

Since 1991, the Remote Sensing Lab has conducted work using laser scanning for forests (Nilsson 1996), often in cooperation with the Swedish Defense Research Agency (FOI). Two main methods for forest inventory based on laser scanning have emerged. Using low posting density laser data (on the order of one laser pulse per m^2), statistical relationships between field plot measurements and laser data features such as height percentiles can be established and then applied to all laser measured forest. This method has provided stem volume estimates with about 10 to 15 percent root mean square error (RMSE) (Næsset *et al.* 2004, Holmgren 2004). The commercial application of laser measurements for forest inventory has been pioneered in Norway. The first operational-scale test in Sweden was done in 2003 when a 5,000-ha area was laser surveyed (Holmgren and Jonsson 2004). The RMSE on stand level was 14 percent for stem volume, 5 percent for tree height, and 9 percent for mean diameter.

The other main approach is to laser scan densely enough to obtain many laser pulses per tree to detect single trees, which requires a density on the order of five pulses per m^2 or more. Today such data is primarily obtained in research mode using helicopter, but technical developments allowing very-high-density laser scanner data from fixed wing aircrafts is a realistic option for future operational surveys. One contribution to this development is the emerging Focal Plane Array technology that enables many sensor elements to record the return from each emitted laser pulse (Steinvall 2003). In one study of a coniferous dominated forest in Sweden, by using high-density laser scanner data it was possible to locate more than 70 percent of the trees that represented more than 90 percent of the stem volume; tree height and canopy diameter were also automatically measured, both with a precision of 0.6 m (Persson *et al*. 2002). Using features derived from laser data belonging to automatically detected tree canopies, we have also been able to discriminate spruce from pine with an accuracy of 95 percent (Holmgren and Persson 2004). Current work includes the combination of laser data and optical image data for improved tree species determination. The Remote Sensing Lab is also working with estimation of stem diameter distribution using dense laser scanner data (Holmgren and Wallerman 2006) and with laser-data-aided segmentation.

Airborne Low-Frequency Radar

FOI and Ericsson Microwave Systems have developed CARABAS, which is a unique low-frequency synthetic aperture radar (SAR) system (Hellsten *et al.* 1996). At present only one system is available but the development of civilian systems is being discussed. Because CARABAS operates with 3- to 15-m long radar waves in the VHF band, the radar signal penetrates the forest canopy and is reflected predominantly from the interaction between ground and tree stems. A long series of CARABAS research studies in Sweden shows the potential of VHF SAR for stem volume assessment in boreal forests. Typically the RMSE for stand level assessment of stem volume is about 20 percent. In contrast to optical imagery, no signal saturation for high stem volumes has been found for Swedish forests (e.g., Fransson *et al.* 2000). Optical satellite data is, however, better correlated with stem volume up to about 100 m^3 per ha than CARABAS data. Subsequently, the best estimation results have been obtained by combining the data sources, where satellite data is weighted more for low volumes and CARABAS data more for high volumes (table 1).

It has also been shown that wind-thrown trees often provide a stronger radar return and a different texture than standing trees, and that they often can even be detected under a canopy of remaining standing trees (Fransson *et al*. 2002, Ulander *et al*. 2005). At present a CARABAS survey is being carried out for a 15,000 km^2 storm damaged area in southern Sweden to detect remaining storm-felled trees that could contribute to increased insect populations.

Mapping of Single Forest Stands Using Unmanned Airborne Vehicles

The Swedish forests are managed with a clear felling after about 100 years. The large forest companies make special prefelling inventories to create a database that could be used to select and cut the right type of stands at any given time, according to industry needs. Today these timber inventories are entirely field based and there is a need to find remote-sensing-aided methods. In addition, after final felling, there is a need to survey the area for regeneration planning and also for documenting nature conservation actions. There is also a need to follow up the regeneration of young forest and determine the areas and timing for precommercial cleaning cuttings. The common requirement for all of these applications is a need to, at a given point in time, survey specific stands that are scattered through the landscape. In Sweden today, photographs of new clear felled areas are often taken from small aircraft, using medium format digital cameras. A future time- and cost-effective alternative could be to use small unmanned airborne vehicles (UAVs) with cameras and/or other sensors that are operated by the foresters themselves on location. Members of our group have experimented with the development of UAVs and, after a series of tests, have arrived at a model with a wing span of about 1.2 m and a weight of about 800 g. It is driven by an electric motor and can take a payload of more than 500 g. Using a standard digital camera, it is possible to take a series of 5-cm pixel photographs from an altitude of about 150 m, which can be block triangulated and corrected to map projection.

Discussion

The operational use of satellite data in Sweden has provided new opportunities for forest authorities and researchers alike. The boundaries and date of final cuttings are now well documented and the new regeneration of forests could be efficiently monitored. The combination of NFI plot data and satellite remote sensing data has provided the first nationwide map database of forest resources. Furthermore, post-stratification has provided the possibility to produce reliable statistics for smaller areas than the NFI plots alone can provide. The largest problem for the continuation of these developments is the lack of firm international long-term planning for the supply of suitable satellite data. Many of the systems that could replace the present Landsat generation only have scenes with sizes in the order of 60 by 60 km, which are more problematic to use because they encompass far fewer NFI sample plots than the Landsat scenes; furthermore, they often lack a mid infrared band, which is important for forestry. Fortunately, the United States has now made a commitment to develop a Landsat 8, but similar commitments are also needed in Europe.

In Sweden the more detailed inventories needed for forest management planning are carried out at an individual estate level and are so far seldom coordinated with neighboring properties. This is in contrast to the situation in Norway and Finland where government subsidies are used to ensure more coordinated forest mapping. Since aerial photos are the only data source acquired by a government plan, there are in reality no other data options for the small forest owners who manage half of the forest land in Sweden. The possibility of working with high-quality photos from digital surveying cameras, which could be interpreted in the new user friendly digital photogrammetric work stations, as well as the emerging possibilities to automatically interpret aerial photos, opens up new possibilities. The large forest companies that manage millions of hectares could also consider other remote sensing methods. For them, laser scanning appears to be an attractive add on to the aerial photos. For large areas, the cost of acquiring laser scanner data is on the order of 15 percent of the cost for the final forest management plan. In the boreal coniferous forest, laser scanner data will provide better stem volume estimates and equally good tree height estimates as today's field-based methods. The field plots needed for training the laser scanner data could be used also for planning on a strategic level. Laser scanner data could also aid in automated stand boundary delineation. With future high-density laser scanner data, it will also be possible to estimate within stand stem diameter distributions and, in combination with digital air photos, it will also be possible to obtain information about tree species distributions.

The possibility to detect storm-felled trees with the CARABAS SAR is interesting, especially because the sensor is not dependent on weather or sun illumination, and is mounted on a jet plane. An operational scenario could be to survey areas with high stem volume and high risk for storm damage using CARABAS approximately every 5 years. These images could be used to enhance the stem volume estimates in databases based on optical satellite data. This combined estimate might be of sufficient quality to make it useful also for the private forest owner. The main motivation for such a regular survey, however, would be to have an early reference with radar data that could be used in change detection when new images acquired directly after a major storm should be analyzed. Because storm-felled trees will give higher radar response and ordinary cuttings and removing of trees will give a lower response, the two types of changes will not be mixed up in the radar data, which might be the case with optical data.

For timely mapping of single stands, the use of small UAVs could provide a breakthrough. Such UAVs driven by electric motors are already widely used by the military and the technology will most likely spread to civilian applications. There are no expensive or classified components needed to construct a UAV that can carry a digital camera. The main obstacle so far has been air traffic regulations, but, at least in Europe, guidelines and procedures for integrating small UAVs in civilian airspace will soon be established. Civilian professional use of small UAVs is already permitted in some countries, such as the UK and Finland, and will most likely be in others.

Even with the straight-forward, simple, and realistic approaches to remote sensing of forests discussed here, it can be concluded that we are currently in a rapid development in which new sensors and platforms, such as digital cameras, laser, radar, and UAVs, as well as a sound and realistic combination of the satellite technology and field data, provide new possibilities that will improve the supply of data about our forests. Beyond that, many new developments not discussed in this paper will provide additional possibilities over the coming 25 years. Examples include the use of time series data and data assimilation techniques; automated interpretation of high-resolution optical data using learning techniques; new laser scanner technology with very dense posting; ground based laser scanners that will be easy to handle and provide data that can be integrated with airborne measurements; feedback of data from harvester machines to similar stands according to remote sensing; and sensors onboard permanent high-altitude UAVs. One major conclusion is, however, that government policy plays a key role regarding which technically feasible data capture options will, in the end, be economically and practically feasible. This statement is valid regarding the supply of satellite data, for policies for airborne data acquisition as well as for permissions to fly UAVs.

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Austrian National Forest Inventory: Caught in the Past and Heading Toward the Future

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Abstract.—The Austrian National Forest Inventory (AFI) started in 1961 on a temporary plot design with a systematic grid and a period of 10 years. For the first 30 years it was conducted as a continuous forest inventory. Since 1981 a permanent plot system has been used and the assessment period was reduced. Only slight changes in the plot design have occurred since the beginning of the inventory. During the past 45 years AFI changed from a survey of forest area, growing stock, and increment to a complex monitoring system covering many aspects of the forest ecosystem. Up to now the assessments have been restricted to the forest area but in the future AFI could be extended to become a landscape monitoring system. An ongoing project uses satellite imagery from Landsat with a *k*-Nearest-Neighbour technique over all of Austria aiming at maps and estimates with higher accuracy for small regions.

Introduction

The Austrian National Forest Inventory (AFI) is carried out by the Federal Research and Training Center for Forests, Natural Hazards, and Landscape (BFW), which until 2005 was a subordinated institution of the Ministry for Agriculture, Forests, Environment, and Water Management. In the meantime its legal status was changed and BFW has become a body of public right, which is similar to a limited liability company. AFI is a binding mandate and embodied in the Austrian forest law, including the right to assess data periodically in every forest in Austria. No legally binding time schedule for the assessment periods exists. Therefore, each assessment cycle is the outcome of negotiations with the ministry. Austria has about 8.4 million ha of total land and about 3.9 million ha of forest land.

AFI provides comprehensive and basic data for forest management on country, provincial, and subprovincial levels. It is used as a tool for forest policy decisionmaking and forest administration, as a database for scientific forest studies, and a source of information for the wood industry. During the last decade, more and more international reporting systems require AFI information. The smallest spatial units for which results are provided are identical with the smallest forest administrative units, from 10,000 ha to 250,000 ha in size. The statistical features of the results for the small units are rather weak.

Statistical Design

In the 1950s when the AFI system was established, Scandinavian forest inventories already existed for more than 30 years (fig. 1). Therefore, some of the approaches of the third Swedish forest inventory were adopted by the AFI. The sources of the first local forest inventories in Europe date from much earlier, however.

Back to the Roots

The oldest document found by the authors dates back to 1459 (Trubrig 1896), which describes the mandate to a forest survey done by horse-riding foresters aiming at a very rough estimation of harvestable growing stock. In the course of centuries the survey methods were improved. The aim of these so called “Waldbeschaue” (e.g., Anon. 1674, Braun 1974) was the estimation of growing stock and the potential for harvest including the efforts to be taken (Braun 1974). The reasons

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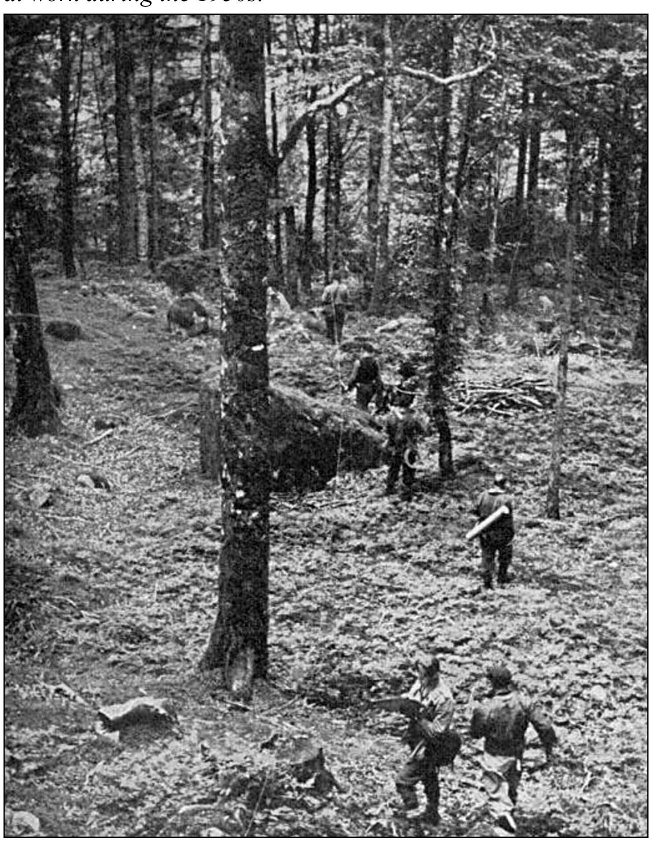
were the increasing wood demands for mining and salt industry. The assessment teams also were instructed to look for what they called forest damages, meaning illegal logging at that time. In the middle of the 18th century the concept of sustainable use of forest resources was developed (Baader 1933). The latest developments are now documented in the Ministerial Conference on the Protection of Forests in Europe (MCPFE) and the Montreal Process. So the aims for developing forest inventories did not change so much during the past 500 years.

The Scandinavian forest inventories started their work in the 1920s with a strip sampling concept (e.g., Heske 1926, Simak 1951). Due to the prevailing topographic conditions and higher variability of growth conditions in Austria, the responsible authorities were obliged to conduct special surveys to find the most adequate layout for the inventory in Austria. These included tract grid density, sample plot sizes, stand and site characteristics, the selection of a nationwide basal area factor

Figure 1.—*Field crew of the Swedish National Forest Inventory at work during the 1950s.*



for Bitterlich's angle count method, as well as sample tree characteristics to be used as input parameter for new volume and form factor functions.

The idea of a systematic grid of sample plots goes back to Zetzsche (Schmidt 1891) and was already applied in practice at the end of the 19th century. The idea to use a systematic grid of clusters (so-called tracts) also in a large-scale inventory stems from Hagberg (1955) and was field tested in the mid-1950s. It was adopted by several national forest inventories.

Actual Design

The AFI uses the following approach (Gabler and Schadauer 2006):

- Nationwide uniform survey criteria and manuals.
- Systematic grid of tracts on the whole federal territory.
- Several sample plots per tract (satellite sample).
- Determined sample plot (300-m^2 circular area) to identify area data.
- Bitterlich's angle count method.
- Line survey (landscape diversity and forest roads).
- Flexibility and creativity for the methodical treatment of ecological issues and special surveys.
- Volume determination of single trees through measurement to identify growing stock, increment, and harvesting.
- Evaluation of results through ratio estimation.
- Indication of a standard error for the individual average value (estimation value).
- Up-to-date measurement equipment.
- Computer-aided data capture and evaluation.

Only a small part of the total area of Austria (0.008 percent) is used for sampling by AFI. The results of the assessment are evaluated (scaled up to the selected geographical level such as the federal territory or the provinces). The average assessment values are indicated with their standard errors.

The survey and assessment unit is the tract consisting of four circular plots 300 m^2, each which are arranged at the corners of a square with 200 m of side length (fig. 2). The side lengths of this square are located in north-south and east-west directions.

The tracts are systematically distributed over the whole federal territory and the number of tracts is about 5,600. This implies about 11,000 sample plot on forest land.

Each sample plot of a tract is subdivided into two concentric circular plots. The small rigid sample circle with a radius of 2.60 m is used for the assessment of trees with a diameter at breast height (d.b.h.) between 50 and 104 mm. Sample trees with a d.b.h. larger than 104 mm are selected according to the Bittlerlich angle count method and the basal area factor 4. The relascope is installed at the centre of the circular sample plot of 300 m^2.

The whole sample circle with an area of 300 m^2 is used to identify the forested area and its structures. These sample plots can be further subdivided. If there is a district, estate, or ownership borderline crossing the sample plot, the plot is subdivided into parts of tenths. If the sample plot is divided by a forest edge, it is subdivided into tenths between forest and nonforest. This division is applied also if other reasons exist for subdivision to be applied only on forested areas. They can both be site related and stand related.

The land cover type *forest* is defined as follows:

- Areas stocked with wooden plants and shrubs.
- Forested areas temporarily unstocked due to harvesting.
- Permanently unstocked areas provided they are in direct relationship with a forest (e.g., forest logging area, timber yards).

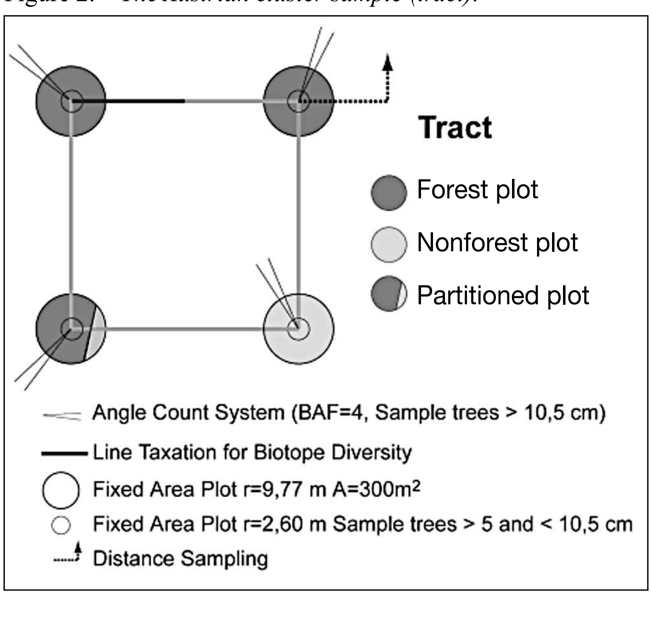
The cover type must fulfil the following criteria:

- Minimum canopy density: 3 parts of tenths.
- Minimum surface: 500 m^2.
- Minimum width: 10 m.

The criteria of minimum surface area must meet an additional test. A sample plot of a tract is only 300 m^2. As the minimum area is 500 m^2 the survey team must look over the borders of the fixed circular plot and consider also the stand characteristics beyond the 300 m^2 circular plot for the evaluation.

Volume estimates are obtained by applying tree measurements (d.b.h., height, upper diameter) from about 80,000 sample trees to tree volume equations. Volume data are gross volume of the stem over bark including stump and top. Dead standing trees (snags) are not excluded from volume estimates. Tree height and upper diameters are measured on a subsample of the 80,000 sample trees. To get the corresponding tree heights and upper diameters for all sample trees, data models are used (Gschwantner and Schadauer 2004).

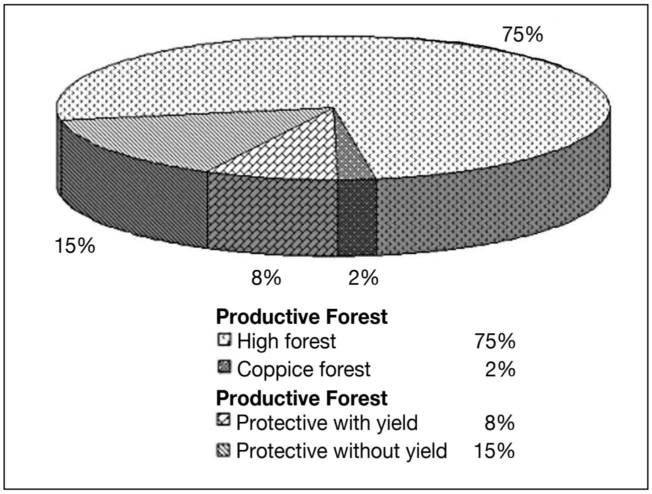
Figure 2.—*The Austrian cluster sample (tract).*



Short Overview of the Austrian Forest Land

The Austrian forest land is mainly owned by farmers with a forest area smaller than 200 ha (54 percent of total forest area); only 16 percent of the forest area belongs to the Republic of Austria. The forest area reaches from 100 to 1,800 m above sea level and has a medium slope of about 40 percent. Eighty percent of the forest area is covered by coniferous species, mainly Norway spruce (*Picea abies*); the dominant broadleaf species is beech (*Fagus sylvatica*). The Alps dominate the ecological conditions and split the area into relatively small-scaled units of homogeneous conditions leading to a forest picture with high spatial variability. Approximately 80 percent of the forest area is used primarily for timber production (fig. 3). One-fifth has a mainly protective function including 4 percent of the total forest land which is not accessible due to extreme topographic conditions. The forest cover in the Alps has a very important

Figure 3.—*Management types of forest use.*



function for the maintenance of fresh water resources and soil quality. Main risks relevant for the Austrian Alpine region are avalanches and torrents.

Challenging Tasks for AFI

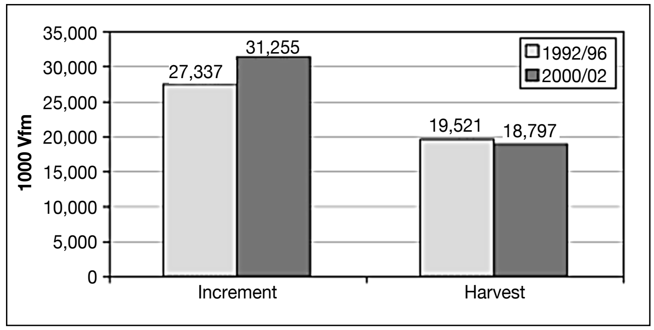
Sustainable Forest Management

Since the first set of Pan-European Indicators for Sustainable Forest Management was developed in the early 1990s, experience has shown that criteria and indicators are a very important tool for European forest policy. Indicators include forest area, growing stock, increment and fellings, forest under management plans, tree species composition, dead wood, etc. (MCPFE 2003).

Data for these indicators are assessed and supplied by the AFI. The increment and fellings indicator highlights the sustainability of timber production over time as well as the current availability and the potential for future availability of timber. For long-term sustainability, the average annual fellings must not exceed the average net annual increment. For example, figure 4 shows that the sustainability concerning that indicator is satisfactory for Austria.

The result for each criterion and indicator is given by the Republic of Austria (2005).

Figure 4.—*Information to Indicator 3.1 "Increment and Fellings" based on the evaluation of the inventory periods 1992–96 and 2000–02.*



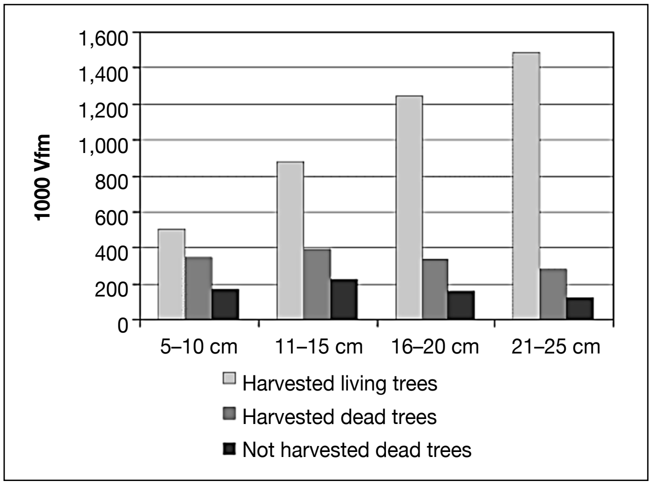
Biomass for Energy Production

Biomass used to produce electricity and thermal energy is increasingly needed. The estimated additional sum for the next two years is about 4 million cubic meters per year; the total annual amount of harvest according to the 2000–02 AFI is 19 million cubic meters. Special assessments and evaluation of the AFI show that there is a huge amount of so called "thinning backlog" available in the forest (17 million cubic meters), which could partly be used for energy production. But according to the actual prices the harvesting of small dimensions is not profitable. An evaluation of mortality and felling per year according to d.b.h. classes can be found in figure 5, falling into three categories: harvested living trees, harvested dead standing trees, and not harvested dead trees. The figure indicates clearly that the total amount of harvested living trees for the lowest d.b.h. classes is less than the volume of dead trees.

Climate and Growth

The AFI has collected permanent sample plot data from 1981 to 2002. Five years after establishment the plots were remeasured in the years 1986–90 for the first time. The consecutive remeasurements took place during 1992–96 and 2000–02. From these measurements 17 increment periods (1981–86, 1982–87, …, 1995–2001, 1995–2002, 1996–2002) can be derived. With this sample plot data a logarithmic basal area increment model was developed according to Monserud and Sterba (1996), who describe the basal area increment as a function of tree size, competition, and site variables:

Figure 5.—*Fellings and mortality for small d.b.h. classes according to a special evaluation of AFI 2000–02.*



AFI = Austrian National Forest Inventory; d.b.h. = diameter at breast height.

$$\ln(BAI) = a + b * SIZE + c * COMP + d * SITE \quad (1)$$

where:
BAI = the basal area increment.
a = the intercept.
b = the vector of coefficients for tree size variables.
c = the vector of coefficients for competition variables.
d = the vector of coefficients of site variables.

To estimate the growth trend in basal area increment, Gschwantner (2006) included dummy variables coding for the 17 increment periods *INT* in the basal area increment model according to Monserud and Sterba (1996):

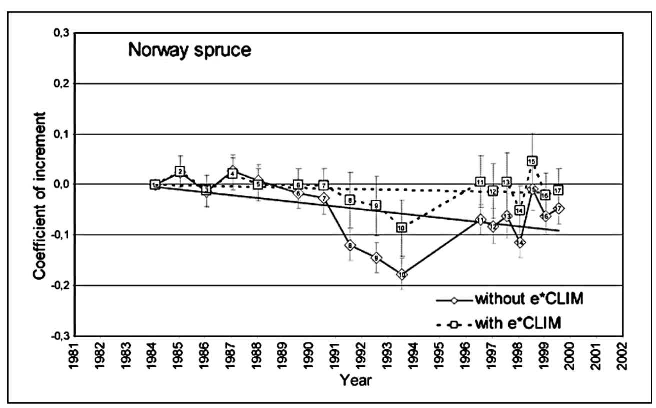
$$\ln(BAI) = a + b * SIZE + c * COMP + d * SITE + f * INT \quad (2)$$

The coefficients *f* describe the variation of basal area increment between the 17 increment periods *INT*. Linear regression was applied to estimate the trend in basal area increment from the coefficients *f*. In a further step, Gschwantner (2006) evaluated the role of climate as a cause of the variation in basal area increment between the 17 increment periods. A point version of DAYMET adapted by Petritsch (2002) for Austrian conditions provided climate variables (temperature and precipitation) for each sample plot. These temperature and precipitation values were converted following Kublin *et al.* (1988) into climate parameters relevant to increment. The importance of climate in basal area increment changes was then assessed by additional inclusion of climate parameters *CLIM* into the model:

$$\ln(BAI) = a + b * SIZE + c * COMP + d * SITE + e * CLIM + f * INT \quad (3)$$

As we did from basal area increment model (2), we also obtain coefficients *f* from model (3). Again, linear regression was employed to estimate the trend in basal area increment when climate parameters are considered in the model. If the observed growth trends were caused by climate variations, the additional inclusion of climate parameters should have a diminishing effect on the coefficients *f* of the 17 increment periods *INT* and should reduce the slope of the growth trend. This means that the included climate parameters explain the observed growth trend in basal area increment. Figure 6 illustrates this diminishing effect of the inclusion of climate parameters in the basal area increment model for Norway spruce. Thus, we assume that climate parameters are considerable relevant in explaining the observed trend in basal area increment of Norway spruce. Temperatures during the cold season were identified to be of special importance for increment changes.

Figure 6.—*The change of coefficients of the 17 increment periods due to inclusion of climate parameters.*



Application of Remote Sensing Techniques

AFI does not use any remote-sensing techniques for prestratification purposes. Within an ongoing project the satellite image data are combined with field data aiming at mapping of forest attributes and estimates for these attributes with higher accuracy for small regions compared to the existing estimations. In a prestudy, the main emphasis was placed on the incorporation of topographic correction into the *k*-Nearest-Neighbor-based assessment of forest attributes (Koukal 2004). A relatively new radiometric correction method (sun canopy sensor model) is used in combination with atmospheric correction methods. This approach turned out to be suitable also for operational applications. At the moment only results for the eastern part of Austria (more flat) are available. They reveal satisfying agreement with the ground-based results of the attributes: forest area, forest cover type, volume of the main tree species (species groups), and the percentage of the main tree species.

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Italian National Forest Inventory: Methods, State of the Project, and Future Developments

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Abstract.—A primary objective of the Italian National Forest Inventory (NFI) is to provide information required by the Kyoto Protocol and the Ministerial Conference on the Protection of Forests in Europe in relation to sustainable forest management practices. For this reason, the second Italian NFI was aimed at providing data in a way that is consistent with the international standards, such as the adopted definition of forest area. Particular attention was paid to the quality of the data collected to obtain good accuracy and high precision at the national level. This has been achieved with a three-phase sampling for stratification that allowed for a high sampling intensity in the first two phases and careful control of the data inputs with continuous feedback from the surveyors.

Introduction

The updating of information on national forest resources is of primary importance for national forest programs and local forest policies. National forest inventories (NFIs) based on statistical surveys provide nations with reliable quantitative forest information.

The first collection of data on Italian forests based on statistical sampling was performed between 1983 and 1985 with the first Italian NFI. The Forest and Range Management Research Institute (ISAFA) designed the project plan and the procedures for data collection and processing, while the field surveys were carried out by the National Forest Service (NFS). The results were published in 1988 (Castellani *et al.* 1988). On the other hand, official statistics on Italian forests were provided by the Italian Institute for Statistics (ISTAT) and derived from annual questionnaires, completed by the NFS. These statistics show few details, particularly on dendrometric and ecological features, and the most recent available data are referred to 1999.

Between 1985 and 2003, local forest inventories at a regional or subregional level were carried out by some administrative regions of Italy. The framework derived from these projects, however, is neither complete, as the local inventories cover only half of the Italian territory, nor homogeneous, because they differ in their sampling schemes, survey procedures, and reference dates.

Therefore, at the end of the 1990s the information on Italian forests appeared to be dated and lacking, especially in meeting the information requirements of international standards. Italy

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has ratified international conventions and agreements that bind the country to provide information on several aspects of national forests. Italy committed itself to use the criteria and indicators developed by the 2003 Ministerial Conference on the Protection of Forests in Europe (MCPFE) in international reporting on the status and conditions of Italian forests. Furthermore, the agreement of the Kyoto Protocol has bound the Italian government to report on greenhouse gas emissions and, for this purpose, the assessment and monitoring of land use, land use change, and forestry activities is required.

In 1998–99, ISAFA was asked by the Ministry of Agriculture and Forestry to conduct a feasibility study for a new NFI (ISAFA 1999). At the end of 2001, a Ministerial Order instituted a permanent NFI to be carried out by the NFS with the scientific and technical support of ISAFA. The "National Inventory of Forests and Forest Carbon Sinks" (INFC) started in 2002 with the design of the sampling scheme and the survey procedures for the first phase. The inventory design of the INFC is based on a three-phase sampling for stratification, while the previous NFI had adopted one-phase sampling (INFC 2004b). Moreover, the two NFIs differ on the forest definition adopted, the sampling intensity, the distribution of sampling points, and the sources of the data and the attributes surveyed. The old inventory was conducted on approximately 30,000 sample units distributed on a 3 by 3 km systematic grid that were classified as forest or nonforest by field surveys combined with information from available maps. Sample points identified as forest were measured in the field (Castellani *et al.* 1988). The INFC adopted a new sampling scheme to improve the precision of estimates, which meant that it wasn't possible to use the previous NFI's sample points.

Many aspects of the INFC project, such as the survey procedures and the data sources, were designed to meet the international commitments described above. The list of attributes to be assessed was defined with particular attention to the international standards, mainly the United Nations Food and Agriculture Organization definition of forest and also the set of pan-European indicators of sustainable forest management (MCPFE 2003). Many different sources of information were used, such as the national cover of digital orthophotos, national and regional maps, databases and interviews, as well as field data. Lastly, the same framework used for dendrometric measurements is being used for collecting data on many aspects of forest ecosystems, according to a multiresource approach.

Methods

The Sampling Design

The sampling design adopted for the INFC is a three-phase sampling for stratification (fig. 1), in which the first two phases are required to estimate the forest area and its classification into forest categories, while the third is needed to collect dendrometric data (INFC 2004b).

In the first phase, systematic unaligned sampling is used to select sample points to be observed on orthophotos. The first phase sample is formed by approximately 301,000 points distributed on a grid covering the whole Italian territory (30,132,845 hectares), with one sample point drawn randomly within each 1 by 1 km grid square. Through photo interpretation, the sample points are classified by land cover/land use class (fig. 2) to estimate the area of the strata by administrative region, and to identify the sampling units from which the subsamples of the following phases would be selected. The strata derived from the first phase classification are consistent with the first level of the CORINE Land Cover System (European Commission 1993) and with the FAO-Forest Resources Assessment (FRA) 2000 forest definition (UN-ECE/FAO 1997), with a single class including both *forest* and *other wooded land* (OWL) (INFC 2003a). In the second phase, a subsample is randomly selected from the *forest and other wooded land* stratum according to the proportion of the land cover class in the 21 administrative regions of Italy. Approximately 30,000 sample points in the second phase were surveyed in the field to discriminate forest from OWL, to identify different forest types, and to collect information on other qualitative attributes of forest stands (INFC 2004a). The assessment of the main tree species or species group is the basic step to identify the forest type and subtype. On the whole, 23 types and 91 subtypes have been defined (fig. 2) (INFC 2003c). Lastly, a third phase subsample of

Figure 1.—*Diagram illustrating the sampling design adopted by the second Italian National Forest Inventory.*

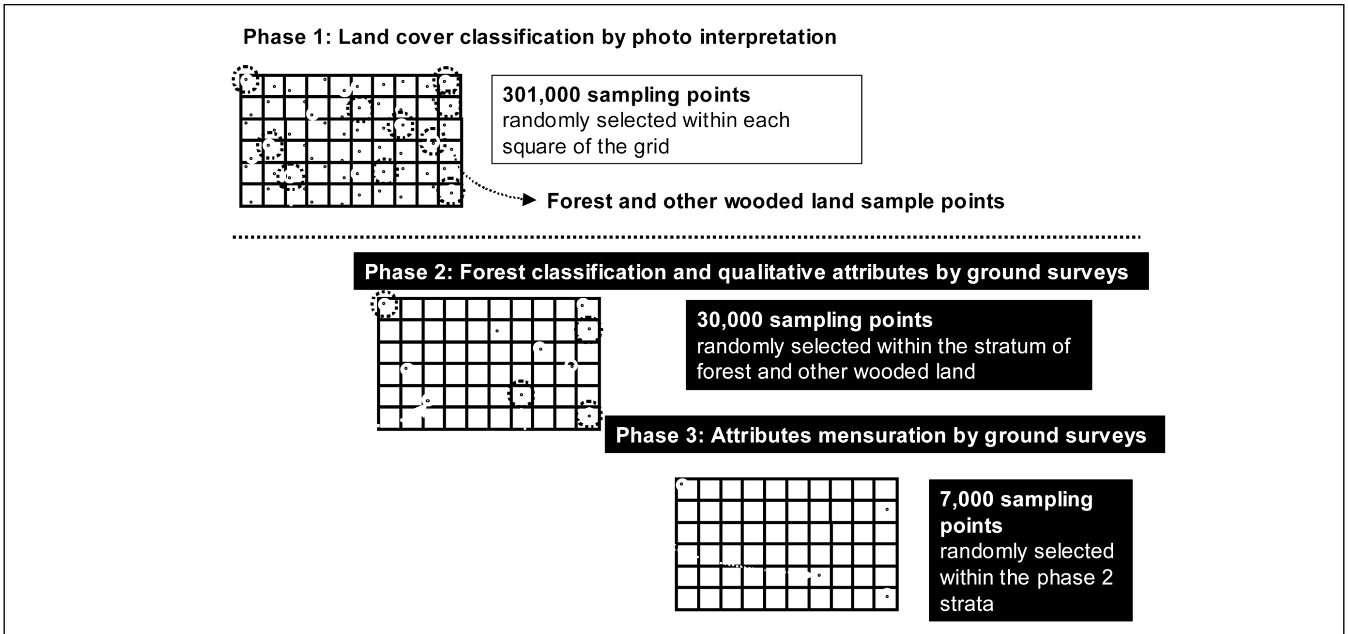
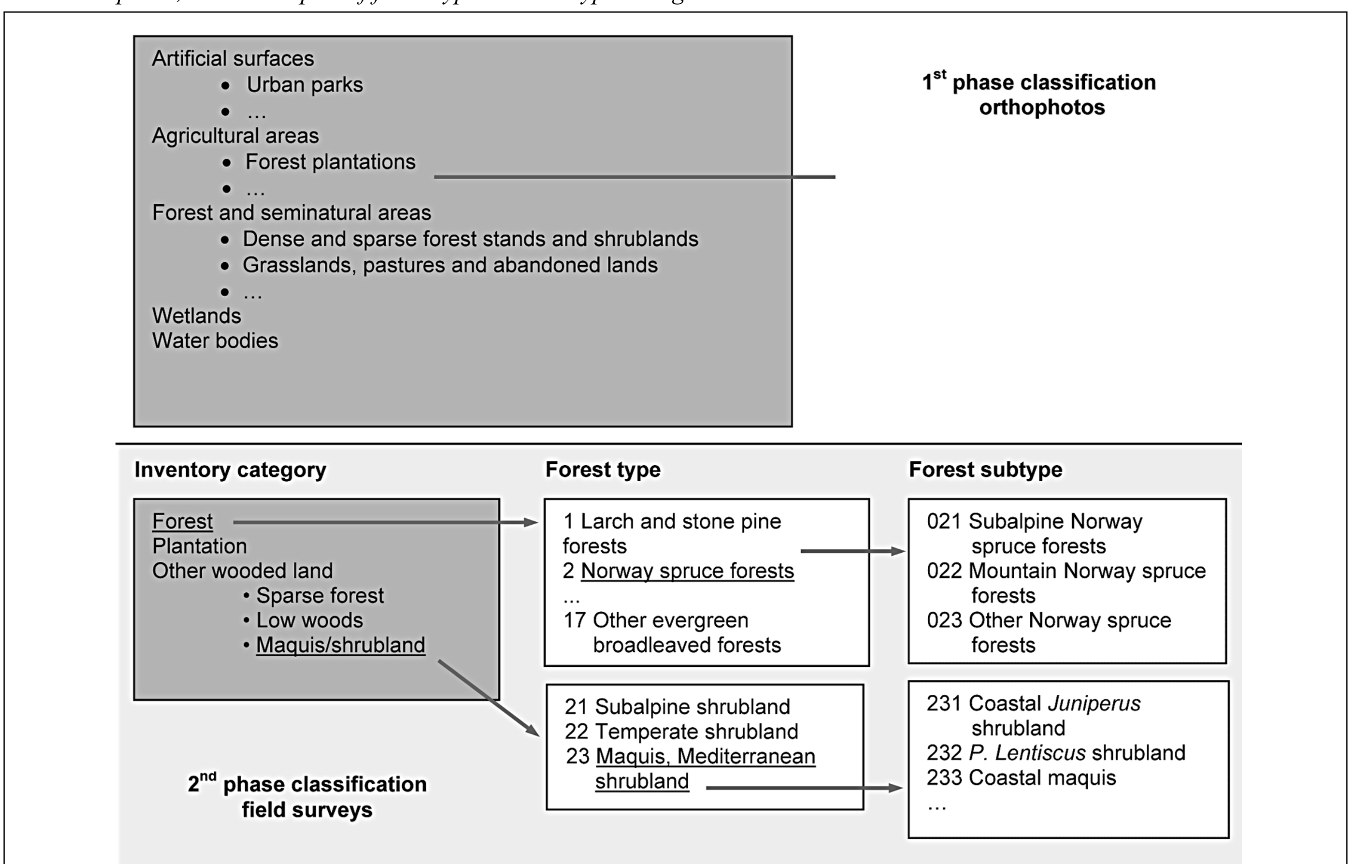


Figure 2.—*Scheme for land cover/land use and forest type classification adopted by the second Italian National Forest Inventory; for the second phase, some examples of forest types and subtypes are given.*



approximately 7,000 points is selected from the second phase sample, then stratified by administrative region and forest type. The third phase subsample is used for dendrometric measurements and for the collection of quantitative data on understory vegetation, dead wood, and other attributes.

Estimation Techniques

As already mentioned, the first two phases are aimed at estimating the area of the inventory strata. The first phase measures the land cover/land use classes and the second phase measures the forest types, both divided by administrative region. The weight of each second phase stratum is derived from the proportion of the first phase sampling points falling in the *forest and other wooded land* class in each administrative region and the proportion of the second phase points falling in each forest type and subtype for the same region. The area of each forest category is then estimated by multiplying its weight by the area of the whole country. The second phase sample is also used to assess the distribution of the forest area according to qualitative attributes (for example property, coniferous trees vs. broadleaves composition, naturalness, etc). The estimators used for area and variance estimates are reported in INFC (2004b) and discussed in Fattorini *et al.* (2004).

For the volume estimation, a new set of 26 models is being developed to predict volume and above-ground phytomass from diameter at breast height (d.b.h.) and total tree height measured in the third phase. In these models, the dependent variables are stem and branch volume, stem and branch dry weight, slash dry weight, dead portion dry weight, stump dry weight, and total above-ground dry weight. To construct these models, approximately 1,300 sample trees from across the country were measured between 2002 and 2005. The models developed for a pilot study area in the eastern Alps are reported in Fattorini *et al.* (in press) and Gasparini *et al.* (2005).

Data Collection and Information Sources

In the first phase, the photo interpretation was carried out by a team of 50 photo interpreters of the NFS working in different regional offices connected to a central database that was continuously updated with the results of the classification. The land cover/land use classes and subclasses were observed on black and white digital orthophotos with a nominal scale of 1:10,000 and a reference date between 2000 and 2003. Photo interpreters used Geographic Information System (GIS) functions implemented within a national GIS, which is a public service with several geographic information strata (cadastral, digital elevation model, land use, ownership, etc.) distributed by a Geographical Area Network or by Internet.

For the second and the third phases, more than 100 crews of two to three people formed by NFS and local forest service personnel were involved in the data collection. Phase two aimed at collecting in-field qualitative information related to forest stands and their ecological features. The field data were taken within a circular plot of 2,000 square metres with the sampling point at the plot center. In addition, administrative information (e.g., ownership, protected areas, restrictions, etc.) are collected by interviews or public database queries, while digital orthophotos are used (on video or in print) to observe the crown cover, the texture (horizontal spatial distribution of trees), and forest edges. For each sample point, approximately 40 forest qualitative attributes, as well as several attributes related to spatial positioning, were recorded (INFC 2004a). In phase three, a number of quantitative attributes will be measured that are related to dendrometric and silvicultural aspects, carbon stock, biodiversity, stand health, and nonwood products. As shown in figure 3, the measurements are taken in different sized plots for each sampling unit. The set of attributes assessed in the Italian NFI, listed by groups and with the indication of the information source, is shown in table 1.

Figure 3.—*Sample plot configuration adopted for the third phase of the second Italian National Forest Inventory, illustrating the different sized plots used to assess the attributes surveyed.*

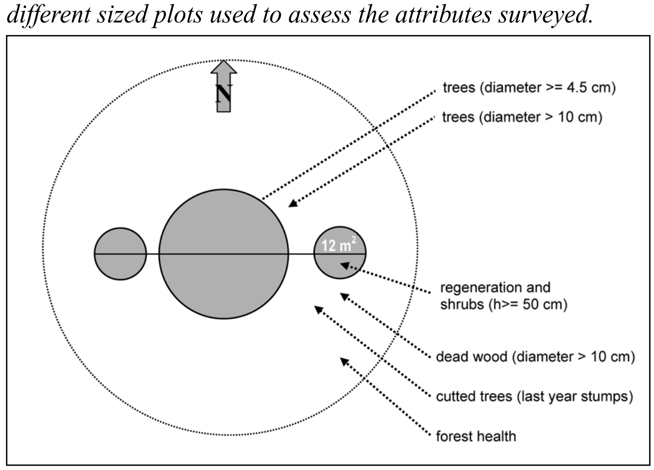


Table 1.—*Set of attributes assessed in the second Italian NFI, listed by groups and with the indication of the information source.*

Attribute group	Source	Attribute	Phase
Land use, land cover	Photo interpretation	Broad land cover classes	I
Forest classification	Field survey	Inventory category, forest type and subtype	II
General information	Field survey, interviews, local laws and regulations, GIS	Ownership, protected areas and other restrictions, forest management, regulations on recreational activities	II
Site information	Field survey	Aspect, slope, local land shape, logging possibilities, natural hazards	II
Stand assessment	Field survey	Stand structure, stand development stage, main species composition, naturalness, microhabitats and artificial infrastructures	II
Road network	Field survey, maps	Roads, logging roads, paths, accessibility	II
Canopy closure and spatial attributes	Photo interpretation	Crown cover class, horizontal structure (texture), forest edges	II
Dendrometric attributes	Field survey	d.b.h., tree height, growing stock (trees with d.b.h. > 4.5 cm), increment, stand age, fellings volume	III
Carbon stock	Field survey	Whole-tree above-ground phytomass, shrub, litter phytomass, organic C soil content (special survey)	III
Biodiversity	Field survey	Tree (and shrub) species, volume and decay rate of dead wood (trees and parts with diameter > 10 cm), saproxilic insects (special survey)	III
Silviculture	Field survey	Type (intensity) of management, cutting method, wood extraction method, regeneration and underbrush (species, density, damages)	III
Forest health condition	Field survey	Primary damaging agent, biotic damages and disturbances assessment, defoliation class	II—III
Nonwood products	Field survey	Presence of special harvesting or picking practices	III
Primary function	Field survey, interview	Primary (or multiple) function assessment	III

d.b.h. = diameter at breast height; GIS = Geographic Information System; NFI = National Forest Inventory.

Data Quality Control

During the first phase, the control of data quality was carried out by the researchers and technicians of ISAFA, who repeatedly checked the classification of the photo interpreters to assure the quality of the final results. From three to eight control samples per region, each one formed by 50 sampling points, were used to test the accuracy of classification during the work. At the end of the first phase, 2 percent of the sampling points were randomly selected and independently reclassified. To compare the classification of ISAFA's and NFS's photo interpreters, quality standards were set for each cover class depending on the importance of the class and on the difficulty of its recognition on orthophotos (INFC 2003b).

For the second phase, control ground surveys were carried out for each region to assure the final quality of the data. Moreover, the data input was checked automatically by the data storage software INFOR2 (Muscaritoli *et al*. 2004), while periodic checks on the data stored in the central database were undertaken to control the consistency of the data and the progress of data collection. A similar procedure is planned for quality control of third phase surveys.

Technology and Data Flow

The great amount of data collected by the INFC required a sophisticated survey system and overall structure for both the database and the data flow.

The following main principles guided the design:

1. Use mobile GIS techniques, with a double client/server architecture and possibility of immediate, safe, and easy data transfer between crew stations and the central server.
2. Ensure the integrity of data through the different phases of the project.
3. Use user-friendly software for personnel without a high level of specialization in computer procedures. Both

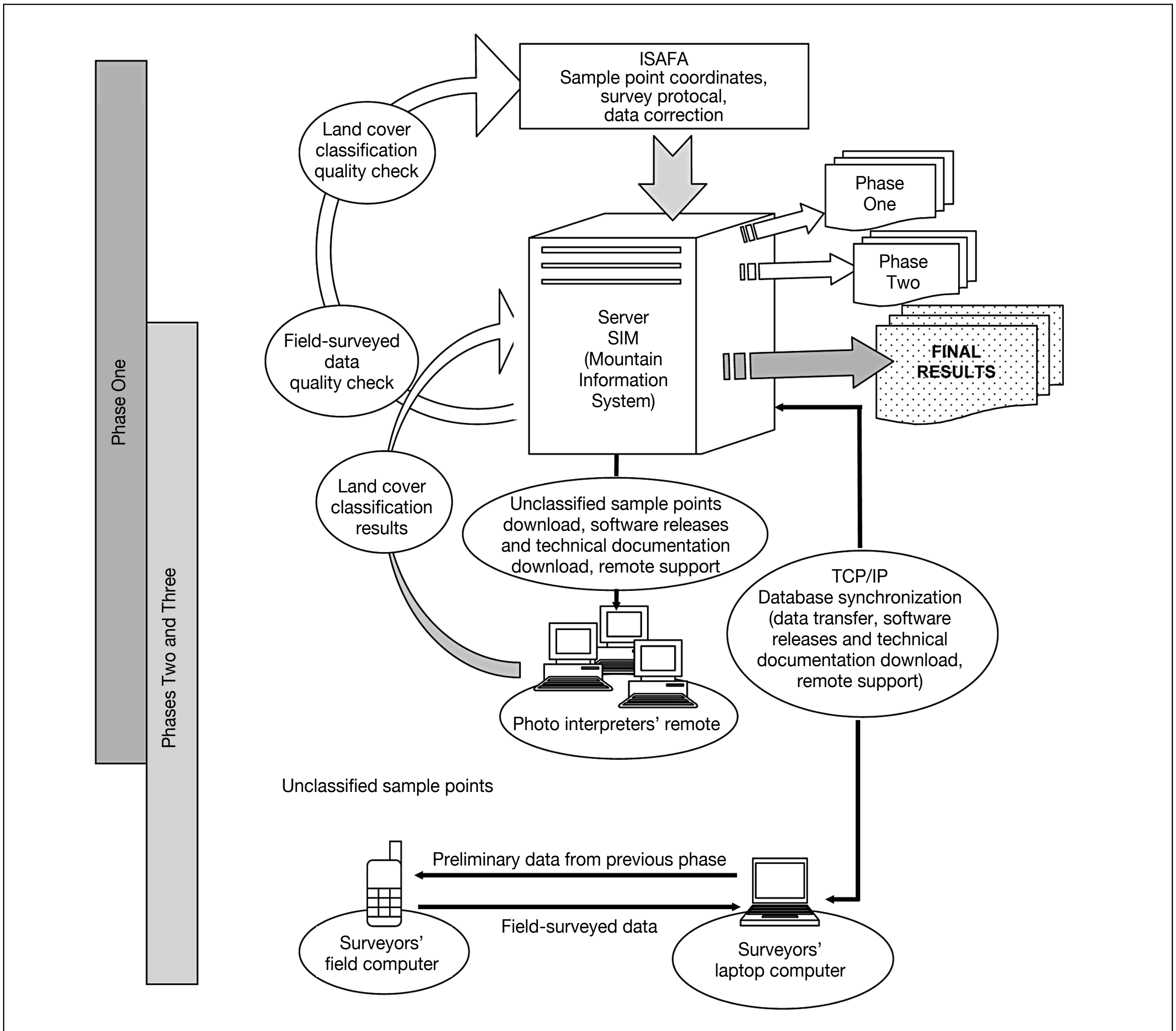
standard software packages (such as ArcPad and IBM DB2) and specifically developed software applications (such as INFOR2 mobile and desktop, and the SIM GISWEB) were used.

4. Integrate between different information sources.
5. Enable remote monitoring of data collection, aimed at early quality control, test, and correction.

During the ground surveys, each crew uses a handheld computer (client) to gather data in the field and a laptop personal computer (client/server) to check, complete, and send the collected data to the central server. Other field instruments used were Global Positioning System (GPS) receivers, digital cameras, laser rangefinders, and more common forest mensuration tools.

Figure 4 shows the dataflow during the different phases of the INFC.

Figure 4.—*Scheme illustrating the data flow of the second Italian National Forest Inventory.*



ISAFA = Forest and Range Management Research Institute.

Ground Positioning Method and Technologies

Because about two-thirds of Italian territory is hilly or mountainous, high-quality GPS receivers were used to acquire accurate measurements under tree coverage and in areas of high relief.

A navigation procedure was defined to avoid any subjectivity in the choice of the field position of the sample point (BCRIC 2001). For this reason, a reference point (F) had to be chosen at a distance of 15 to 25 m from the target sample point (C), in a location suitable for GPS signal reception, collecting a minimum of 180 GPS positions during a maximum time of 15 minutes. Distance and bearing from this point feature (average coordinates) to the target sample point were calculated, allowing for an objective field position of the sample point. A static GPS point (with a minimum of 180 positions) was acquired at the plot center sample point, as well. GPS points were post processed using differential GPS.

Results

The final results of the second Italian NFI are not available at present, as the end of the project is scheduled for 2006. At the moment, the first phase of INFC is finished and the results are published on the Internet (www.ifni.it). The second phase ground survey is almost complete, while the third phase is planned to start in spring of 2006. The final results of the NFI, including quantitative information on the dendrometric features of Italian forests, are expected in the first half of 2007.

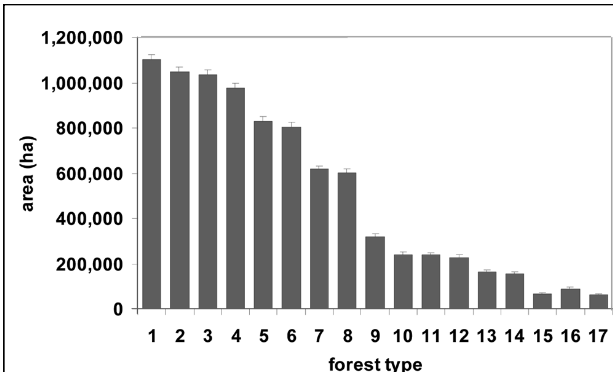
Forest Area, Forest Types Area

The first results of the INFC are shown in table 2 and figure 5 and are based on the first phase data and on the provisional second phase data. These data refer to 78 percent of the sampling points (23,383) that had been already surveyed at the end of March 2005. Table 2 gives the extent of the land cover classes forest and OWL for the whole country with their standard errors. Concerning the forest area by administrative regions, a high precision of estimates was obtained thanks to the sampling design and the high number of sampling points surveyed in the first two phases of the NFI. The standard error of estimate was 1.12 percent for Toscana, one of the larger administrative region of Italy with the largest forest area (the provisional estimate of forest plus OWL area is 1,156,682 hectares and the total area of the region is 2,298,448 hectares). Puglia and Valle d'Aosta had standard error of estimates of 3.96 and 3.38, respectively. Puglia is the region with the smallest proportion of forest (approximately 8 percent of the regional territory) and

Table 2.—*Provisional estimates of forest and other wooded land area provided by the second Italian National Forest Inventory*.

Land use	Area (ha)	Standard error (%)
Forest	8,767,720	0.43
Other wooded land	1,662,099	1.76

Figure 5.—*Provisional area estimates for the 23 Italian forest types defined for the second Italian National Forest Inventory.*



1 Oak forests (*Quercus petraea* (Matt.) Liebl. , *Quercus robur* L., *Quercus pubescens* Willd.)
2 Oak forests (*Quercus cerris L., Quercus fraineto* Ten., other oak species)
3 Mixed deciduous broadleaved forests
4 Beech forests (*Fagus sylvatica* L.)
5 Chestnut forests (*Casatnea sativa* Mill.)
6 Hornbeam forests (*Carpinus spp., Ostrya carpinifolia* Scop.)
7 Norway spruce forests (*Picea abies* (L.) Karsten)
8 Holm oak forests (*Quercus ilex* L.)
9 Larch and stone pine forests (*Larix decidua* Miller, *Pinus cembra* L.)
10 Mediterranean pine forests (*Pinus domestica* L., *Pinus maritima* Miller, *Pinus halepensis* Miller)
11 Hygrophilous forests
12 Black pine forests (*Pinus nigra* Arnold, *Pinus laricio* Poir., *Pinus leucodermis* Ant.)
13 Coark oak forests (*Quercus suber* L.)
14 Scots pine (*Pinus sylvestris L.*) and Mountain pine (*Pinus uncinata* Mill.) forests
15 Fir forests (*Abies alba* Mill.)
16 Other evergreen broadleaved forests
17 Other coniferous forests

Valle d'Aosta is the smallest region of Italy (325,121 hectares as provisional estimate of forest plus OWL area).

As explained in the description of the sampling design, the forest type was classified in the field on the basis of the prevailing tree species or species group in the sample plot. Figure 5 gives the provisional results on the proportion of the different types of Italian forests. The standard error of estimates calculated from the provisional data are quite small, ranging from 1.9 to 2.1 percent for the largest strata, the extent of which is approximately 1,000,000 hectares (*Oak forests*, *Beech forests*), to 2.6 to 2.8 percent for middle-sized strata of approximately 600,000 hectares (*Norway spruce stands*, *Olm oak forests*). The standard errors for the smallest strata are 8.8 percent for *Other coniferous forests* (approximately 63,000 hectares) and 8.6 percent for *Fir forests* (approximately 65,000 hectares).

Positioning Accuracy

The following positioning data are based on about 93 percent of the total sample. If we exclude nonforest (6 percent) or unapproachable[8] (13 percent) points, as well as points with technical problems on the GPS files (1.4 percent), we have positioning data on about 80 percent of the surveyed sample.

Table 3 shows the distribution of the data according to classes of distance between field and theoretical coordinate values of the sample points. These distances can be considered an accuracy index of the field positioning. Our results are promising in that the average distance value was 2.73 m.

An earlier study carried out by the ISAFA (Scrinzi *et al*. 2003) on GPS performances in INFC conditions had estimated expected accuracies within 8 m (standard GPS mode, 90 percent probability level). According to INFC field survey results, roughly 93 percent of the data are within the expected accuracy. The upper class (> 30 m) includes very high and improbable values, which can be thought of as outliers; for this reason they have been excluded from the average calculation and will need further processing.

Table 3.—*Distribution of the second phase sampling points by class of distance from their nominal position.*

Distance classes (m)	Frequency (number of points)	Frequency (% of points)
No data	560	2.52
≤ 2	10,432	46.85
> 2 to 5	8,441	37.91
> 5 to 8	1,875	8.42
> 8 to 15	640	2.87
> 15 to 30	123	0.55
> 30	194	0.87
Total	**22,265**	**100.00**

Concerning the operational performances of GPS, the system failed to collect positions on the sample point location in only 2.5 percent of cases. Failures were due mainly to severe topography and high tree coverage conditions. Alternative navigation procedures (compute-aided traverse path by means of conventional techniques) were necessary only in 24 cases (0.11 percent).

Discussion

One of the main aims of the new Italian NFI is to produce information needed for international reporting activities such as FAO assessments, carbon sink estimates for the Kyoto Protocol reporting, and the production of national reports on the sustainability of forest management within the MCPFE process. Therefore, by defining the inventory domain and the survey procedures of INFC, particular attention was paid to the international standards and commitments. It has been decided to base the inventory domain on the FAO-FRA 2000 definitions and to include both forest and other wooded land use. Moreover, besides the more traditional dendrometric and silvicultural attributes, the data collection involves more detailed measurements about above-ground phytomass and ecological features to provide data on carbon sequestration and to meet most of the commitments related to the MCPFE.

[8] **Unapproachableness** of a sample point could be declared, by the crew, according to the following criteria: crew safety (first priority), permission denied in private properties, and impenetrable vegetation. Most of the unapproachable points were remotely observable and therefore used for main forest type classifications.

In relation to the carbon stock estimates, the INFC provides our country with updated and reliable data on the extent of forests, on the volume and the dry weight of above-ground phytomass and dead wood, on growth rate, and on the carbon content of litter and organic soil. Concerning the indicators of sustainable forest management, the INFC data enable us to provide information on 20 of the quantitative pan-European indicators of sustainable forest management (table 4). The remaining indicators are not suitable to be assessed by an NFI as they involve aspects that are either not observable by sampling procedure or require very detailed and time-consuming surveys.

A second important goal of the inventory project is to assure the quality of the data collected to obtain a good accuracy and a high precision of results at the national level. This has been achieved both by defining a suitable sampling design and

Table 4.—*Attributes of the second Italian National Forest Inventory and their consistency with the pan-European indicators of sustainable forest management*.

Criterion	Quantitative indicator	Consistency with MCPFE standards
1 Maintenance and appropriate enhancement of forest resources and their contribution to carbon cycle	1.1 Forest area	Yes
	1.2 Growing stock	Yes
	1.3 Age structure, diameter distribution	Yes
	1.4 Carbon stock	Yes, but no measurements on below-ground phytomass
2 Maintenance of forest ecosystem health and vitality	2.1 Deposition of air pollutants	No
	2.2 Soil condition	Partly: organic C content only
	2.3 Defoliation	Yes
	2.4 Forest damage	Yes
3 Maintenance and encouragement of productive functions of forests	3.1 Increment and fellings	Partly: no data on natural losses and on annual fellings for d.b.h. < 20 cm
	3.2 Roundwood	Partly: data on roundwood with d.b.h. > 20 cm; no data on marketed volume and value
	3.3 Nonwood goods	Some qualitative information
	3.4 Services	Some qualitative information
	3.5 Forest under management plans	Yes
4 Maintenance, conservation, and appropriate enhancement of biological diversity in forest ecosystems	4.1 Tree species composition	Yes
	4.2 Regeneration	Yes
	4.3 Naturalness	Yes
	4.4 Introduced tree species	Yes
	4.5 Deadwood	Yes
	4.6 Genetic resources	No
	4.7 Landscape pattern	Partly: information on texture and forest edges
	4.8 Threatened species	No
	4.9 Protected forests	Yes
5 Maintenance and appropriate enhancement of protective functions in forest management	5.1 Protective forest extent (for soil and water protection)	Yes
	5.2 Protective forest extent (for infrastructure protection)	Yes

Table 4.—*Attributes of the second Italian National Forest Inventory and their consistency with the pan-European indicators of sustainable forest management (continued).*

Criterion	Quantitative indicator	Consistency with MCPFE standards
6 Maintenance of other socioeconomic functions and conditions	6.1 Number of forest holdings	No
	6.2 Contribution to gross domestic product	No
	6.3 Net revenue of forest enterprises	No
	6.4 Expenditures for services	No
	6.5 Forest sector workforce	No
	6.6 Occupational safety and health	No
	6.7 Wood consumption	No
	6.8 Trade in wood	No
	6.9 Energy from wood resources	No
	6.10 Accessibility for recreation	Yes
	6.11 Cultural and spiritual values	No

MCPFE = Ministerial Conference on the Protection of Forests in Europe.

monitoring data collection and data storage. The three-phase sampling design for stratification, with the interpretation of orthophotos in the first phase and expeditious ground surveys in the second phase, made it possible to use a large sample size, which assures a high reliability of inventory results. Indeed, the provisional estimates of forest and other wooded land area presented in this paper are very precise, with low percent standard errors. Forest type area estimates at national scale follow the same trend, with percent errors of less than 3 percent for most types considered. It should also be noted that our procedures allowed for accurate spatial positioning of samples with average distance errors of less than 2.8 m.

As a consequence of its ambitious aims, the NFI project requires a great effort, both from an organizational and from a technical point of view. Among the different aspects of the inventory, the technical support together with the monitoring of the data flow required quite a sophisticated survey system. The management of the data flow and the database is indeed one of the most critical issues of this project, due to the large amount of data coming from many different parts of the country and the large number of people involved.

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A New Flexible Forest Inventory in France

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Abstract.—The French National Forest Inventory was created in 1958 to assess metropolitan forest resources. To stick to new national and international requirements as well as to enhance reactivity, a new inventory method was implemented in 2004. This new method is based on a systematic sampling grid covering the whole territory every year. The size of the mesh is variable, locally adapted to the diversity and the fragmentation of French forests. The sample is defined for 5 years. It is divided into 5 annual systematic subsamples, each of which covers the whole country. The estimation method uses poststratification to enhance statistical accuracy.

Introduction

The mission of the French National Forest Inventory (NFI) is to collect information about forest and natural lands all over the European part of France. It describes forest, other wooded land, heathland, and hedges. It draws a precise map of forest types and heathland. It estimates areas per land cover and land use, and assesses forest resources including growing stock and carbon stock with their increment as well as biodiversity.

Data are produced at national, regional, or "département" (administrative unit covering each nearly 1/90th of the country) levels to help policymakers in their decisions. It also proposes results at the scale of "forest regions," which are small, continuous ecological areas. Aggregated results are available for free on the NFI Web site and particular requests can be asked. The NFI staff also conducts specific studies based on NFI results for many institutions. For example, it evaluated wood fuel resources in France (French NFI 2005) or updated indicators for forest sustainable development (French NFI 2001), as well as international level delivery to the United Nations Food and Agriculture Organization and the United Nations Economic Commission for Europe.

The Previous Method

The forest inventory was conducted since 1958 per "département" (French NFI 1985). Results were very precise at the scale of the "département," but data were updated on these areas every 12 years only. No intermediate results were available. To produce results at the regional level (22 units) and more over at the national level, the aggregation of diachronic results was used. For field observations, a stratified sampling plan was used. The stratification variables were ownership, forest regions, forest types, land use and cover. It enhanced the quality of the forest area evaluation and tree measurement results, but the impact on ecological variables remained difficult to estimate.

National and International Context

In France, administrative regions become more and more a level of policy decisionmaking, and data are needed at this level to prepare political decision. At a different level, nonadministrative management units (e.g., regional and national natural parks) need forest mensuration and ecological results from the NFI to guide their action. As a consequence, a higher geographical flexibility is required.

Reactivity is also expected. The NFI must be able to evaluate quickly consequences from important disturbances (storm, drought, forest fires, or parasite attacks) that have an impact at the regional or at the national level. The envisaged solution is to come back on the surveyed plots but the sample must be recent.

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At the international level, the French government has to provide data about forest resources every 5 years to the Food and Agriculture Organization (FAO) and to report on sustainable forest management indicators for the Ministerial Conference for the Protection of Forests in Europe. It needs data about forest carbon stock and sinks to compute the greenhouse gases balance according to the convention on climate change of the United Nations and its Kyoto Protocol. To meet these requirements, regularly updated information at the national level is necessary.

Flexible Sampling Design

Principle: A Countrywide Systematic Sampling Each Year
To respond to these requirements, the NFI changed its sampling design. At first, the sample was prepared for 10 years and was divided into two 5-year systematic subsamples, each of which covers the whole of France. It finally started with a 5-year slice. The new sampling is based on a systematic square grid covering the entire country. The size of the grid-mesh is 2 km^2. Plots are georeferenced using the Lambert II extended projection and New French Triangulation.

The whole grid is scheduled to be measured in 5 years. The 5-year sample is divided into five systematic annual subsamples consisting of square grids interpenetrating each square (fig. 1), covering the entire country (model also presented in Roesch and Reams 1999).

1.1. Adapting the Sampling Effort: A Multilevel Grid
Some collected data are required with a very high confidence level, even in small areas. For other variables, precision is only required at the national level or when an approximate value is sufficient. Some variables, such as the volume of growing stock, can be evaluated on all plots using models, volume measurements being only necessary on a subsample to calibrate the models.

Due to the diversity of precision requirements, a mechanism was found to adapt sampling intensity to each variable (or set of variables), by defining a system of nested subgrids from the basic one. If the entire annual sample is, say, of level 1, the level 2 subsample is obtained by taking out of level 1 every second plot in staggered rows (fig. 2). Level 3 is obtained in removing in the same way every second plot from level 2, etc. There are half as many plots at the level n as at the level n+1.

In this way, nested systematic annual samples are generated with a sampling rate divided by 2 at each level. Measurements are made at a defined level, depending on the expected result accuracy. For each variable, an observation level is defined, corresponding to the subsample on which it is to be observed.

1.2. Invariance Properties
The properties of interrelated systematic square samples are preserved at every level in an annual sample as well as in a 5-year sample (fig. 3). The only difference is the density of

Figure 1.—*A 5-year sampling grid divided into five annual interpenetrating sampling grids.*

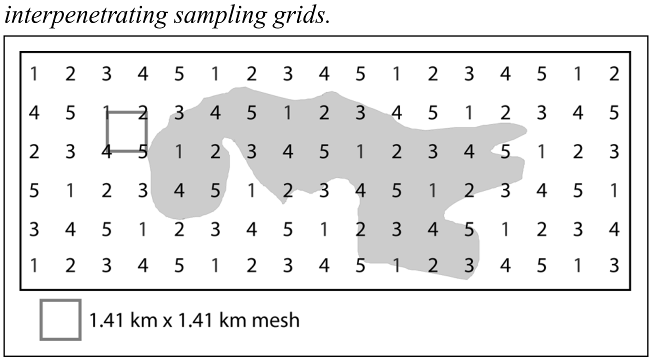
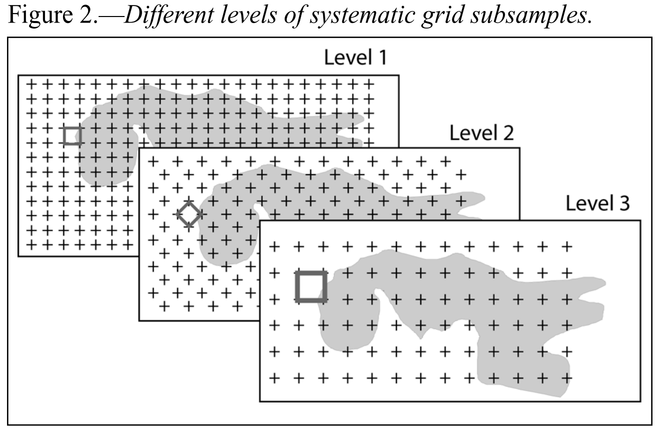


Figure 2.—*Different levels of systematic grid subsamples.*



sample plots. As a consequence, the same computation scheme can be used every year and for every level.

As years will go by, the density of the observations and measurements will increase. The use of several consecutive annual measurements will be interesting to enhance the precision of the results and to enable local reporting.

Spatial Adaptation of the Sampling Rate to Optimize Field Work

Delimited Areas With Reduce Sampling Rate

Some areas in France are very homogeneous, for example, the maritime pine (*Pinus pinaster)* massif in the Southwest. In such areas, fewer measurements are necessary to obtain precise enough results.

In other parts of the country, some forest ecosystems are not very productive and the economical use of the wood is of a little importance; e.g., green oak (*Quercus ilex)* or strawberry tree *(Arbutus unedo)* stands in the Mediterranean region or forests on steep slopes in mountainous areas. No detailed resource assessment is expected. Fewer measurements can be made to obtain estimations corresponding to the needs.

In both cases, the concerned areas (called forest zones) are mapped (fig. 4) and the density of the sample is adapted. Field operations are then carried out at a higher level subsample than the usual one, for example at level 3 instead of level 2 (fig. 5).

This geographical adaptation of the sampling rate makes it possible to go through the whole sample in 1 year with a constant number of field crews.

A Higher Sampling Rate for Poplar Stands

Poplar trees are economically important in France. Plantations are usually small and felling cycles are rather short. To make a precise inventory of these areas, a higher density of plots is required in the parts of the territory where the poplar stands are often clustered (valleys especially). Therefore, observations are conducted on 16-plot square clusters instead of single plots. These clusters are systematic 1 by 1 km grids. The mesh is square with 250 m between plots. This process multiplies the

Figure 3.—*Invariance of the subsample properties every year and at every level.*

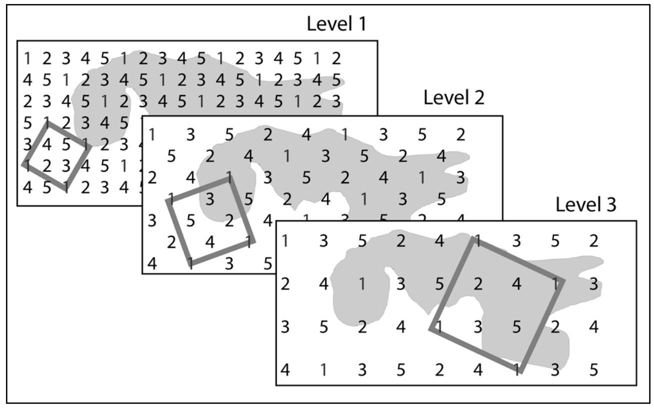


Figure 4.—*Map of the forest zones with a reduced sampling intensity.*

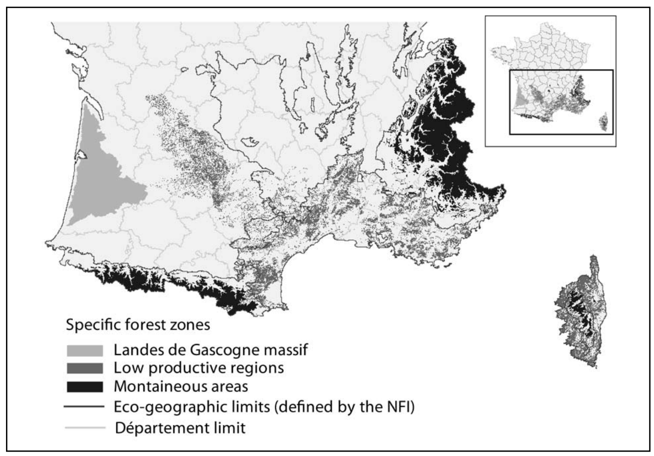
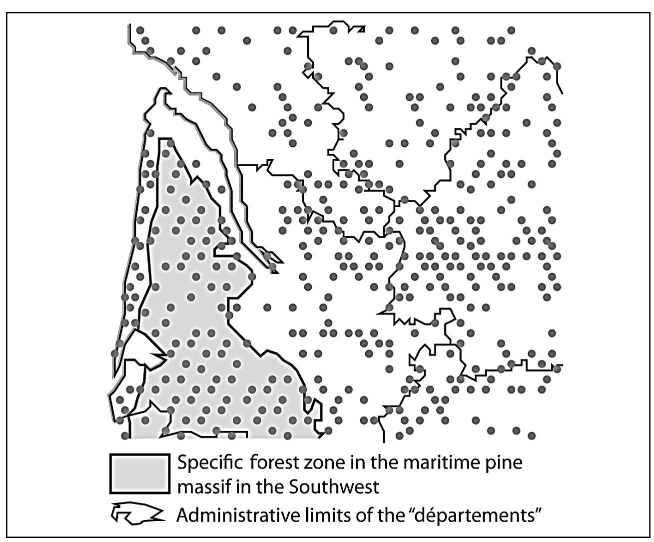


Figure 5.—*Example of reduced sampling intensity in the Southwest.*



number of observations on poplar stands. To limit this number, clusters are only used in areas where poplar plantations are localized. These areas, called poplar zones, are mapped (fig. 6). Whenever a knot of level 1 grid is located in the poplar zone, a cluster of plots is attached to the knot (fig. 7). All plots from the cluster are surveyed (even if they are out of the poplar zone).

As a conclusion, the 5-year sampling design divided into systematic annual samples offers much flexibility with its several levels of systematic subsamples and its clusters. The density of observations can thus be adapted, depending on the variable measured and on the area.

Figure 6.—*Map of poplar zones.*

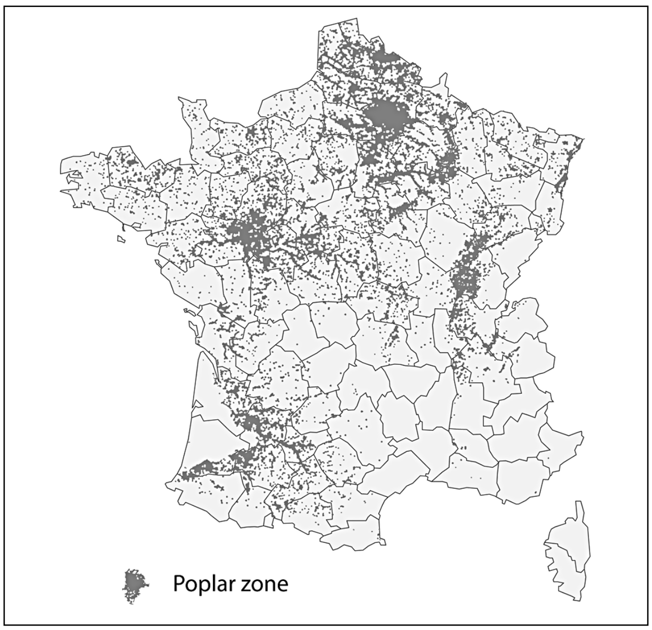
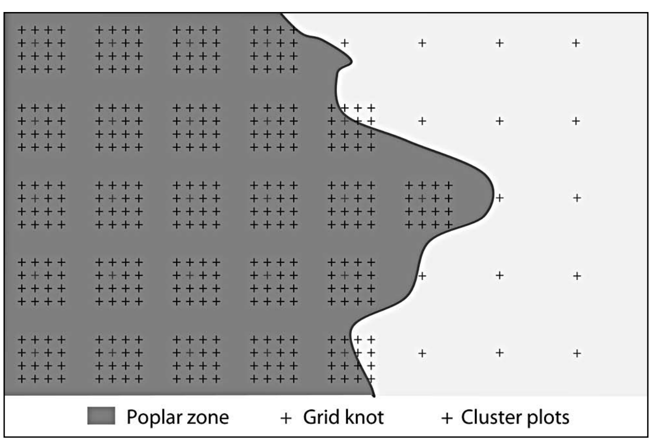


Figure 7.—*Use of clusters inside poplar zones and single plots outside.*



Level for Data Collection

Photointerpretation

The whole annual sample (level 1) is observed on the French aerial orthophoto map called BD Ortho, which is a product of the French National Geographic Institute. Land cover and use is determined on each knot of the grid. Land cover nomenclature consists of open forest, dense forest, heath and moorlands, artificial or natural area without vegetation, other artificial areas and water. In case of doubts, controls are made in the field.

Poplar plantations are included in forest since November 2005, but they are still singled out during the photointerpretation. Their occurrence is detected in plots from clusters in poplar zones and also in plots from the level 1 annual sample out of poplar zones.

The photointerpretation produces results about land cover. It is also a key operation to determine the type of measurement that will be conducted in the field.

Field Measurements in Forests

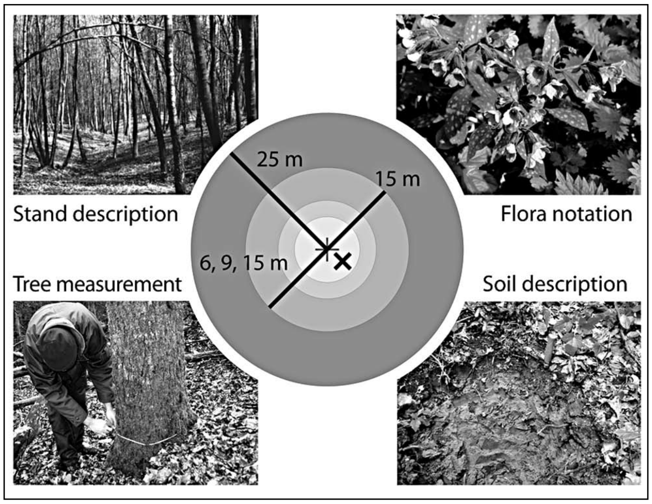
Field observations are conducted on plots determined as forest on the photographs at level 2 or 3. A forest is defined by the French NFI as a stand of more than 0.05 ha and wider than 20 m in which crowns from forest trees or noncultivated trees that can reach 5 m *in situ* cover more than 10 percent of the area. To fit the FAO definition, it is determined whether the stand is larger than 0.5 ha.

The fieldwork, including stand description, tree, soil and ecological measurements, is done on four concentric circular plots (fig. 8):

- On a 25-m radius plot, the stand is described: land cover, land use and stand description (composition, structure, age, logging possibilities, etc.).

- On a 15-m radius plot, flora species (woody and nonwoody plants including pteridophytes and bryophytes) are identified and their abundance is noted.

Figure 8.—*Data collected in forests on four concentric circular plots.*



- Trees are measured on three concentric plots, depending on their circumference at 1.3 metres. Trees more than 23.5-cm circumference are measured on a 6-m radius plot. Trees more than 70.5-cm circumference are measured on a 9 m radius plot. Trees more than 117.5-cm circumference are measured on a 15-m radius plot. Trees less than 23.5-cm circumference are not measured.

On every forest plot observed in the field, the species, shape, and the number of stems of the tree are noted. Simple measurements are made: circumference at 0.1 m and at 1.3 m, total height, diameter and height increment during the last 5 years, and wood quality classes. Additional measurements such as timber height, mid-diameter, and mid-timber diameter are made on level 4 subsample plots. The results are used to fit volume estimation models.

Soil observations are conducted on a 1-m deep soil pit in a representative part of the plot. Humus (structure, litter, type) and soil (texture, carbonation, moisture) are described. Other information is collected, such as topography, exposure, parent rock, etc.

Heaths or Moorlands

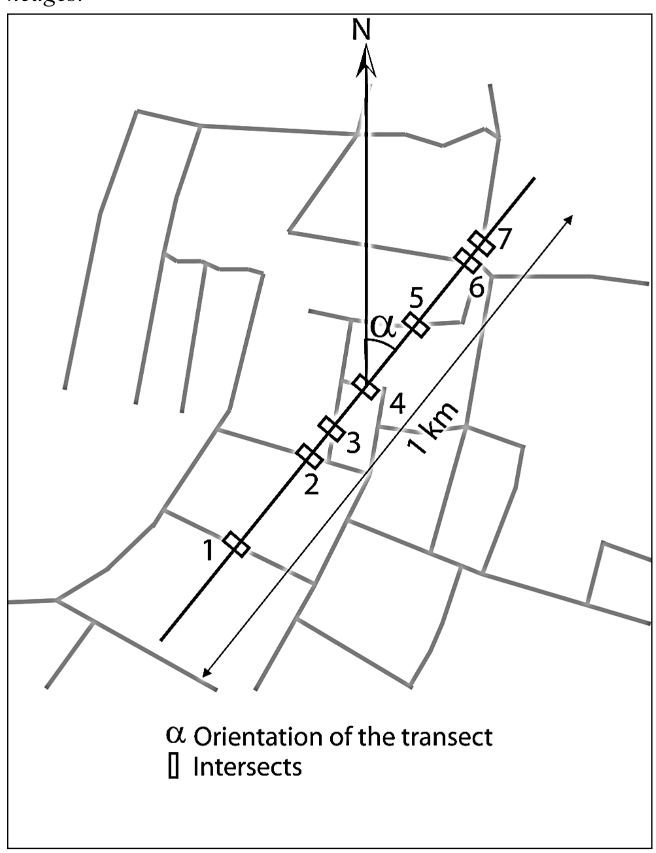
Heaths surveyed by the NFI are covered with noncultivated vegetation. Their size exceeds 0.05 ha and their width is more than 20 m. The crown of noncultivated trees covers less than 10 percent. Part of these heaths belongs to the other wooded land FAO category.

Heaths are inventoried in the field on every plot from the level 3 grid. Soil and topography are described. Their ecological type determination is based on shrub cover and type of soil. These data are the only statistics about heaths available all over France.

Hedges and Tree Rows

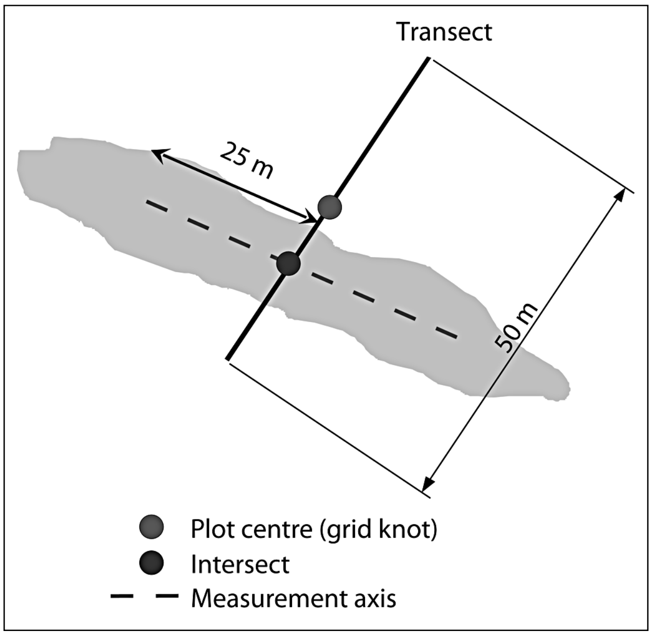
Hedges and tree rows are observed on orthophoto maps during photointerpretation on every plot from the level 1 sample. A transect method is used. A 1-km long line transect is centred on each grid knot with a randomly varying orientation. The number of intersects (fig. 9) between tree rows or hedges and the transect is counted to evaluate the length of these alignment in the territory.

Figure 9.—*Example of a photointerpreted transect intersecting hedges.*



In the field, operations are conducted on every alignment intersected at less than 25 m from the transect centre at a specific level (fig. 10). The type (hedges with or without trees, trees row with forest trees or poplar), species (tree, shrub and bush), the length, the width, the coherence with other linear elements (wall, river, etc.) are noted. The shape and ligneous species are observed and the permeability is evaluated. Specific measurements are conducted on trees at level 5 to evaluate the volume and the increment of growing stock.

Figure 10.—*Example of a tree row plot.*



Estimation and Computing Methods

Every year, at every level and for all inventoried structure, data are collected in the same way. Consequently, estimation procedures are the same in all cases for annual results.

Results, Details, and Precision

As a result of the annual sampling plan, sufficient precision will be obtained with data collected in 1 year on large areas only, for example, one-fifth of France or the whole territory. It is interesting to mention, however, that the possibility of annual national reporting allows fast countrywide update of the results in case of major disaster. It also gives the possibility to follow regularly the evolution of forest and other wooded areas and to highlight general trends.

Results can be obtained at a more local level and/or with more details using observations from several consecutive annual campaigns. A general estimation shows that regionwide results are available in 3 to 4 years. For the département level, at least 8 years of survey may be required, depending on the variable and the forest area.

Geographical Restitution Unit

With a systematic sampling design, the number of plots in a studied area is directly related to its size. Results will be more precise on larger areas. If data are required on small areas, two possibilities are offered by the new sampling design: (1) wait until enough data is gathered to compute the results, or (2) increase the level of annual collection for data that must be better evaluated in a given area.

The precision of the evaluation of a variable is also related to its variability in a given domain. This statistical property is interesting, because areas where less variability for some variables is expected can be delimited. It leads to the possibility of using post-stratification to enhance the precision of the results.

Computation Principle: A Yearly Computation Using Post-stratification

The French NFI maps forests and moorlands. In its Geographic Information System, the limits of administrative units such as département and ownership are also integrated. These are pieces of information that can be used to compute the results. Firstly, at the département or the region level, decisions to develop and encourage specific sylvicultures are taken. Secondly, the French national forestry board manages public forests differently if it is state forest or other public forest. Private foresters also have another behaviour. Thirdly, the forest type is determined on stand types, main species, structure, etc. As a result, in stands located in the same area, with the same forest type and ownership, less variability is expected.

Results from the French NFI will be computed using map post-stratification by département, stand type, and ownership category. This processing method will enhance the precision and the consistence of the results at the local and the national level. For totals, national results are then the exact sum of results calculated in each strata. This ensures, for example, that national results equal the sum of département results.

Results will be computed for every campaign. When the combination of several campaigns is necessary, the information will firstly be computed on the given area for each annual slice, actualized if necessary, and then averaged (Johnson and Williams 2004, McRoberts 2001).

For specific results on specific areas, two possibilities will be offered: (1) use the established post-stratification, or (2) establish a new post-stratification adapted to the area and to the variable that must be evaluated.

Conclusions

The new sampling design of the French NFI offers new opportunities. It is a flexible tool working annually at the national level and able to produce results on any part of the country. The NFI can compute results on smaller part of the country after a number of years depending on the area, the variability of the variable to be considered, and the sampling rate. This new tool allows fast reaction in case of exceptional events. Thanks to an efficient post-stratification, the loss of precision at the local level compared to the older method should be limited.

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An Investigation of Condition Mapping and Plot Proportion Calculation Issues

Demetrios Gatziolis[1]

Abstract.—A systematic examination of Forest Inventory and Analysis condition data collected under the annual inventory protocol in the Pacific Northwest region between 2000 and 2004 revealed the presence of errors both in condition topology and plot proportion computations. When plots were compiled to generate population estimates, proportion errors were found to cause underestimation of forested area. We identified reasons for the errors and offered recommendations for error prevention. Modifications were made to the condition proportion module in the compilation system as a result of these findings, and recommendations to reduce error incidence in the field in 2005 have already reduced the error rate by 70 percent.

Introduction

The annual Forest Inventory and Analysis (FIA) protocol uses the term *condition* for a set of five mutually exclusive land use/land cover classes that describe all landscapes sampled by FIA: accessible forest land, nonforest land, noncensus water, census water, and nonaccessible land. Within accessible forest land, conditions are refined to reflect differences in vegetation density and size classes, or ownership regimes. The spatial extent of conditions is determined by ocular assessments performed in the field following rules from field protocols. Adjacent conditions are delineated by a boundary line with a maximum of two segments. Boundary line vertices are recorded in reference to annular/subplot (partial plot) centers by using azimuth and distance measurements. Where determining the boundary between two conditions is difficult or impossible due to a gradual transition from one condition to another, the entire annular/subplot component is assigned to the condition present at its center. Field crews use hard copies of plot design templates to sketch the plot conditions before transferring all pertinent information to the data logger. Crew members have the option, usually at the end of the field day or sometimes later, of using a boundary visualization program available on their laptop computers to examine condition boundaries and make any necessary corrections. Conditions recorded in the field are also examined in the office as part of the programmatic quality assurance (QA) effort. Condition mapping errors detected during QA are flagged for follow up and resolution by data collection staff. All plot condition data is loaded into the FIA National Information Management System database (NIMS), where Procedural Language extensions to Structure Query Language (PLSQL) scripts use the condition mapping data to calculate condition proportions. These proportions are used to scale inventory sample plot data and generate State and regional population estimates.

Problem Identification

Random examination by Pacific Northwest FIA (PNW-FIA) analysts of condition-related data in NIMS for the years 2000 to 2004 revealed topological errors, related either to the locus of condition boundaries or condition labeling. Even for plots with topologically consistent condition data, the condition area proportions calculated in NIMS were often incorrect. Because the condition proportion is the first module in the NIMS compilation and the estimates it produces are widely used by other modules, errors in condition proportion were propagated forward, affecting much of the rest of the compilation.

Study Objectives

The study had the following objectives:

1. Determine the frequency and type of topological errors in condition mapping.

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2. Identify circumstances that tend to generate topological errors.
3. Compute the correct condition proportions for all plots.
4. Generate maps of conditions to be used as reference for future plot visits.

To handle the large number of plots to be examined, we generated a collection of linked, custom Arc/Info Workstation Arc Markup Language (AML) scripts. All FIA plots in California, Oregon, and Washington visited during the 2000–04 period were included in the study and their related data processed by the scripts. AML-script output was evaluated and compared to information available in hard copies of plot folders and to digital data contained in the NIMS database. Recommendations for reducing condition error rates were conveyed to field data collection staff as part of field training, and to FIA analysts. All field recommendations were implemented during the 2005 field season. Post-implementation error rates were compared to previous error rates.

Sources of Condition Errors

Condition mapping and proportion calculation are complex for several reasons. First, dense understory vegetation and/or steep terrain sometimes preclude a clear line of sight between the center and the limiting distance perimeter of the partial plot. Second, field crews must simplify what is sometimes a meandering or indistinct condition boundary to two straight line segments. In either case, condition boundaries recorded are drawn in the field by inference rather than observation, and errors are introduced, most often resulting in intersections of condition boundaries. Intersections also appear in instances in which more than two distinct conditions converge, resulting in condition boundaries that are in close proximity. During computation of condition proportions, the module used originally by NIMS used Euclidean geometry embedded in a small set of heuristic rules to convert geometric boundary information to condition proportions. Condition relationships not considered by the simple rules would produce condition proportion errors that were related to the complexity of the boundary relationship. On the other hand, condition mapping and proportion calculations based on the Geographic Information System (GIS) are analytical (i.e., data oriented), and, hence, capable of computing proportions correctly, regardless of boundary complexity.

Results

Condition Topology

A total of 12,303 plots were processed by the AML scripts. Of those, 11,647 at the annual (macroplot) design and 12,251 at the subplot design had consistent, error-free topology. Nearly 42 percent of all plots contained at least one forested condition. For 17 plots, the condition boundary segment corners were found to be at a distance from partial plot centers larger than or equal to the limiting distance of the partial plot. Table 1 shows the distribution of topology errors types by plot design. Practically all errors (87 out of 98 errors, or 89 percent) occurred in plots with at least one forested condition. Error incidence on the annular design far exceeded the rate at the subplot design, a result that is not surprising given that the much larger annular limiting distance is more likely to encompass a greater number of conditions. Nearly 70 percent of errors involved boundary intersections or erroneous condition labeling. Table 2 shows the error rate by topology error type. The rate computation considered only plots with condition topology that rendered them susceptible to a particular error type. For example, intersections are possible when there are at least two boundaries on a partial plot. The approximately 20 percent of errors classified as

Table 1.—*Distribution of condition topology errors across plot designs. Brackets indicate number of plots with at least one forested condition in each error type class.*

Error type	Design		Total
	Annular plot	Subplot	
Same condition on both sides of boundary or condition label conflict	27 [25]	15 [14]	**42**
Condition boundary intersection	23 [22]	4 [3]	**27**
Condition boundary intersects (or is within 0.1 feet from) subplot center	6 [6]	3 [3]	**9**
Other	14 [14]	6 [6]	**20**
Errors total	**70 [62]**	**28 [25]**	**98**

other (tables 1 and 2) involved conditions which, if considered independently, violate no field protocol rules. Considered in the context of the whole plot, however, the condition delineations implied the presence of a highly improbable spatial arrangement of conditions. Figure 1 shows the annular design condition map of such a plot where condition 2, classified as accessible forest land, is confined by the remaining three nonforest conditions and cannot reasonably expand outside the plot to reach the 1-acre minimum size required by the protocol rules. Figure 1 also shows that condition 3 appears in annular plot 2 while condition 2 first appears in annular plot 3, in violation of the rule stating that the condition numbering sequence should follow the numbering of partial plots. Checking against the hand-drawn sketches on the plot cards revealed these to be cases of one or more condition labeling errors. Examining the relationship between the number of condition boundaries in a partial plot and the frequency of topology errors (fig. 2) indicates that the probability of an error increases with the number of boundaries in a partial plot. It is unclear whether the probability of an error differs between subplots and annular plots.

Condition topology errors identified via the AML scripts were collated by error type and reviewed by FIA analysts and experienced field crew leaders. The consensus was that the errors were in part due to human mistakes, but also related to ambiguities in the field instructions and poor collection habits (e.g., conversion of measured sloped distances to horizontal by assessing visually, rather than measuring, the slope gradient) carried forward from the periodic inventory protocols that

Table 2.—*Error rates per condition topology error type and plot design.*

Error type	Error rate (percent)	
	Annular plot	Subplot
Same condition on both sides of boundary or condition label conflict	1.6 [27/1735][a]	1.4 [15/1086]
Condition boundary intersection	3.5 [23/653]	1.7 [4/236]
Condition boundary intersects (or is within 0.1 ft from) subplot center	0.3 [6/1735]	0.3 [3/1086]
Other	0.8 [14/1735]	0.6 [6/1086]

[a] *Fractions represent the number of plots with an error divided by the number of plots where the error was theoretically (based on the number of condition boundaries present) possible.*

Figure 1.—*Condition mapping of an annular design plot containing logical error in the spatial arrangement of conditions.*

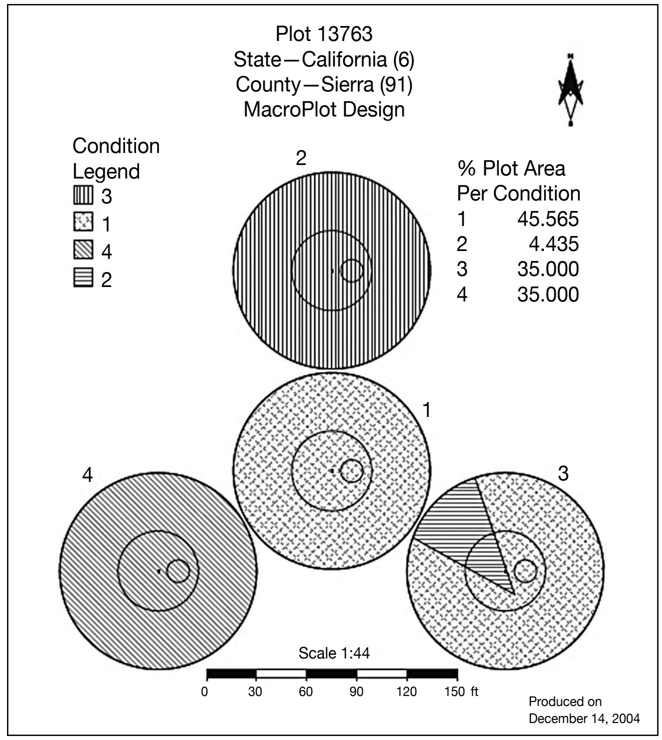
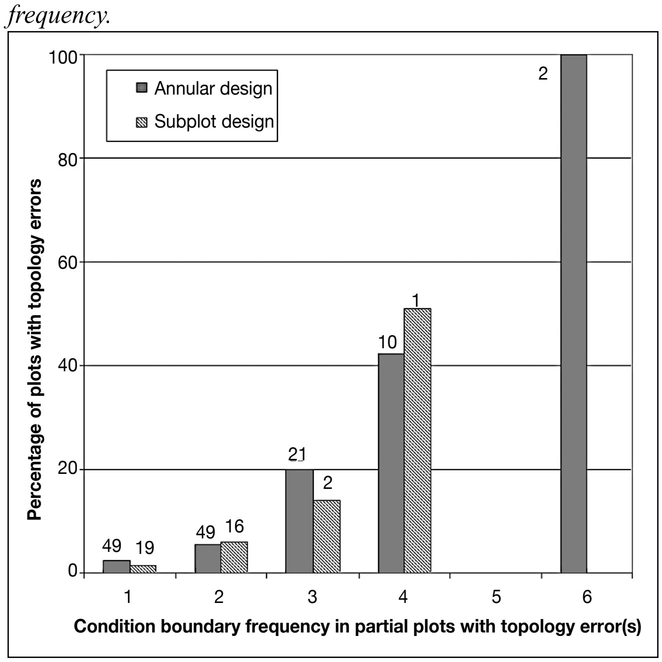


Figure 2.—*Percentage of plots with topologically incorrect condition boundary by boundary frequency per partial plot and plot type and design. Numbers above the bars indicate plot frequency.*



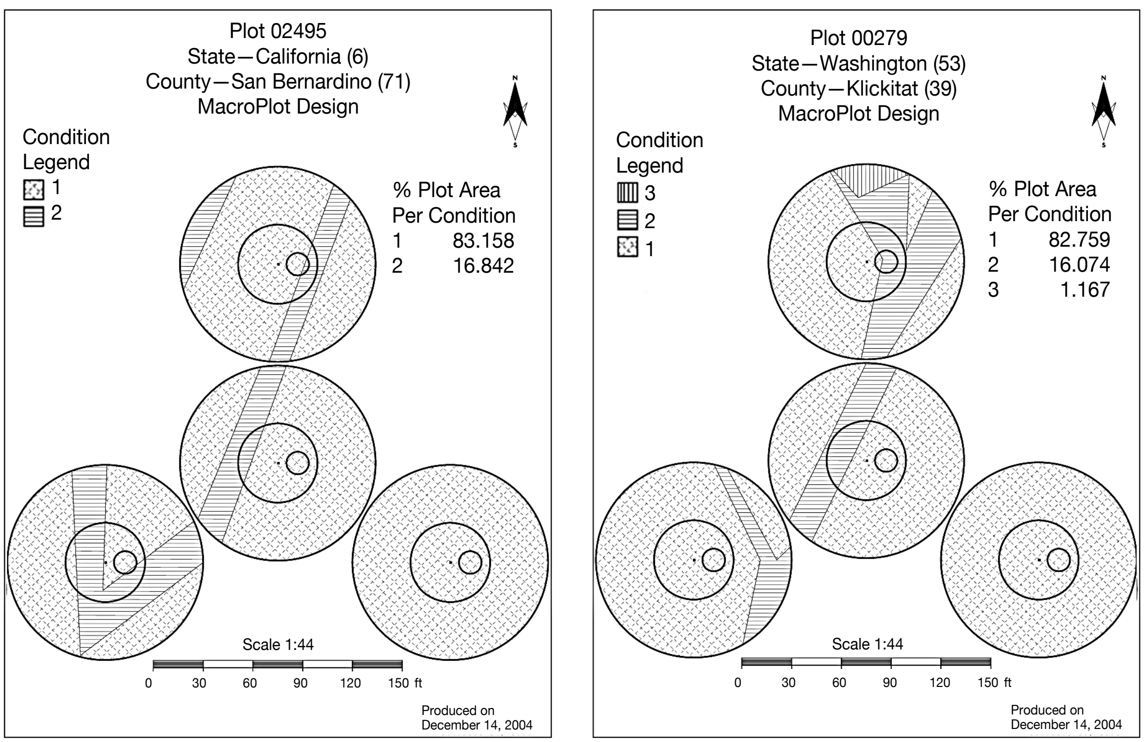
guided field data collection before the start of annual inventory at PNW-FIA. Plot maps of condition topology errors and recommendations on the proper interpretation of protocol rules were conveyed to the field personnel during the annual training sessions in 2005. Preliminary analysis of condition data acquired during the 2005 season suggests that the adoption of the recommendations resulted in a condition topology error rate approximately one-third of the rate in the previous 5 years.

Proportion Calculation

For plots without topological errors, condition proportions computed via the AML scripts were compared to those produced by the NIMS compilation. Proportion discrepancies smaller than 0.01 percent (of the total design-specific plot areas) were attributed to rounding error. Discrepancies exceeding 0.01 percent were found at the annular design on 61 plots and at the subplot design on 12 plots. Visual examinations of plot cards from field visits and of the maps produced by the scripts for plots exhibiting a proportion discrepancy reveal that, in all cases, the proportion computed by the AML scripts was correct (fig. 3). Henceforth, proportion discrepancies are referenced as *proportion errors*. Unlike the topology errors, proportion errors appear to be independent of topology complexity (table 3). When examined separately for forested

Figure 3.—*Discrepancies between AML- and NIMS PLSQL-computed proportions for two annular design plots.*

AML script output



Data in NIMS

Plot 2495			Plot 279		
Condition #	Proportion	Error (percent)	Condition #	Proportion	Error (percent)
1	0.6745	– 15.71	1	0.7700	– 5.76
2	0.3255	15.71	2	0.2183	5.76
			3	0.1170	0.00

and nonforested conditions, the distribution of proportion error showed evidence of bias, with forested condition underestimated and nonforested conditions overestimated at both partial plot designs (table 4). The bias was statistically significant. Two-tail t-tests for equal mean proportion error in forested versus nonforested conditions had p-value ≈ 0 for the annular plot design and p-value = 0.002 for the subplot design. The test assumed unequal variances.

Documenting condition proportion errors led to rewriting the condition proportion module. The new condition module is capable of detecting the majority of topology errors and computes proportions correctly for all plots with consistent topology. A small number of errors (labeled *other* in tables 1 and 2) pertaining to improbable condition arrangement remain undetected.

Table 3.—*Proportion errors in the NIMS database computed via PLSQL modules by error magnitude and plot design. Quantities in parentheses represent the mean number of condition boundaries present in each plot. At least one forested condition was present in each plot.*

Error magnitude (percent of plot area)	Frequency			
	Annular plot design		Subplot design	
< 1	14	(2.00)	4	(4.25)
1–5	35	(2.35)	4	(1.75)
> 5–10	8	(3.00)	3	(2.50)
> 10	4	(1.75)	1	(3.00)
Total	61	(2.32)	12	(2.88)
Mean absolute error (percent plot area)	3.223		3.522	
Standard deviation	3.183		4.120	

Discussion

Observing the number of boundary intersections at the subplot design (table 1) could generate the impression that such intersections are rare. When the number of partial plots with at least two condition boundaries is considered (table 2), however, the error rate becomes noticeable, with boundary intersections present at 1.7 percent of such plots at the subplot design and twice as frequent (3.5 percent) at the annular design. This observation could partially be attributed to the reduction of visibility in the field as boundary distance from the partial plot center increases, and partially attributed to the larger area occupied by an annular plot. Errors in condition labeling and instances of boundary intersection with partial plot centers are likely independent from field visibility considerations and plot design sizes. Results indicate that the rate of occurrence for these error types does not differ between designs (table 2). Irrespective of design, an increase in the number of condition boundaries present on a plot increases the probability of condition boundary errors (fig. 2).

Proportion errors in a plot are complementary; an overestimation in one or more conditions must be balanced by underestimations in others. In absolute value terms, the mean proportion error of 3.2 percent corresponds approximately to one-eighth of the area of a partial plot. Visual examination of condition maps produced by the AML scripts revealed that the majority of plots with a proportion error involve a nonforested, elongated condition splitting a forested condition into two, unequally sized parts (fig. 4). The smaller of the two forested polygons (northwestern part of annular plot 3) in figure 4 is approximately one-eighth of a partial plot. This observation helped trace the cause of discrepancies observed between

Table 4.—*Distribution moments of proportion calculation errors for forested and nonforested conditions present in the NIMS database calculated by using PLSQL modules.*

Condition	Design	Number of plots	Error moments (percent of plot area)			
			Mean	Standard deviation	Maximum	Minimum
Forested conditions	Annular	61	– 2.254	3.887	– 15.708	12.378
	Subplot	11	– 3.830	4.602	– 15.018	0.452
Nonforested conditions	Annular	60	1.796	4.237	– 12.378	15.708
	Subplot	10	2.736	4.351	– 2.612	15.703

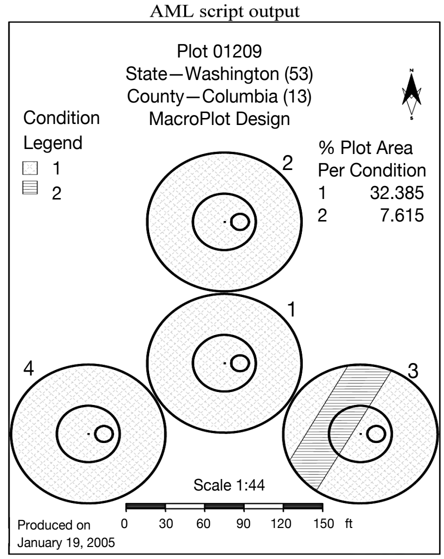
condition proportions calculated via the AML scripts and those computed in NIMS (table 4) to an inaccurate PLSQL script structure. Given that only spatial information is used in the computation of proportions and assuming spatially random arrangement of condition types, there is no reason to anticipate condition-type-related bias in the errors detected. Error bias, however, is present. The observed underestimation of forest-condition proportion is likely due to the shape and position of nonforested conditions that are frequently found on partial plots in areas dominated by forested conditions. In the example shown in figure 4, the previous NIMS PLSQL module failed to appropriately account for the smaller of the two forested conditions separated by the nonforested component and, by lumping the small forested condition's area with that of the nonforested condition, generated an area bias toward nonforest.

Despite higher fidelity in condition boundaries mapped and condition proportions computed in 2005, condition errors are still present in NIMS, both in the data and compiled information. Although these errors can potentially be flagged automatically by heuristics embedded in the database compilation procedure, their logical rather than topological nature would always necessitate manual inspection of all pertinent information, an option that is laborious and costly. The best alternative is to identify condition errors while the crew is still in the field. The current data recorder used by FIA could easily employ consistency checks for condition topology and offer visualization of the condition mapping for crews to evaluate before leaving the plot. Rather than relying on abstract perception of geometric relationships between conditions, crew leaders would examine their condition maps on the data recorder while viewing the actual condition breaks on the plot. This process would virtually eliminate all of the condition-related errors identified in this analysis.

Because of differences among FIA regions, for example, in dominant vegetation biomes, land use practices, and ownership regimes, a data compilation procedure that performs well in one region may be problematic in another. Rocky Mountain

Figure 4.—*Typical NIMS condition proportion error case involving an annular design plot and resulting from lumping the nonforest area with the smaller of the forested parts.*

AML script output



Data in NIMS

Condition #	Proportion	Error (percent)
1	0.8902	– 3.37
2	0.1098	3.37

FIA analysts rarely find two condition boundaries on the same partial plot. The legacy NIMS condition module performed well under such circumstances, but it has proven inadequate for compiling more complex condition arrangements present in the Pacific Northwest. This experience suggests that caution should be exercised every time new data collection and compilation approaches are considered for adoption at the national level to ensure that such changes will not have untoward consequences for regions in which patterns or ranges of data are different.

Acknowledgments

The author acknowledges Phyllis Adams, Olaf Kuegler, and Alison Nimura, all with PNW-FIA, for their help in this study.

Deriving Simple and Adjusted Financial Rates of Return on Mississippi Timber Lands by Combining Forest Inventory and Analysis and Timber Mart-South Data

Andrew J. Hartsell[1]

Abstract.—This study compares returns on investments in Mississippi timber lands with returns on alternative investments. The real annual rates of return from mature, undisturbed timber lands in Mississippi over a 17-year period (1977–94) were computed. Southern Research Station Forest Inventory and Analysis (FIA) timber volume data and Timber Mart-South (TMS) data on timber prices were employed. FIA trees were assigned a TMS dollar value based on species, size, and condition. The dollar value of each plot was derived by summing the per acre value of all trees on the plot. Simple and adjusted financial maturity concepts are investigated and compared. Simple financial maturity reflects the value of the timber only, while adjusted financial maturity reflects the implicit costs of holding timber. Average annual rates of change in monetary value and volume change were computed and compared for three distinct time periods: 1977–87, 1987–94, and 1977–94. These rates of return are compared to those for alternative investments such as stocks, bonds, certificates of deposit, and treasury bills. The effects of various plot- and condition-level strata such as ownership, forest type, survey unit, and ecoregion on financial rates of return are investigated.

Methods and Procedures

This study investigates biological and financial growth rates of undisturbed stands in Mississippi by applying Timber Mart-South (TMS) stumpage prices to Forest Inventory and Analysis (FIA) sample trees. Each FIA sample tree was assigned a dollar value based on species, size, and condition. Saw-log trees were divided into multiple products (saw log and topwood) and rough cull trees were treated as pulpwood. The tree values were summed for each plot to derive the total plot value in dollars per acre.

Study Area

The study area consists of the 82 counties of Mississippi, with the emphasis on timber lands. Timber land is defined as land that is at least 10 percent stocked by trees of any size, or formerly having such tree cover, and not currently developed for nonforest uses. Minimum area considered for FIA classification and measurement is 1 acre.

Time Periods

Three distinct time periods were investigated. These time periods coincide with FIA surveys of Mississippi. These three time periods are 1977–87, 1987–94, and 1977–94.

Plot Selection

Value change computations require input from two points in time. For this study, the earlier time period will be referred to as time 1. The later time period is time 2. Therefore, when the 1987–94 period is discussed, 1977–87 is time 1 while 1987–94 is time 2.

All plots must be classified as forested for all survey periods in question. All time 2 plots must be classified as saw-log-size stands, while time 1 plots may be either poletimber-size or sawtimber-size stands. Stands classified as seedling/sapling

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in either survey are omitted. All time 2 stands must have at least 5,000 board feet of timber per acre. Several plots were classified as having elm-ash-cottonwood forest. These were excluded because sample size was inadequate (< 10 plots for each survey period). All stands with evidence of management, disturbance, or harvesting for the survey periods in question, as well as the previous survey period, were excluded.

Tree Selection

All live trees ≥ 5.0 inches in diameter at breast height (d.b.h.) were included in the sample set, except rotten cull trees. Rough cull tree volumes were given pulpwood value. No cull trees were used in sawtimber computations. Tree selection was performed by variable radius sampling (37.5 basal area factor). Since tree selection was performed by variable radius sampling, new trees appear over time. These new trees were included in all computations and therefore affect growth and value changes. Trees that died between survey periods were included only in the survey year(s) in which they were alive. This factor has the potential to create negative biological and economic value growth between surveys.

Timber Mart-South Data

This study uses TMS price data to calculate individual tree values. TMS has been collecting delivered prices and stumpage prices for 11 Southern States since December 1976. All TMS price data are nominal. Real prices were calculated using the U.S. Bureau of Labor and Statistics all commodities Producer Price Index. As 1986 was the midpoint of the study period, all TMS prices were inflated or deflated to 1986 levels.

Tree Products and Tree Values

The following logic was used for determining tree products: (1) all poletimber-size trees are used for pulpwood; (2) the entire volume of rough cull trees, even sawtimber-size trees, is used for pulpwood; (3) the saw-log section of sawtimber-size trees is used for sawtimber; and (4) the section between the saw-log top and 4-inch diameter outside bark pole top is used for pulp and often referred to as topwood.

In 1981, TMS began to report Southern pine chip-n-saw prices. Therefore, the two survey periods after this time included a third product, Southern pine chip-n-saw. Chip-n-saw trees are Southern pines 9.0 to 12.9 inches d.b.h. All trees < 9.0 inches d.b.h. are still treated as pulpwood, and trees ≥ 13.0 inches d.b.h. are treated as sawtimber trees. This modification was made for the 1987 and 1994 survey periods.

FIA traditionally computes all board-foot volumes by international 1/4-inch log rule. Most of the TMS price data is in Doyle log rule. To accommodate the price data, all FIA tree volumes were recalculated using the Doyle formula. In a few instances, prices are reported in Scribner log rule. To accommodate this, the Doyle prices for these few instances were converted to Scribner prices by multiplying the Doyle price by 0.75 (Timber Mart-South 1996).

The TMS reports include a low, high, and average price for standing timber for various products. This report does not consider peeler logs or poles and piling as possible products because determining these products from FIA data is questionable. Omitting these classes allows for a slightly conservative approach to estimating tree and stand value. FIA data has information on species, product size (poletimber or sawtimber), and quality (tree class and tree grade). Prices for each section of the tree were assigned based on these factors. These prices were then applied to the different sections of a tree. Table 1 details how TMS prices where assigned to individual trees.

Growth Models

Timber volumes and values are summed for each plot. These totals are then used as inputs for the growth models. Three growth models were used in this study. Each is based on the formula used in determining average annual change.

Table 1.— *Logic used in assigning TMS prices to FIA sample trees.*

Tree characteristic	Price assignment
Growing-stock pine poletimber	Average pine pulpwood price
Nongrowing-stock pines	Low pine pulpwood price
Hardwood growing-stock poletimber	Average hardwood pulp price
Hardwood nongrowing-stock, nonoak trees	Low hardwood pulp price
Pine sawtimber topwood	Low pine pulpwood price
Hardwood sawtimber topwood	Low hardwood pulp price
Southern pine chip-n-saw	Average chip-n-saw price[a]
Tree grades 1 and 2 oaks[b]	High oak sawtimber price
Tree grade 3 oaks[b]	Average oak sawtimber price
All other growing-stock, sawtimber-size oaks[b]	Low oak sawtimber price
Post oak, Delta post oak, and black oak	Low mixed sawtimber price
Tree grades 1 and 2 Southern pine	High pine sawtimber price
Tree grade 3 Southern pine	Average pine sawtimber price
All other pine sawtimber—growing-stock	Low pine sawtimber price
All nonoak tree grade 1 hardwoods	High mixed sawtimber price
All other nonoak tree grade 2 and 3 hardwoods	Average mixed sawtimber price
Any remaining growing-stock hardwoods	Low mixed hardwood price

[a] *Except for the 1977 survey, in which this category does not exist. For 1977, all Southern pines < 9.0 inches d.b.h. are treated as pulpwood, larger trees as sawtimber.*

[b] *Except for the following species: post oak, Delta post oak, and black oak.*

Timber Value Growth (TVG) is a simple financial maturity model that considers only the actual change in value for a plot for the survey period in question. Incomes derived from future stands are ignored. The basic formula for TVG is:

$$TVG = [(TVF/TVP)^{1/t} - 1] * 100 \quad (1)$$

where
TVG = timber value growth percent.
TVF = ending sum of tree value on the plot at time 2.
TVP = beginning sum of tree value on the plot at time 1.
t = number of years between surveys.

Forest Value Growth (FVG) includes the value of land in the computation of economic value change. The formula for FVG is:

$$FVG = [((TVF + LVF) / (TVP + LVP))^{1/t} - 1] * 100 \quad (2)$$

where:
FVG = forest value growth percent.
TVF = ending sum of tree value on the plot at time 2.
LVF = ending land value.
TVP = beginning sum of tree value on the plot at time 1.
LVP = beginning land value.
t = number of years between surveys.

FVG is an adjusted financial maturity model. Adjusted financial maturity concepts account for all implicit costs associated with holding timber. These implicit costs are sometimes referred to as opportunity costs. Thus, adjusted financial maturity concepts account for revenues from future stands. One method of adjusting the model is to include bare land value (LV) in the equation, because LV accounts for future incomes and the inclusion of LV adjusts the simple financial maturity model. This study computes multiple FVGs using LVs ranging from $50 per acre to $550 per acre in $50 increments.

Biological Growth Percent (BGP) is similar to TVG, except it uses timber volumes instead of timber values. The BGP model accounts for the actual annual change in tree volume for a plot over a survey period. The BGP model is the same as the TVG model, except it uses the sum of tree volumes on the plot instead of the sum of tree values.

Results

Initial investigations analyzed value growth based on various plot strata such as county, ownership, and forest type. Table 2 details the sample size, BGP, TVG, and FVG of Mississippi timber lands by forest type for the 1977–94 period. FVG is computed in $250 increments ranging from $250 to $1500. This sample set is more likely to represent the true trend for the extended period as it contains only plots that met the selection criteria for all three surveys. All financial rates of return are real. Table 2 reveals that pine stands outperformed all other stands in terms of biological and economic growth. Average pine stand volume increased 5.2 percent per year, while average pine stands earned more than 16 percent per year using the simple model. The adjusted rates of return for mature pine stands ranged from 4.9 percent to 10.9 percent per year depending on land value. While stands consisting primarily of pine outperformed other types, they did not do so to the degree that many would expect. A common perception in the South is that loblolly pine is the only economically viable species. This may not be the case, as even oak-gum-cypress stands, the weakest performers in this study, had TVG greater than 12 percent per year and FVG ranging from 3.5 to 8.25 percent per year.

Figure 1 illustrates the FVG estimates from table 2. If landowners know the value of their land, or the value of nearby lands, then they can use this graph as a guide to the rates of return they might expect to earn on their holdings. This graph clearly shows the effect that land value has on rates of return. As LV increases, rates of return decrease. There will be a point at which land value plays a greater role in determining land use than do timber values.

Another avenue is to investigate value change spatially and temporally to determine if there are any regional patterns or shifts in value change over time. This is accomplished by mapping out rates of return across the State and comparing these rates to ecological strata such as forest type and ecoregion, or comparing these distributions over time. To accomplish the first, an ecological benchmark is needed. Figure 2 shows the distribution of plots by 1994 forest type. Pine stands dominate the southern/southeastern portion of the State, while hardwoods form the plurality along major waterways. The northern part of the State is almost an even mix of the three types. Traditional wisdom dictates that the greatest rates of return would occur in the southern part of the State, due to the high frequency of yellow pine. The following queries tested this idea as well as looking for any spatial/temporal patterns.

Figure 1.—*Forest value growth percent by forest type and land value, Mississippi, 1977–94.*

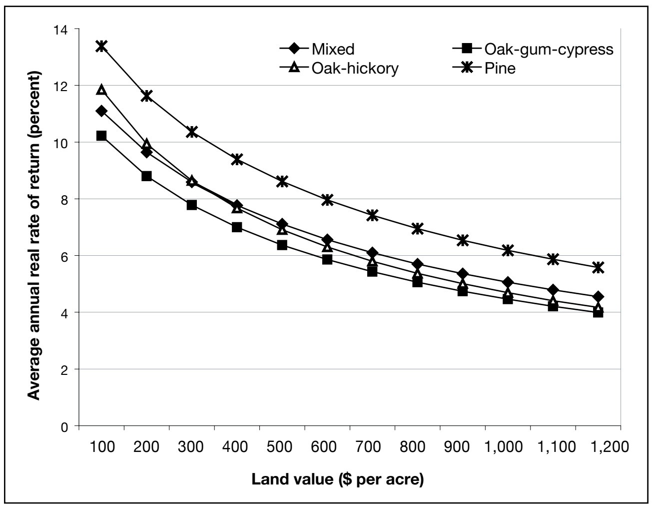


Table 2.—*Average annual growth percent, real timber value growth percent, and real forest value growth percent by forest type, Mississippi, 1977–94.*

Forest type	Plots	BGP (%)	TVG (%)	FVG 250 (%)	FVG 500 (%)	FVG 750 (%)	FVG 1000 (%)	FV 1250 (%)	FVG 1500 (%)
Pine	25	5.22	16.14	10.95	8.61	7.18	6.18	5.45	4.88
Mixed	26	3.63	13.36	9.08	7.11	5.89	5.06	4.44	3.96
Oak-hickory	38	4.35	15.14	9.23	6.91	5.57	4.69	4.06	3.58
Oak-gum-cypress	70	3.16	12.43	8.25	6.37	5.23	4.46	3.89	3.46
Total	**159**	**3.84**	**13.82**	**9.05**	**6.97**	**5.73**	**4.88**	**4.27**	**3.79**

Interesting patterns emerge when each plot's forest value growth (LV = $750 per acre) by survey period is mapped. The southern portion of the State tended to have slightly higher rates of return for 1977–87. It is interesting that 11 plots scattered across the State experienced negative value-growth, even in the southern portion. While rates of return where slightly higher in the south, the degree to which they outperformed the rest of the State was relatively small along with the certainty that they would "earn money" (fig. 3).

Conversely, the majority of the highest earning plots in the 1987–94 survey occur outside of the southern region and in areas of the State that are dominated by hardwood and mixed stands. This result is due to increases in hardwood stumpage prices that occurred in this time frame. Another interesting point is that no negative value-growth plots were in this data set and all plots "earned money," with the majority of the highest earning plots occurring in the northern and central regions of the State (fig. 4).

The true long-term economic trend is best ascertained by combining inventories and using the plots that meet selection criteria in both surveys. The results of the extended 1977–94 period are similar to those for the 1987–94 period in that no plots lost money and the majority of the highest earning plots occurred outside the southern portion of the State. The moderating effect of time, along with the first inventory's lower rates of return, produce overall lower rates of return (fig. 5).

Figure 2.—*Distribution of plots by major forest type, Mississippi, 1994.*

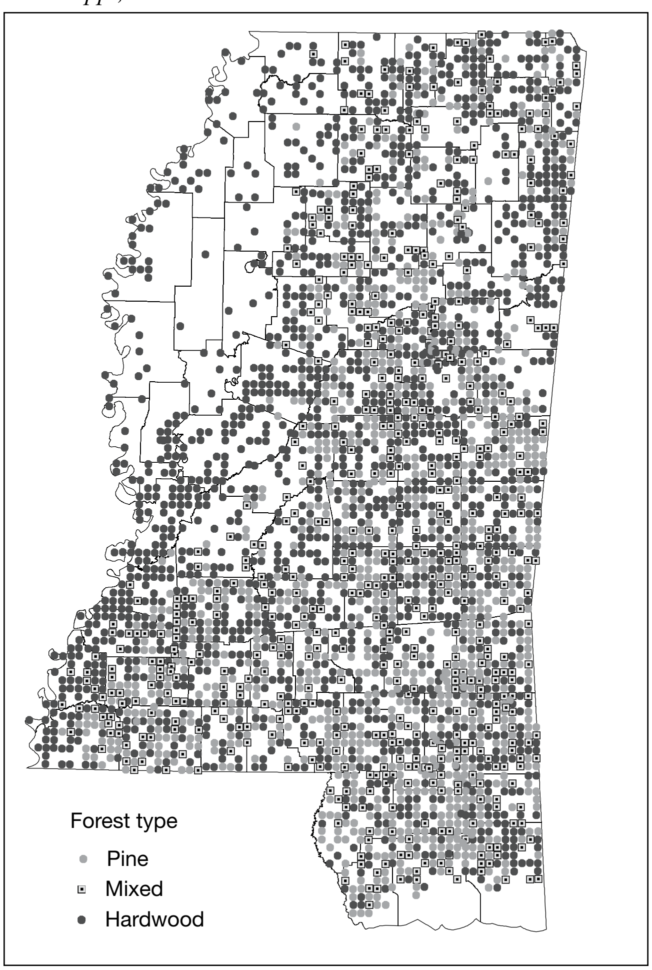


Figure 3.—*Distribution of plots by forest value growth, land value = $750 per acre, Mississippi, 1977–87.*

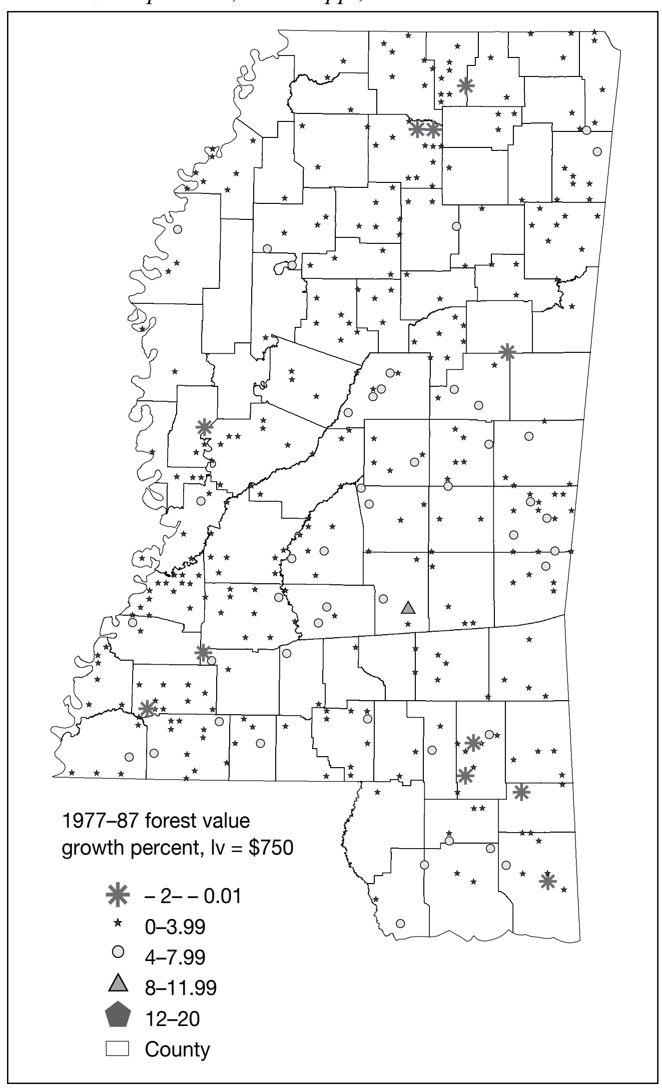


Figure 4.—*Distribution of plots by forest value growth, land value = $750 per acre, Mississippi, 1987–94.*

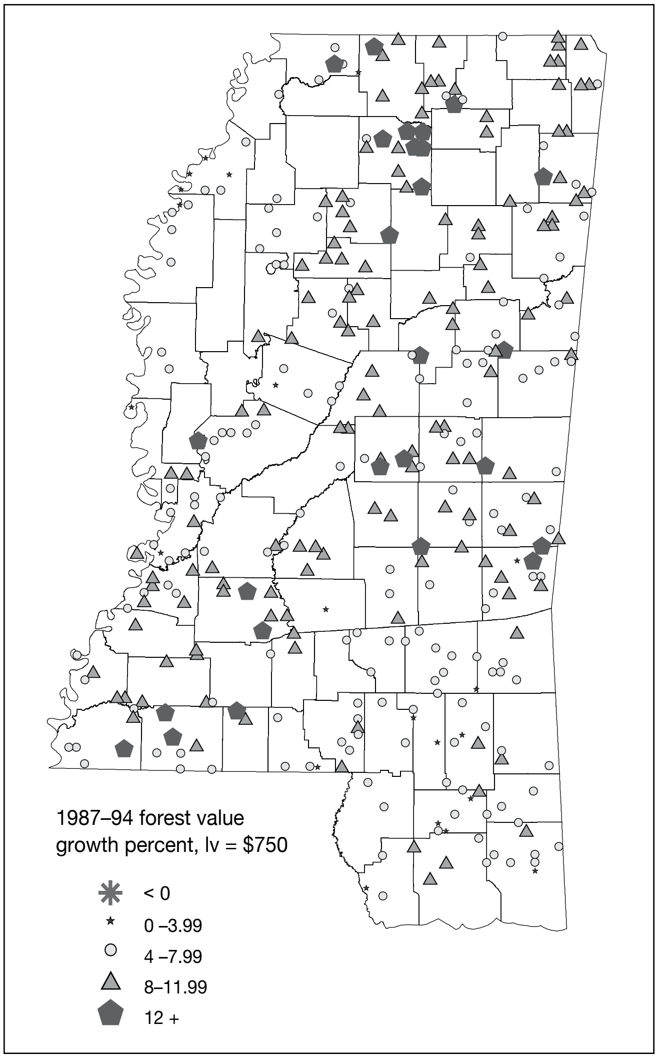
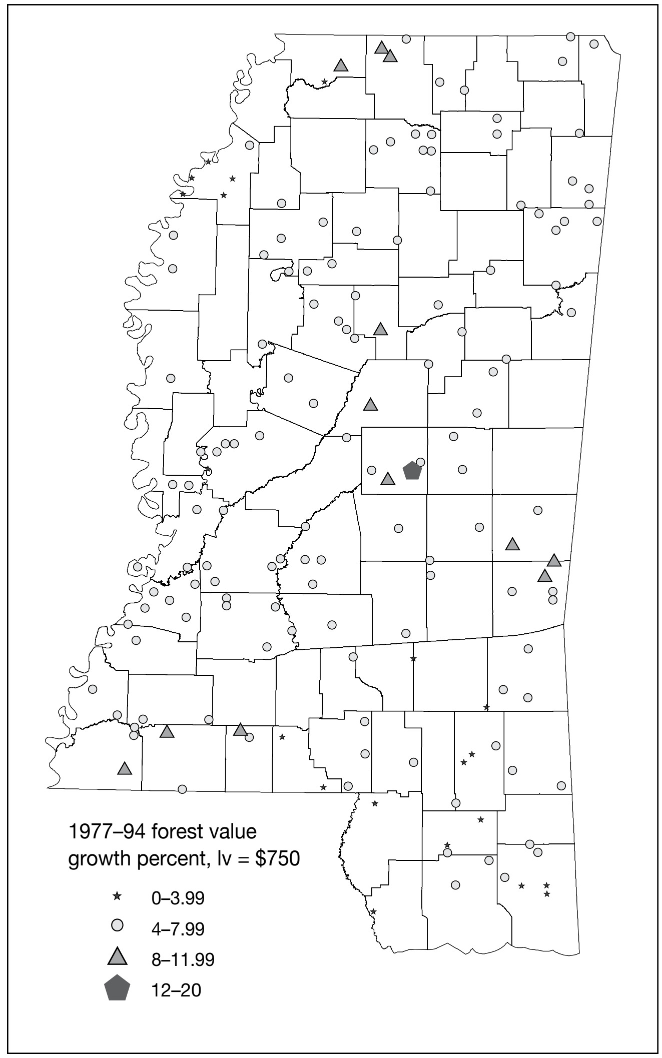


Figure 5.—*Distribution of plots by forest value growth, land value = $750 per acre, Mississippi, 1977–94.*



Another avenue of investigation involves stratifying value change not on a plot- or condition-level variable such as ownership or forest type, but on ecoregion. Figure 6 combines Bailey's ecoregions with the data from figure 4. There is an apparent correlation between ecoregion and economic value change for the State, as the majority of the highest earning plots occur in the Coastal Plains middle section. Indeed, the plots in this section averaged more than 9 percent per year real rate of growth for the period. This rate of return is significantly higher than those for the other sections (table 3).

Comparing the rates of return from timber lands to those for other investment options yields interesting results (table 4). The simple financial maturity model (TVG) outperforms all other investment options for all survey periods. The results differ, however, when using the adjusted model. Between 1977 and 1987, certificates of deposit, AAA corporate bonds, and the S&P Stock Index (S&P 500) rank higher than FVG. During this survey, the adjusted model's rates of return compare favorably with the Dow Jones Industrial Average and Treasury Bills. The outcome is better for both the next time frame (1987–94) and the extended period (1977–94). In both instances FVG outperforms all other investment options except the S&P 500.

Figure 6.—*Distribution of plots by forest value growth, land value = $750 per acre, by ecological section, Mississippi, 1977–94.*

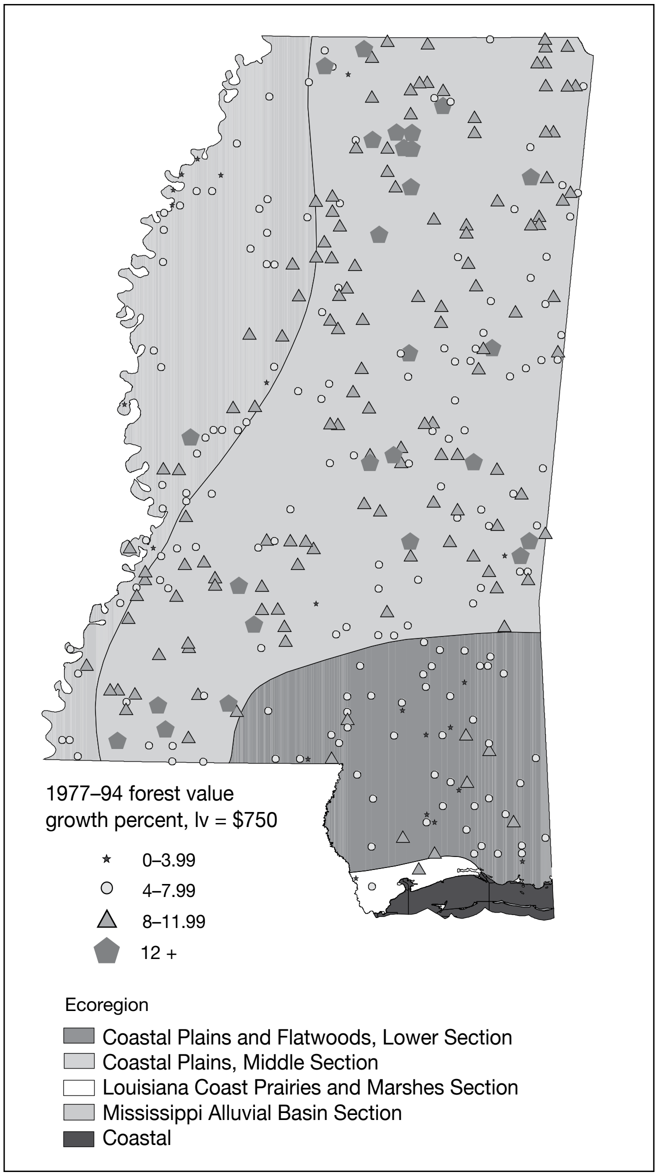


Table 3.—*Average annual forest value growth percent by ecoregion, Mississippi, 1987–94.*

Bailey's ecological section	N	Average forest value growth[a]
Coastal Plains and Flatwoods Lower Section	62	6.25
Coastal Plains Middle Section	221	9.05
Louisiana Coast Prairies and Marshes Section	3	6.08
Mississippi Alluvial Basin Section	56	4.45

[a] *Forest value growth percent calculated using bare land value = $750 per acre.*

Table 4.—*Average annual real rates of return, expressed as a percentage, for Mississippi timber lands and alternative investment options by survey period.*

Investment options	1977–87	1987–94	1977–94
TVG	8.05	18.58	13.82
FVG[a]	2.40	8.09	5.73
1-month certificate of deposit	2.93	2.11	3.32
3-month certificate of deposit	3.06	2.18	2.75
6-month certificate of deposit	3.22	2.30	2.89
3-month Treasury Bill	2.11	1.61	1.96
6-month Treasury Bill	2.24	1.73	2.09
1-year Treasury Bill	2.18	1.86	2.11
AAA corporate bonds	4.23	4.67	4.43
Dow Jones Industrial Average	0.10	5.13	2.21
S&P 500 Stock Index	6.84	8.48	7.92

FVG = Forest Value Growth.
TVG = Timber Value Growth.
[a] *FVG calculated using bare land value = $750 per acre.*

Key Points

This study did not consider the effects of taxes. The impacts of taxes paid or tax exemptions for the various investment options were not taken into account. These have the potential to affect the final rates of return. The stands must be completely liquidated to meet the specified rate of return. The landowner maintains possession of the land. Income from selling the land is not included. LV change over time is not considered. Regeneration costs, and other silvicultural practices, are excluded from the analysis as well. Returns from intermediate harvests, thinning, and costs of land improvements are not included. Therefore, foresters and land managers have the potential to improve on these rates through species selection, intermediate practices, and final products the stands produce.

Conclusions

Economic studies such as this have the potential to increase FIA's user base while informing landowners of the value of their holdings. This could lead to a higher awareness of all the management options available to them, and open the doors to new ones. For example, hardwood management may now be a viable management option to many landowners who previously ignored this resource. In addition, investment institutions such as banks and timber management organizations would find this type of product useful, increasing the demand for FIA data and products.

Literature Cited

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Identifying Areas of Relative Change in Forest Fragmentation in New Hampshire Between 1990 and 2000

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Abstract.—Forest fragmentation potentially can impact many facets of natural ecosystems. Numerous methods have been employed to assess static forest fragmentation. Few studies, however, have analyzed changes in forest fragmentation over time. In this study, we developed new classifications from Landsat imagery data acquired in 1990 and 2000 for New Hampshire, assessed fragmentation in both time periods, and created maps depicting the spatial extent of fragmentation change through time. Visual inspection of the resulting maps suggests the method successfully identifies areas of the State where fragmentation is occurring at a relatively high rate.

Introduction

Forest fragmentation continues to be a topic of great interest in the Northeastern United States. The conversion of land cover from forest to other uses by humans and natural processes affects animal behavior, plant-seed dispersal, hydrological processes, and local weather conditions (Forman 1995). When contiguous forest land is divided into smaller, more complex patches, increasing isolation of remaining patches and an increase in forest areas influenced by nonforest edge often results. These factors may lead to changes in the composition and structure of the forest, including an increased potential for nonnative species invasion (Haskell 2000, Trombulak and Frissell 2000).

The U.S. Department of Agriculture Forest Service's Forest Inventory and Analysis (FIA) program continuously inventories the Nation's forest resources. The data collected include information on the extent, condition, and character of U.S. forests. Recently, FIA also has included forest fragmentation information in their State reports (Barnett *et al.* 2002, Wharton *et al*. 2004). In a regional assessment of forest fragmentation in the Northeast, a suite of fragmentation indicators were summarized by county, watershed, and ecoregion (Lister *et al.* 2005, USDA Forest Service 2006). These data sets and other regional and national forest fragmentation assessments (e.g., Riitters *et al.* 2002, Heilman *et al.* 2002) provide information on forest fragmentation at one point in time. Information about the dynamic nature of fragmentation, including changes in the patterns and distribution of forest land, are less abundant in the scientific literature. Although this dynamic component of fragmentation is difficult to assess, it is critical to our understanding of the stability and health of forest ecosystems and to our ability to properly manage forest resources.

Recognizing the importance of forest land dynamics and fragmentation change to forest management, the New Hampshire Division of Forests and Lands is addressing these concerns in their latest revision of the Forest Resource Plan. This comprehensive Statewide plan summarizes the condition of New Hampshire's forests and discusses the desired future forest condition. As a potential input to the 2006 Forest Resource Plan, FIA agreed to conduct a spatial assessment of relative change in forest fragmentation. This ongoing assessment is designed to identify areas of the State where land class conversion is occurring at a relatively high rate, with the purpose of helping managers and policymakers make more

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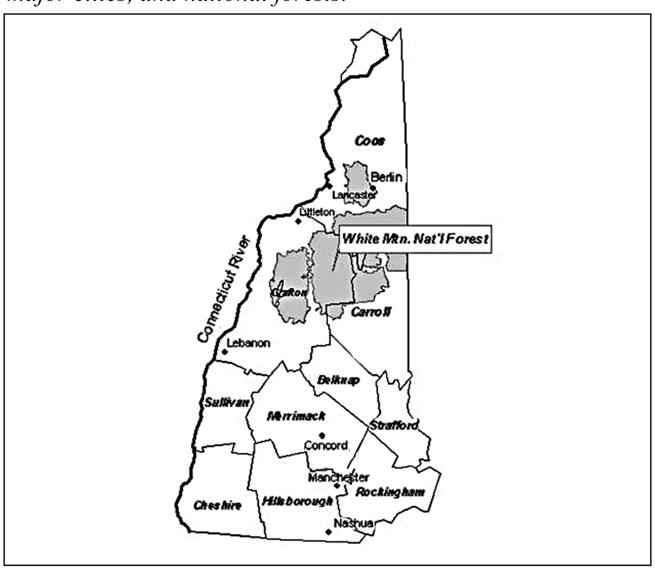
effective and appropriate management decisions. The goals of this article are to describe the methods used to produce the land cover base maps of New Hampshire, to provide a mapped summary of the fragmentation statistics calculated at two points in time, and to discuss preliminary interpretations of the data. Furthermore, this analysis serves as the first in a series of State-level land cover conversion analyses that could become part of the fabric of FIA analytical reports.

Methods

Description of Study Area

Forest land dominates New Hampshire's landscape, covering 84 percent of the total land area, making it second to Maine, the Nation's most forested State (Frieswyk and Widmann 2000). New Hampshire's 4.8 million acres of forest are relatively evenly distributed across the State with all 10 counties made up of at least 65 percent forest. A greater concentration of forest occurs in the northern half of the State, which includes the White Mountain National Forest (fig. 1). The lowest concentration of forest is in the more populated, southeastern section of the State (Frieswyk and Widmann 2000).

Figure 1.—*The State of New Hampshire showing counties, major cities, and national forests.*



New Hampshire's forest products industry adds more than $1.5 billion to the State's economy (NEFA 2001). Sawlogs are the primary industrial use of wood harvested, followed by pulpwood. According to FIA data, the area of forest land in New Hampshire decreased slightly between 1983 and 1997 (Frieswyk and Widmann 2000). An estimated 134,500 acres of forest were converted to other land uses during this period. The greatest decrease in the area of forest land occurred in the eastern part of the state, especially in Carroll and Strafford Counties.

Base Map Classification

Initially we hoped to use previously classified images from two different points in time that would serve as the basis for a moving window fragmentation analysis. The land cover maps that we compared included the Multi-Resolution Land Characterstics (MRLC) 1992 classification (Vogelmann 2001), and classifications created by David Justice (2002). Due to differences in the original images and classification methods, we determined that these classification maps were not comparable. We decided to perform our own classifications to reduce any methods-based discrepancies.

We found spectral differences between a Landsat satellite image collected in 1990 and one collected in 2000. The images used were clipped from Earthsat Geocover mosaics (Earthsat 2006), and consisted of leaf-on bands two, four, and seven. Spectral difference images were created by using band subtraction (band 7–band 7, band 4–band 4, and band 2–band 2) in Leica Imagine[4]. Spectral difference images were created by using band subtraction using Leica imagine[4]. For example, on a pixel-by-pixel basis, the spectral values of band 7 for the 1990 image were subtracted from the spectral values of band 7 for the 2000 image. Once the magnitude of the spectral differences between each of the corresponding bands from the two time periods was determined, we developed heuristics to identify areas of loss, increase, or no change in forest cover. This was done by iteratively thresholding the three band spectral difference image to create potential forest cover loss maps and comparing them visually with National Agricultural Imagery Program files from 2004 (USDA Aerial Photo Field Office 2006), U.S. Geological

[4] The use of trade, firm, or corporation names in this publication is for the information of the reader. Such use does not constitute an official endorsement or approval by the U.S. Department of Agriculture (USDA) or the USDA Forest Service of any product or service to the exclusion of others that may be suitable.

Survey (USGS) digital orthophoto quads from around 1997 (USGS 2006a) and NHAP (USGS 2006b) 1:40,000 aerial photographs from 1993. Photography that corresponded with the dates of the Landsat scenes would have been preferred, but was unavailable.

We then combined the resulting classified forest cover change image with a classification conducted by Justice *et al.* (2002) from 2000 (IM2000), and one conducted by the MRLC program (Vogelmann 2001) from 1990 (IM1990) to produce the land class base maps. Unique combinations of forest cover change and IM2000 allowed us to "backdate" the 2000 classification to create a new 1990 classification, based on IM2000, via a recoding procedure. For example, if IM2000 indicated an urban class and the forest change image indicated forest loss, then a new 1990 image was created by "backdating" IM2000 to a forest class. Similar logic was used for other classes. IM1990 was used primarily to detect areas of forest gain. For example, if IM2000 indicated a forest class, the land cover change image indicated forest gain, and the IM1990 image indicated a nonforest class (not including urban, residential or transportation, which was unlikely to revert to forest), then the new 1990 image was assigned a nonforest class at that location. If the forest cover change image indicated no change, then the IM2000 class was assigned to the new 1990 image.

We combined Geographic Information System coverages of roads from the U.S. Census Bureau's TIGER Line files (U.S. Census Bureau 2002) with both the new 1990 image and IM2000. We then applied a correction methodology described in Lister *et al.* (in press) to convert forested areas with a high road density to the developed class, under the assumption that these areas are probably either residential, or so impacted by the road density as to make them ecologically similar to developed areas.

Map Refinement and Land Class Descriptions

The final classification scheme for both IM2000 and the new 1990 image was based on a collapsing of the original IM2000 classes into six categories: water and background (which consisted of analysis unit edges and roads, and was not included in calculations), developed (residential, urban, forest that was relabeled developed based on road density, and transportation networks not coinciding with the census roads), agricultural areas (including pastures and orchards), forest (including forested wetlands), natural vegetated areas (including herbaceous wetlands, sand dunes, tundra, and exposed bedrock areas with stunted vegetation), and cleared areas that have not been converted to developed land cover classes. We applied a spatial filtering algorithm to these maps (Leica Imagine's "eliminate" procedure) to remove patches consisting of less than four contiguous pixels of the same class.

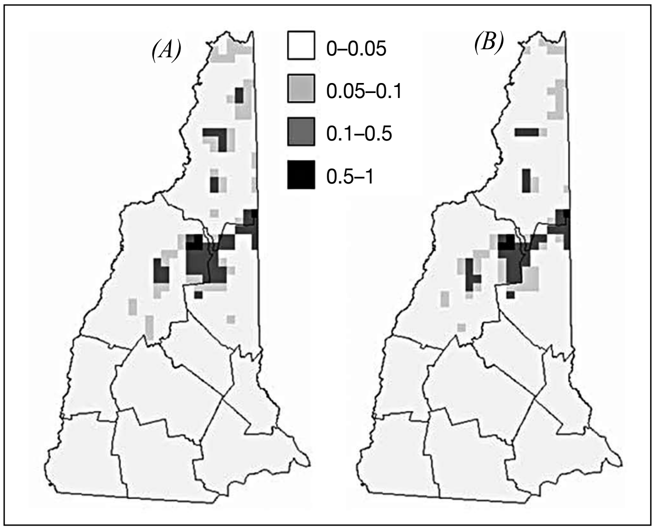
Fragmentation Assessment

Next, we clipped each image into 974 overlapping 10- by 10-km image tiles using Leica Imagine and calculated a suite of fragmentation statistics on the image tiles from each time period using APACK software (Mladenoff and DeZonia 2001). We then normalized each metric's value for each tile by dividing it by the maximum value of that metric across all the tiles. We did this to facilitate interpretation of the fragmentation difference analyses when the classifications from the two time periods varied due to classification error and not true land cover change. In other words, the fragmentation change analyses identify image tiles that show large relative differences, not absolute differences. We merged and joined these normalized datasets to the centroids of the overlapping tiles (which were 5 km apart), subtracted the new 1990 image's normalized fragmentation statistics from those of IM2000, and generated the fragmentation change maps.

Results and Discussion

Although a full suite of fragmentation metrics was estimated and mapped, the following discussion includes a small sample of only the most interesting fragmentation indices. Mean patch size is widely used to characterize forest patches and has been shown to be an important and applicable metric (Lausch and Herzog 2002). As described above, the mean forest patch size is presented as a relative value in figure 2, which shows the distribution of patch sizes in New Hampshire. Not surprisingly, the average patch size is largest in the White Mountains National Forest located in the eastern-central portion of the

Figure 2.—*Relative forest mean patch size calculated within overlapping 10- by 10-km image tiles in New Hampshire in 1990 (A) and 2000 (B).*



State. Although the distribution of average forest patch area is similar in 1990 and 2000, the change map (fig. 3) shows mostly patchy decreases and some increases in average forest patch area in the northern half of the State. A preliminary visual inspection of USGS digital orthophoto quads and aerial photographs at different time periods revealed that many of these areas of change are due to harvesting and forest regrowth.

The forest aggregation index estimates the degree to which forested pixels are clumped together in the landscape. This metric is calculated by dividing the number of forest cells that are adjacent to other forest cells by the total number of possible adjacent forest-forest edges. The more aggregated the forested pixels, the higher the aggregation index. As expected, the forest aggregation index is lowest in the southeastern portion of the State (fig. 4), which has the lowest percentage of forest cover yet hosts the greatest number of forest patches. The area surrounding Manchester also supports the greatest amount of urban land uses. The highest forest aggregation index values are found in Coos, Grafton, and Carroll Counties in the north. Figure 5 shows relatively little change in forest aggregation index between 1990 and 2000. The aggregation index shows some increases along the Connecticut River at New Hampshire's western border with Vermont. Decreases in forest aggregation index in central Coos County may correspond

Figure 3.—*Relative difference in forest mean patch size calculated within overlapping 10- by 10-km image tiles in New Hampshire.*

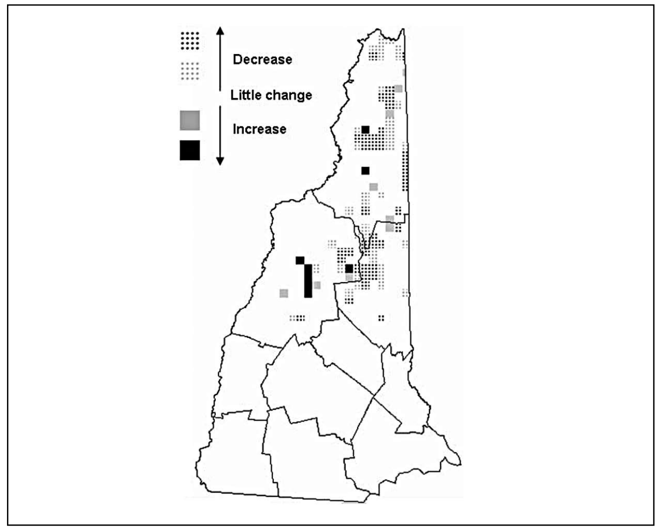
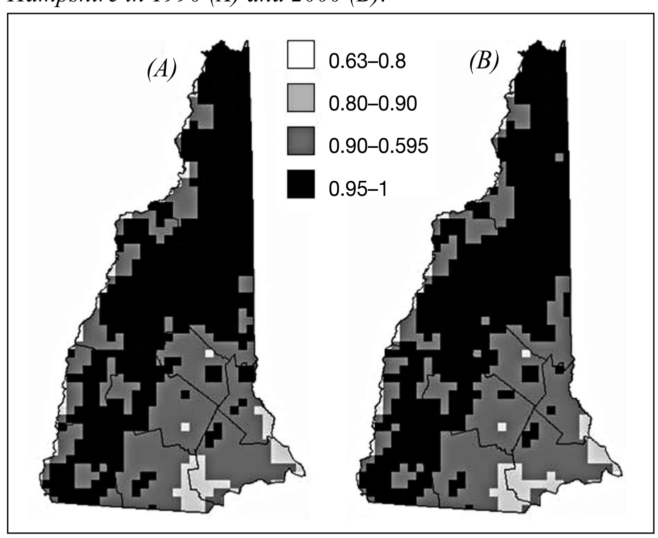


Figure 4.—*Relative values of forest aggregation index calculated within overlapping 10- by 10-km image tiles in New Hampshire in 1990 (A) and 2000 (B).*



with areas influenced by harvest activities as suggested by the images and photography we studied.

Up to this point the changes captured by our preliminary analyses have been attributed to land cover conversion due to harvesting activities as forested land is cleared and regrowth occurs. These changes are significant to evaluate, but generally do not represent a permanent loss of forest land; a change in

Figure 5.—*Relative difference in forest aggregation index calculated within overlapping 10- by 10-km image tiles in New Hampshire.*

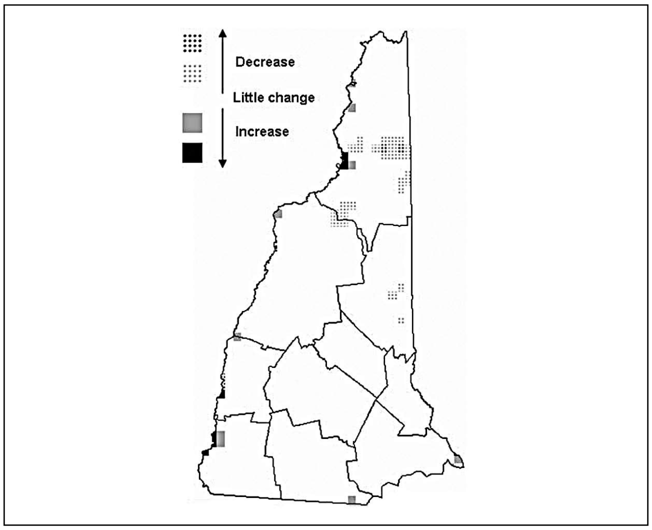
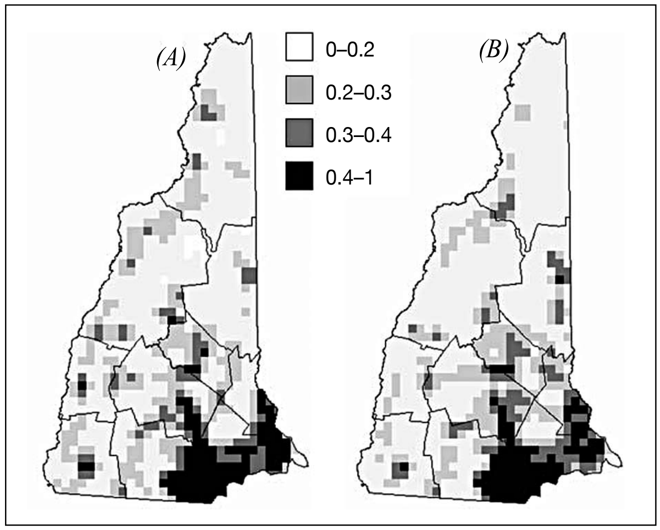


Figure 6.—*Relative values of the number of forest patches less than 10 ac in size calculated within 10- by 10-km image tiles in New Hampshire in 1990 (A) and 2000 (B).*

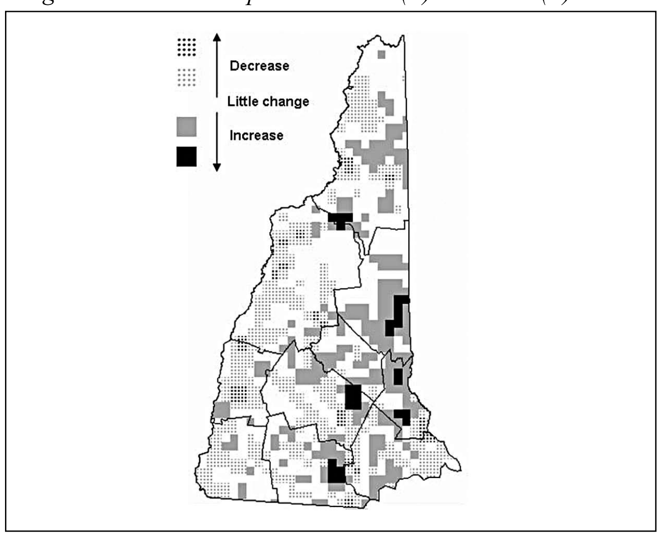


land use has not occurred, just a temporary change in land cover. In an attempt to capture forest loss and fragmentation changes due to urban pressures, we selected two metrics: the number of forest patches less than 10 ac in size, and the length of edge shared between urban and forest patches.

Figure 6 indicates that the more highly developed, southeastern portion of the State has the greatest number of small forest patches. One of the most impressive increases in the number of small forest patches occurred in the southern half of Carroll County (fig. 7). According to FIA data, Carroll County lost more than 10 percent of its forest land between 1983 and 1997 (Frieswyk and Widmann 2000). Forest loss in this county is most likely due to urban and residential growth to accommodate an expanding population. From 1990 to 2000, population in Carroll County increased 23 percent, which was higher than the State and national averages of 11 and 13 percent, respectively.

The influence of forest edge on habitat quality is a matter of great concern. The character of the edge effect depends on the type of land use or class that borders the forest patch. For this article, we were interested in evaluating changes in the amount of forest/urban edge. The length of edge shared by forest and urban land classes was greatest in the areas surrounding

Figure 7.—*Difference in relative values of the number of forest patches less than 10 ac in size calculated within 10- by 10-km image tiles in New Hampshire in 1990 (A) and 2000 (B).*



Manchester and Nashua (fig. 8). The Manchester and Nashua areas also experienced relatively large increases in the length of forest/urban edge between 1990 and 2000 (fig. 9). Southern Carroll County was also a site of relatively high increase in urban/forest perimeter. This finding is consistent with the possibility that urban pressure and population growth in Carroll County is affecting forest patterns and fragmentation. In the northern part of the State, some of the increases in length of

Figure 8.—*Length of edge shared between forest and urban, normalized to the maximum values in the landscape, calculated within overlapping 10- by 10-km image tiles in New Hampshire in 1990 (A) and 2000 (B).*

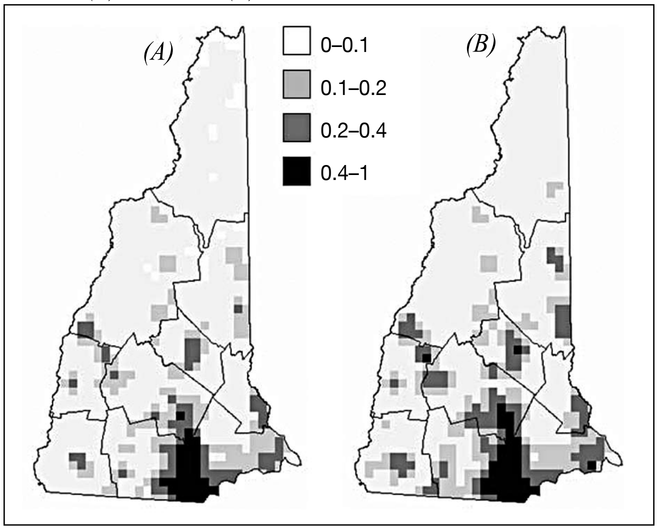
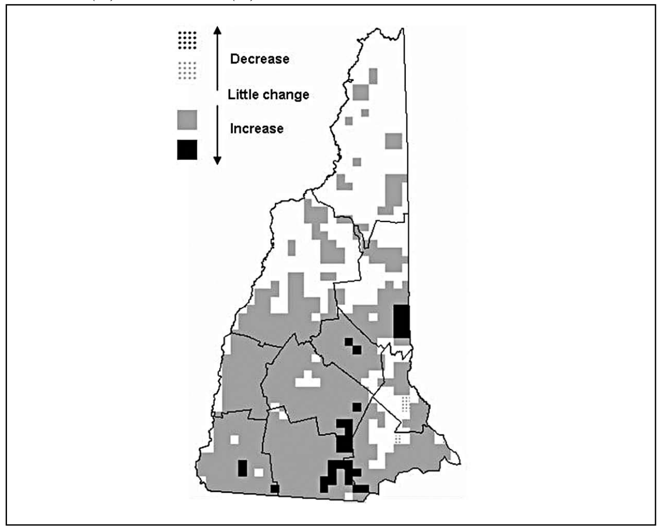


Figure 9.—*Length of edge shared between forest and urban, normalized to the maximum values in the landscape, calculated within overlapping 10- by 10-km image tiles in New Hampshire in 1990 (A) and 2000 (B).*



edge shared between forest and urban are centered on specific cities, including Littleton, Lancaster, and Berlin (fig. 9).

The utility of some fragmentation metrics and patch-based fragmentation metrics in general has been the subject of debate. For example, mean patch size can be misleading—many different landscape configurations can lead to the same mean value. Furthermore, our use of roads as patch-defining borders could lead to false interpretations of the results. Some small roads or land cover changes might not have a strong ecological impact. For example, forest and pasture have less ecological difference than forest and urban areas. We used relative differences in fragmentation metrics between the time periods because we wanted to identify areas of the State that showed anomalous changes in forest fragmentation compared to the rest of the State. If we assume that the classifications are similar to each other with respect to accuracy and have similar minimum mapping units, then we can infer that differences in the fragmentation metrics between the two time periods are the result of actual changes in the landscape, and not artifacts of the classification process or metric calculation algorithms. Future work will involve verifying the accuracy of these maps.

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The Virtual Analyst Program: Automated Data Mining, Error Analysis, and Reporting

W. Keith Moser[1], Mark H. Hansen, Patrick Miles, Barbara Johnson, and Ronald E. McRoberts

Abstract.—The Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture Forest Service conducts ongoing comprehensive inventories of the forest resources of the United States. The Northern Region FIA (NFIA) program has three tasks: (1) core reporting function, which produces the annual and 5-year inventory reports; (2) forest health measurements; and (3) scientific analysis of questions and themes that arise from the data.

Annual reports provide updated views of the extent, composition, and change of a State's forests. These reports have a standard format divided into the three broad categories of area, volume, and change. This reporting process also provides important early trend alerts and error-checking functions. Incorporating our understanding of important trends and relationships, and "cautions" to be aware of, the Virtual Analyst program at NFIA seeks to automate the more repetitive functions of producing reports while highlighting any anomalies that might require further investigation.

This paper discusses the program logic and prototype design. We explore the concepts of data mining and the role it plays in the FIA analysis process. Next, we work backward from the Web-based application product to information-generating vehicles that connect to the forest inventory database. Finally, we will discuss the opportunity to expand this report-writing function into a customized, user-defined data query and analysis function.

Introduction

The Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture Forest Service conducts comprehensive forest inventories to estimate the area, volume, growth, and removal of forest resources in the United States, in addition to taking measurements on the health and condition of these resources. The program's sampling design has an intensity of one plot per approximately 2,400 ha and is assumed to produce a random, equal probability sample. Four regional FIA programs divide up responsibility of inventorying and analyzing data in the United States and the Northern Region FIA (NFIA) is responsible for 24 States in the Northeast, Upper Midwest and Great Plains sections of the United States. In 15 States of NFIA, the plots in each State are sampled on a 5-year cycle; i.e., each state has 20 percent of its plots inventoried each year, while the remaining states are sampled on a 7-year cycle.

Such a process generates tremendous quantities of data. A portion of the data generated is analyzed and published in annual and more comprehensive 5-year State reports. Although the production of the tabular output is automated, data review, analytical text, and report highlights have typically required a great deal of human input.

Background

An important component of the core reporting function is the production of updated annual reports. The annual reports are the most current estimates of each State's forest resources and frequently are the first alert to emerging trends in forest structure, composition, growth, and mortality. The reports are divided into the three broad categories of area, volume, and change. The annual report is the final phase of a continuous quality control process, evaluating the accuracy of the data

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from the data collection on the plot to final dissemination of information and knowledge to our customers. The Virtual Analyst (VA) program at NFIA is designed to serve these multiple needs. Incorporating our understanding of important trends and relationships, and our awareness of important alerts (items warranting further investigation), this program automates the more repetitive tasks of report production.

Data-Mining Theory

With the vast quantity of data generated by the inventory process, an efficient and effective knowledge discovery procedure is critical to providing credible and valuable information to our stakeholders. Frawley *et al.* (1991) defined knowledge discovery as "the nontrivial extraction of implicit, previously unknown, and potentially useful information from data." These authors further defined knowledge as a "pattern that is interesting (according to a user-imposed interest measure) and certain enough (again according to the user's criteria)." One of the more salient aspects of a continuous forest inventory is its ability to detect change. While knowledge of the total volume or biomass present is useful, an equally important type of information details changes in forest extent, composition, and structure. These change estimates are not only indicators of trends of interest (e.g., greater numbers of trees, less mortality, etc.), but also send a signal to policymakers and land managers that there is the potential for different ecological futures.

Data Mining

Data mining uncovers structure within existing databases. Beyond concerns with data collection issues (Hand *et al.* 2000), one of its principal benefits to NFIA is the opportunity for error checking. One of the unique aspects of data mining is its focus on patterns within the data. While most statisticians are concerned with primary data analysis (data collected with a particular question or set of questions in mind), data miners focus on secondary analysis aimed at finding relationships that are of interest or value to the database owners (Hand *et al.* 2000). In the place of statistical significance, we need to consider more carefully substantive significance: is the effect important (Hand 1998b)? Data mining is not a one-time activity, but rather an interactive process involving the data miner and the domain expert (the analyst assigned to report on the inventory of a particular State), as well as the data (Hand *et al.* 2000).

The two types of structure in data are models and patterns (Hand 1998a). A model is an overall summary of the data or a subset of the data, whereas a pattern is a local structure made up of a subset of the data. For NFIA, it is important to practice data mining that examines both types of data. A model may be a summary of the inventory data for specific attributes, while a pattern may document an interesting facet of the data, such as increased mortality or change in the species composition of the overstory.

While statisticians are concerned with characterizing the likelihood an apparent structure will arise in a data set given no such structure in the underlying process, data miners focus on simply locating the structure. The responsibility for deciding whether the structure has meaning in terms of the underlying process is shifted to the analyst (Hand 1998b).

The analyst is looking for two types of patterns: "real" and "inadequate" patterns. A real pattern is a trend or structure indicating an actual and significant characteristic of the forest. For example, data analysis might discover the occurrence of a tree species not previously known to exist in that location. On the other hand, an inadequate pattern can indicate either an error in data collection or an anomaly in data conversion. An example of an inadequate pattern can occur when a plot is divided into multiple conditions, reflecting its past management or a change in forest type. If the condition "slice" of the plot is small, and there happens to be one large tree in that slice, the expanded basal area per unit area of land might be unnaturally large, which would be a function of the random occurrence of one large tree in a small sample area. At the State level, the first pattern might appear as a critical error, while the second pattern might not matter. The knowledge of the analyst is essential to separating critical from noncritical errors or anomalies. Patterns that can be explained are more likely to be real and are often obvious in retrospect. Many unexpected patterns discovered in a data set during data mining, however, will be attributable to data inadequacy (Hand *et al.* 2000).

FIA Database

By the nature of the two-phase, fixed-area, plot-based sampling conducted by FIA (McRoberts 2005), a relational data model with hierarchical components has been used to create the FIA Database (FIADB) (Alerich *et al.* 2004). FIADB consists of 12 linked database tables. Each database table provides a means of storing data, such as data collected on a sample tree or plot, and computed data attributes. The latest version of the FIADB provides all the data required to estimate resource attributes and associated sampling errors. This structure makes it relatively easy to produce flat files for customers who do not have access to the database. All of the core report tables in the State reports can be produced from these database tables.

In this paper, we present initial work on the VA program that produces not only the core tables for these reports, but also the corresponding figures, maps, and text portions of the reports including highlights and analysis. In addition, we discuss the opportunity to expand this automated report writing into a customized, user-defined data query and analysis function.

Methodology

The VA program provides a single interface with the FIADB that will produce an entire report for a selected area with a few clicks of the mouse. Figure 1 is a flowchart that displays the path from the Oracle database to the final report. The figure portrays a sequence of actions that are currently performed by domain experts (analysts) based on their own experiences and education. Humans, however, are not completely separated from the analytical process. While some of the process will be automated and standardized, analysts still need to check the flagged anomalies and make corrections if needed (fig. 2).

The VA program is written as a Web-based application using various software development programs. These programs will interface with the FIADB using assorted PL/SQL procedures that extract the various resource- and sampling-error estimates presented in the application. All comparisons, logic checks, and computation of highlights are performed using PL/SQL procedures and functions. The user interface in VA allows the user to define the population of interest for the report being generated by using pull-down menus to select the State and

Figure 1.—*Flowchart of information flows in Virtual Analyst.*

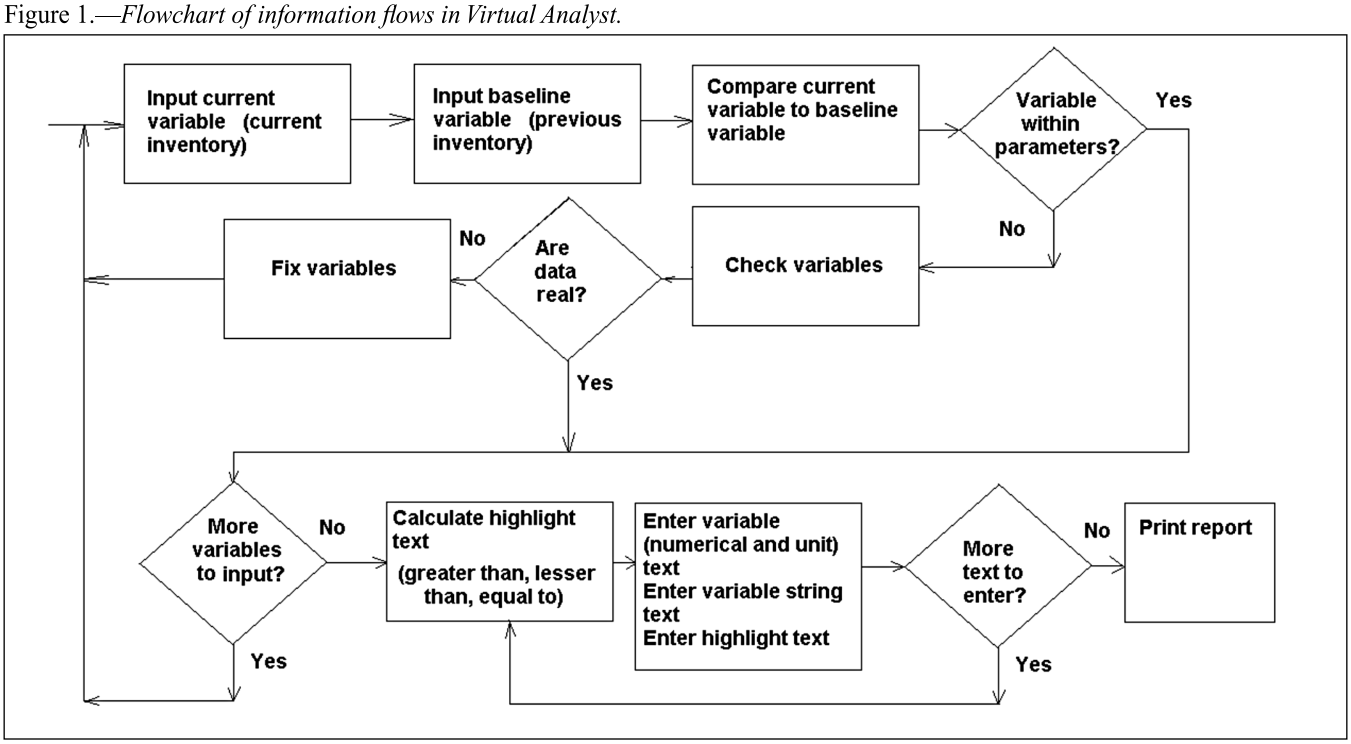
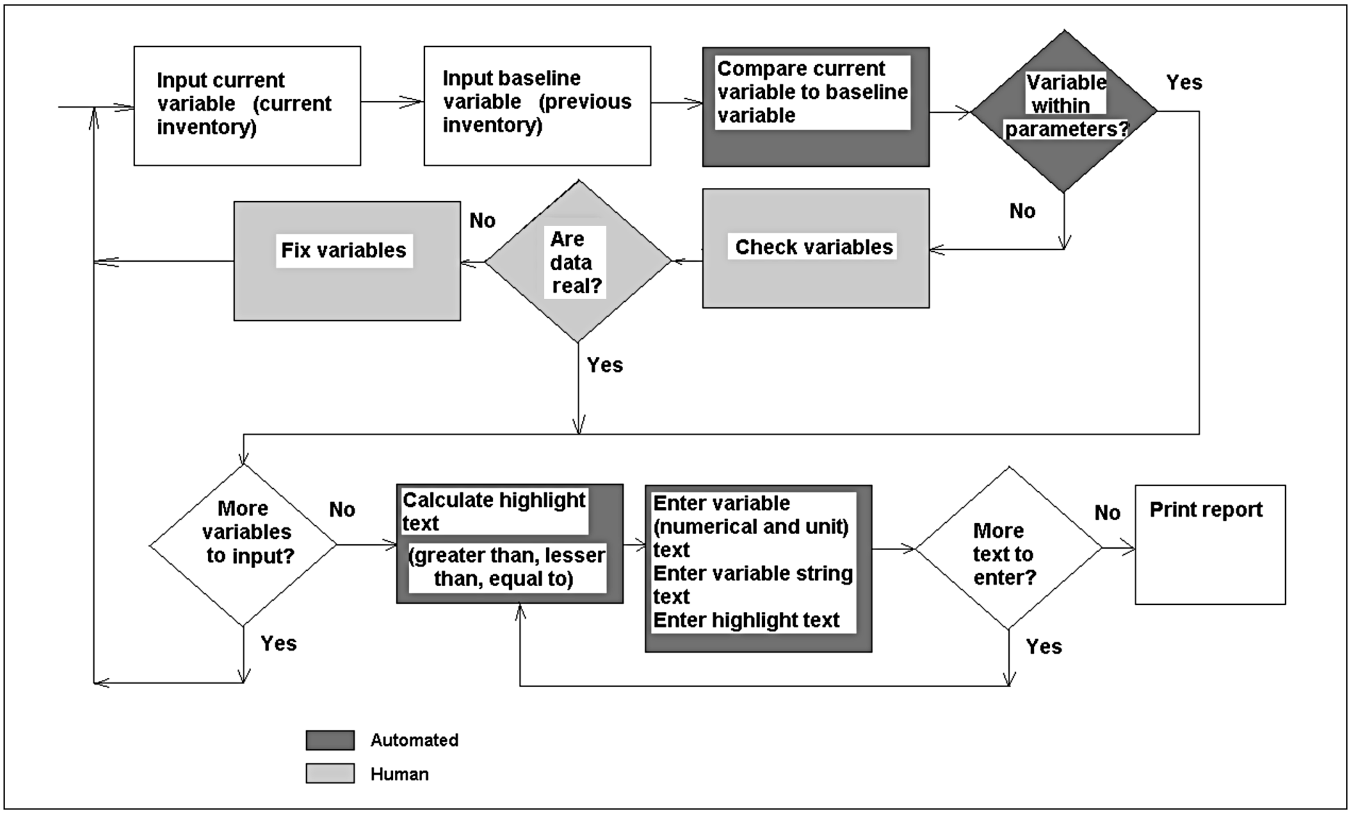


Figure 2.—*Flowchart of Virtual Analyst process, with automated and human-mediated decisions and actions in shaded symbols.*



inventory year. Once the population has been selected, the program executes a series of PL/SQL procedures that generate all the basic report tables for the population (fig. 3). These basic report tables are created as temporary Oracle database tables that exist for the duration of the run and simultaneously display report tables on the Web site and, if requested, as publication-quality PDF files. The VA approach to generating report tables differs from other programs that access FIADB in that catalogs of estimates and sampling errors are created simultaneously in all cases. That is, for every estimate, a corresponding sampling error is computed in a temporary Oracle database table. Other measures of estimation quality, including variance and number of plots where the attribute was observed, are also computed.

Once the report tables are generated for the inventory of interest, identical tables for previous inventories are also computed, using the same PL/SQL procedures. If the data for more than one previous inventory are available for a population, report tables are produced for each of these inventories. These tables are then used to generate charts of the data using .NET charting software.

The estimates and sampling errors in the temporary Oracle database tables can be quickly accessed by simple PL/SQL procedures and functions. These emulate the logic checks and comparisons, and highlight identification procedures typically performed by the analyst (fig. 4). The results of the procedures and functions form the basis of the report text. Output categories from the procedures and functions may be the following:

1. Numerical values (estimates).
2. Units (define the unit of measure for an estimate).
3. Strings (typically describe an estimate).
4. Comments (a special case of a string).
5. Highlights (a special case of a string dependent upon a numerical object).

Numerical values are measured quantities. Units are string objects that define the unit of measure for the values and

Figure 3.—*Flowchart of Virtual Analyst process, with data entry and data checking actions in shaded symbols.*

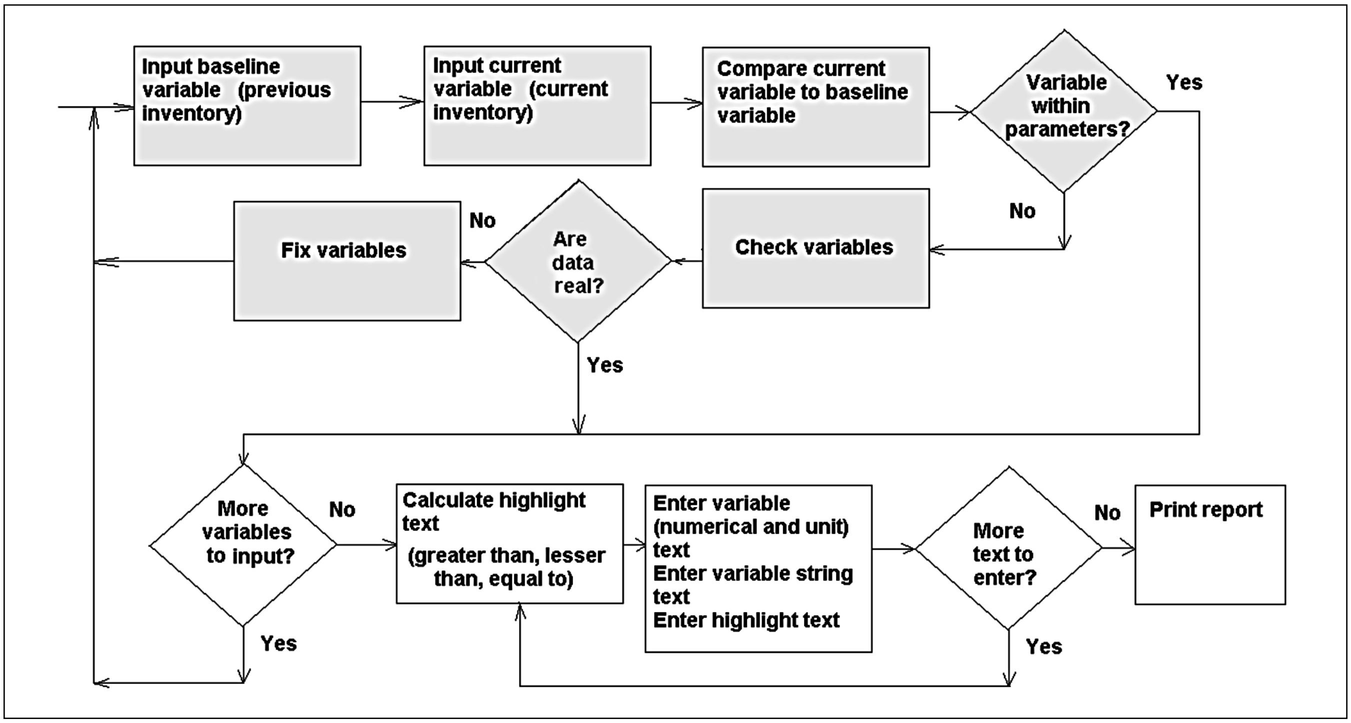
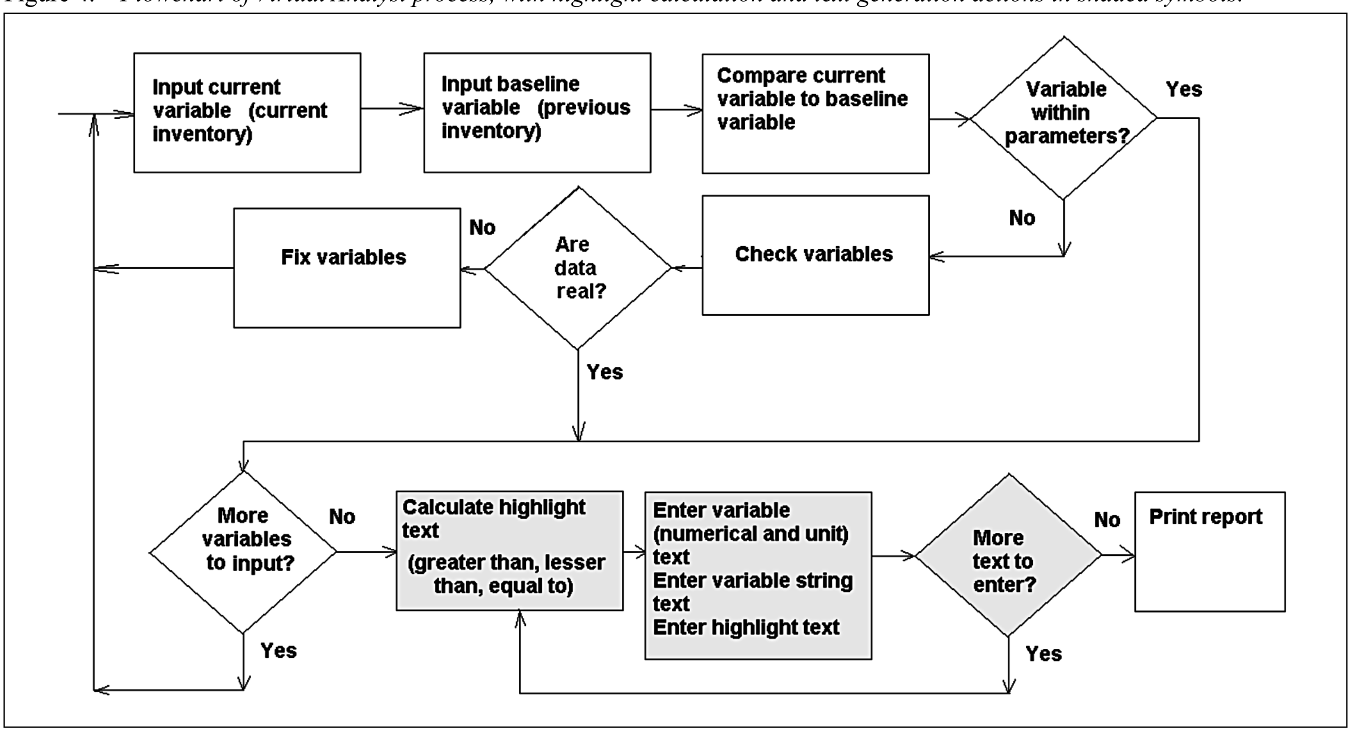


Figure 4.—*Flowchart of Virtual Analyst process, with highlight calculation and text generation actions in shaded symbols.*



are always tied to them. Examples include units of volume, expressed in cubic meters, or area, expressed in hectares or acres. Strings represent categories, such as species or forest type groups. Comments are special types of strings, generally representing a phrase unique to a particular situation. Highlights are terms of precedence or change. Examples include "greater than," "equal to," or "primary."

Calls to procedures and functions that mimic the analytical processes in the data-mining step of the report-writing phase are embedded into the final written report text, such that the resulting text is a complete statement, sentence, or paragraph included in the final document. Some of the functions access a single report table and may simply return the name of the forest type that has the largest estimated area in the most current inventory of all forest types in the population. Other functions may access the same table for multiple inventories, e.g., a procedure that returns the name of the forest type that increased the most in estimated area between the baseline inventory and the current inventory. The complexity and number of tables accessed by these procedures and functions could be increased.

The VA program has the previous inventory tables in the same format as the new inventory, making inventory-to-inventory comparisons relatively easy. Furthermore, with sampling errors for all estimates (including old inventories), we have the potential to conduct statistical tests and avoid highlighting differences that are not statistically significant, or identify small differences that may be statistically significant but that would otherwise go unnoticed.

Results

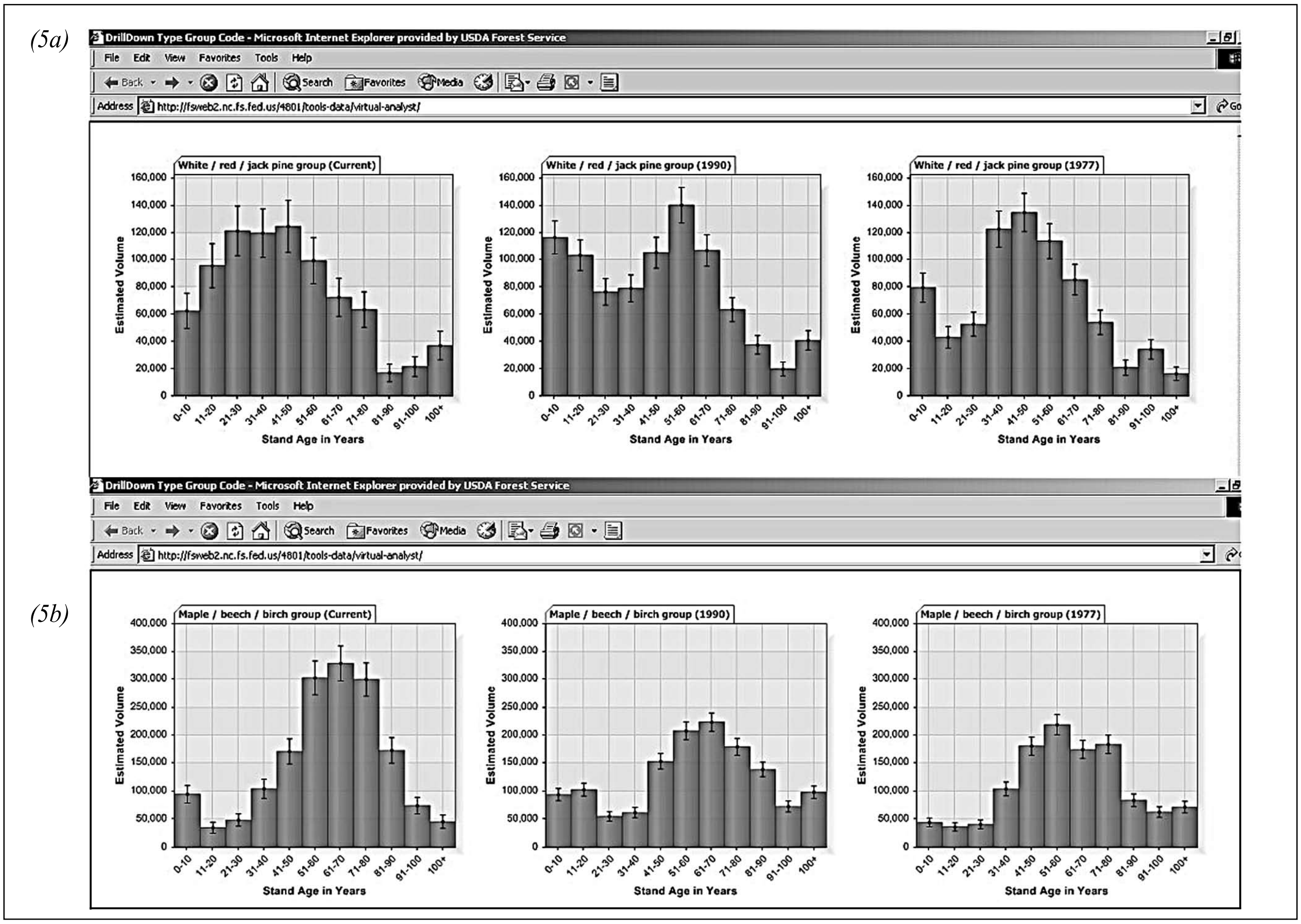
We will limit our discussion to the analysis of some simple report tables, and the associated figures and text portions of the report (highlights and analysis). As an example, we used data from the 1999–2003 Minnesota annual inventory. The VA program generates a basic report table (table 1). Produced at the same time are a matching report table of sampling errors and tables based on the two previous inventories. These tables form the basis of the analysis of forest area by forest type.

Figures 5a and 5b are examples of information produced in association with these tables. The figures show the distribution of timberland area by stand age for the white/red/jack pine and maple/beech/birch forest type groups. The vertical bars at the top of each bar in the histogram show sampling errors for each estimate. These graphics can serve both analytical and illustrative functions. In the pine graph (fig. 5a), the analyst would observe the increased volume in the 11- to 30-year age classes and wish to investigate where these young stands are. The next graph (fig. 5b) provides an example of the illustrative

Table 1.—*Minnesota, 2003 annual estimate, area of timber land by forest type group and stand age class in thousand acres.*

	Stand age class (years)											
Forest type group	0-10	11-20	21-30	31-40	41-50	51-60	61-70	71-80	81-90	91-100	101+	All ages
White/red/jack pine	62.6	95.9	121.6	120.0	124.9	99.7	72.7	63.6	17.0	21.5	37.1	836.8
Spruce/fir	121.2	131.9	144.3	257.8	436.4	401.0	390.4	362.5	255.9	226.1	490.5	3,218.0
Pinyon/juniper			3.6				4.2	6.5	2.7			16.9
Exotic softwoods			1.6	1.5								3.1
Oak/pine	10.5	22.5	26.1	32.2	33.7	36.4	33.2	17.3	17.8	6.9	3.6	240.1
Oak/hickory	46.2	12.9	16.0	54.0	99.0	178.9	171.0	201.8	145.4	86.7	67.1	1,079.0
Elm/ash/cottonwood	66.5	26.0	50.8	101.7	135.8	171.6	180.0	175.3	95.4	66.2	109.3	1,178.4
Maple/beech/birch	95.2	34.9	48.4	104.7	171.5	303.3	329.4	300.5	173.6	74.5	45.6	1,681.7
Aspen/birch	968.6	722.5	631.2	649.8	874.2	950.5	835.1	427.9	137.0	69.3	31.3	6,297.2
Exotic hardwoods			1.7			2.2						3.8
Nonstocked	204.8											204.8
All groups	1,575.6	1,046.8	1,045.1	1,321.6	1,875.5	2,143.4	2,015.9	1,555.4	844.8	551.4	784.4	14,759.8

Figure 5a and 5b.—*Example of graph output from the Virtual Analyst program. The data refer to the white/red/jack pine forest type group (top, fig. 5a) and the maple/beech/birch forest type group (bottom, fig. 5b) on timber land in Minnesota, across three inventories: 1977, 1990, and 1999–2003.*

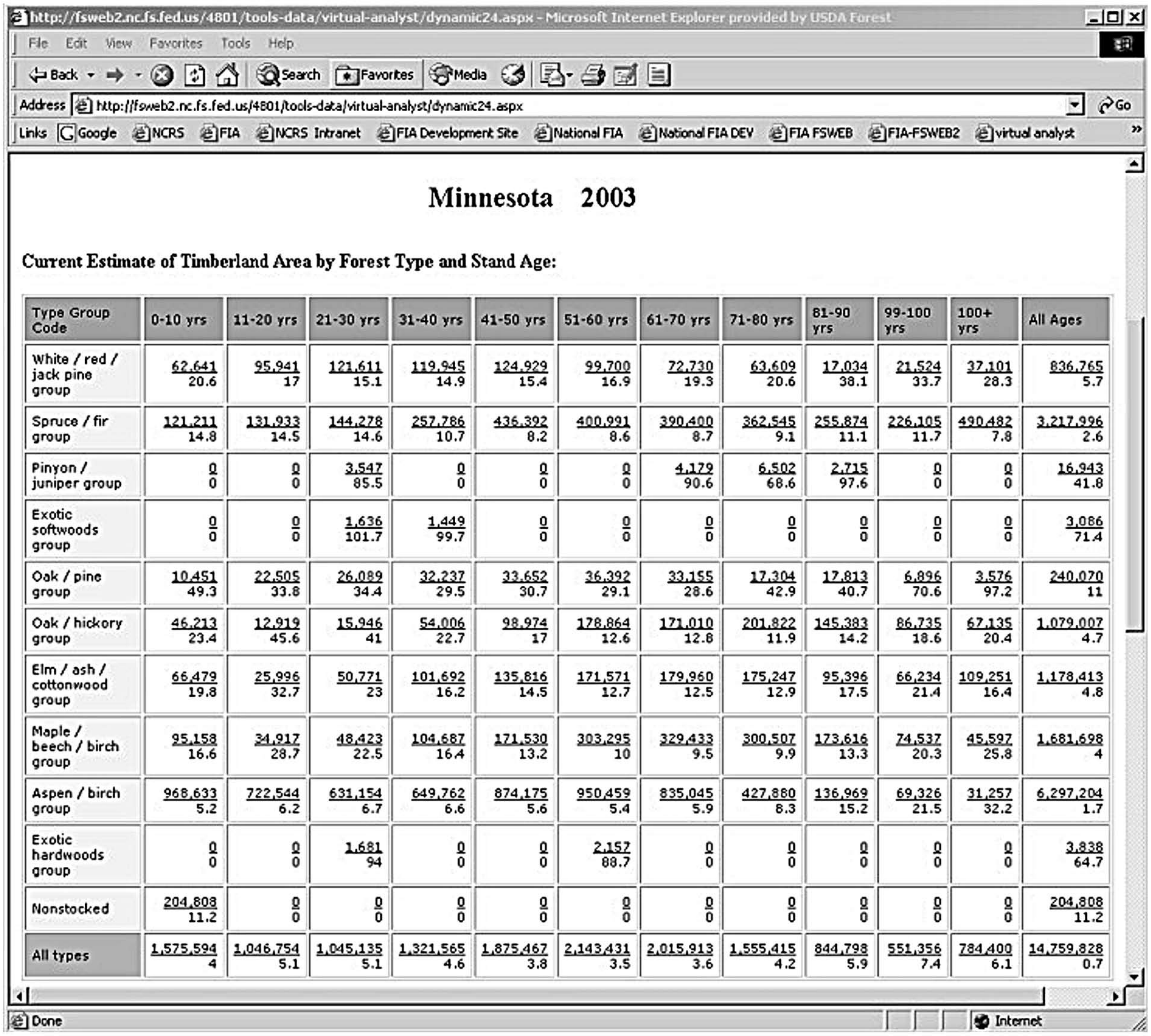


function, where a State resource manager might be interested in seeing the high volumes of wood in the 51- to 80-year age classes. Another example of an illustrative depiction of data is a table of volume, area or other variable of interest, parsed by categories such as age class or forest type (fig. 6). Currently, such tables are generated from the Oracle database into camera-ready PDF files using a separate discrete routine. VA would incorporate final table generation into a seamless data entry–analysis–data display process.

The annual inventory report has traditionally been published as a resource bulletin in the format of several pages of text, including standard definitions and methodology pages, followed by 9 to 12 tables. In the near future, we anticipate that the annual report will be more along the lines of a two-page summary with highlights. Some tables may be published, but most of the data will be available on the Web.

Incorporating this new format, the section below illustrates a hypothetical abstract from the prototype annual report and includes some analysis of the core report table of area by forest type and stand age class and one additional table, volume by species and forest type. The strings and values that can be changed are denoted by output categories in brackets.

Figure 6.—*Prototype tabular output of estimated timberland area by stand age and forest type group generated by the Virtual Analyst program.*



Minnesota 2003

Current Estimate of Timberland Area by Forest Type and Stand Age:

Type Group Code	0-10 yrs	11-20 yrs	21-30 yrs	31-40 yrs	41-50 yrs	51-60 yrs	61-70 yrs	71-80 yrs	81-90 yrs	99-100 yrs	100+ yrs	All Ages
White / red / jack pine group	62,641 20.6	95,941 17	121,611 15.1	119,945 14.9	124,929 15.4	99,700 16.9	72,730 19.3	63,609 20.6	17,034 38.1	21,524 33.7	37,101 28.3	836,765 5.7
Spruce / fir group	121,211 14.8	131,933 14.5	144,278 14.6	257,786 10.7	436,392 8.2	400,991 8.6	390,400 8.7	362,545 9.1	255,874 11.1	226,105 11.7	490,482 7.8	3,217,996 2.6
Pinyon / juniper group	0 0	0 0	3,547 85.5	0 0	0 0	0 0	4,179 90.6	6,502 68.6	2,715 97.6	0 0	0 0	16,943 41.8
Exotic softwoods group	0 0	0 0	1,636 101.7	1,449 99.7	0 0	0 0	0 0	0 0	0 0	0 0	0 0	3,086 71.4
Oak / pine group	10,451 49.3	22,505 33.8	26,089 34.4	32,237 29.5	33,652 30.7	36,392 29.1	33,155 28.6	17,304 42.9	17,813 40.7	6,896 70.6	3,576 97.2	240,070 11
Oak / hickory group	46,213 23.4	12,919 45.6	15,946 41	54,006 22.7	98,974 17	178,864 12.6	171,010 12.8	201,822 11.9	145,383 14.2	86,735 18.6	67,135 20.4	1,079,007 4.7
Elm / ash / cottonwood group	66,479 19.8	25,996 32.7	50,771 23	101,692 16.2	135,816 14.5	171,571 12.7	179,960 12.5	175,247 12.9	95,396 17.5	66,234 21.4	109,251 16.4	1,178,413 4.8
Maple / beech / birch group	95,158 16.6	34,917 28.7	48,423 22.5	104,687 16.4	171,530 13.2	303,295 10	329,433 9.5	300,507 9.9	173,616 13.3	74,537 20.3	45,597 25.8	1,681,698 4
Aspen / birch group	968,633 5.2	722,544 6.2	631,154 6.7	649,762 6.6	874,175 5.6	950,459 5.4	835,045 5.9	427,880 8.3	136,969 15.2	69,326 21.5	31,257 32.2	6,297,204 1.7
Exotic hardwoods group	0 0	0 0	1,681 94	0 0	0 0	2,157 88.7	0 0	0 0	0 0	0 0	0 0	3,838 64.7
Nonstocked	204,808 11.2	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	204,808 11.2
All types	1,575,594 4	1,046,754 5.1	1,045,135 5.1	1,321,565 4.6	1,875,467 3.8	2,143,431 3.5	2,015,913 3.6	1,555,415 4.2	844,798 5.9	551,356 7.4	784,400 6.1	14,759,828 0.7

- Total timberland area is 14.8 [numerical] million acres [units].
- The aspen/birch [string] type is the predominant forest type on the landscape, making up more than 42 [numerical] percent [units] of all timberland.
- Forest types dominated by softwood species make up more than 27 [numerical] percent [units] of the timberland acreage.
- Spruce/fir [string] is the primary [highlight] softwood component by acreage and volume.
- Between 1990 [date] and 1999–2003 [date], the net volume of growing-stock trees on timberland increased [highlight] by 0.9 [numerical] percent [units], from 15.1 [numerical] billion cubic feet [units] to 15.2 [numerical] billion cubic feet [units].

Conclusions

The VA program facilitates the rapid production of annual reports while introducing automated data-mining and error-checking capabilities. Although the program presented here is a prototype, the full version will allow more rapid dissemination of analytical reports to our stakeholders while ensuring the quality of the data contained therein. Future versions of this program could include custom report generation available directly to the stakeholders, allowing fully interactive data analysis and report production. The VA program is just one component of a suite of data analysis/data quality tools, including a sophisticated statistical analysis tool, being developed by the Pacific Northwest FIA program. These tools will enhance resource analysis and improve information quality assurance for the national FIA program.

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A Comparison of Tree Crown Condition in Areas With and Without Gypsy Moth Activity

KaDonna C. Randolph[1]

Abstract.—This study compared the crown condition of trees within and outside areas of gypsy moth defoliation in Virginia via hypothesis tests of mean differences for five U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis phase 3 crown condition indicators. Significant differences were found between the trees located within and outside gypsy moth activity, but no crown condition indicator was consistently different across the 4 years included in the study. Results suggest that the crown condition indicators may provide some benefit in pinpointing the presence of a known stressor and also may provide a starting point for identifying unknown stressors.

Objective

The U.S. Department of Agriculture (USDA) Forest Service, which is responsible for reporting the status of and trends in forest ecosystem health, has programs in Forest Inventory and Analysis (FIA), Forest Health Monitoring (FHM), and Forest Health Protection that cooperatively monitor forest health by means of aerial detection surveys and on-the-ground inventories. One of the ways in which changes in forest health are detected on the ground is through the measurement of a suite of ecological indicators on a network of plots known as FIA phase 3 plots (formerly FHM detection monitoring plots) (Riitters and Tkacz 2004).

Among the ecological indicators assessed on the FIA phase 3 plots is tree crown condition. Crown condition has long been recognized as a general gauge of forest health because healthy crowns are usually distributed symmetrically in a predictable manner along the stem and careful examinations for deviations from this pattern may indicate a tree undergoing stress (Waring 1987). Researchers have different conclusions about the relationship between crown condition and tree vigor (Anderson and Belanger 1987, Innes 1993, Kenk 1993, Solberg and Strand 1999), and even though crown condition indicators have been measured since the outset of the FHM program in 1990 few studies have sought to determine the usefulness of crown condition for evaluating forest health (e.g., Juknys and Augustaitis 1998, Steinman 2000). Thus, the purpose of this study was to assess the practicability of using the phase 3 crown condition indicators to detect forest health problems.

One way to gauge the usefulness of crown condition for monitoring forest health is to determine whether crown condition in areas with a known stress agent differs from that in areas without a known stress agent. If the impact of an obvious stressor cannot be observed, then the ability to detect the occurrence of subtler and unknown stressors is called into question. In this study, tree crown condition in areas of gypsy moth (*Lymantria dispar* Linnaeus) activity was compared to crown condition outside the areas of moth activity. Since the gypsy moth feeds directly on tree foliage, its impact on crown condition should be noticeable if the indicators are adequately sensitive.

Analysis Methods

The study area was confined to Virginia, which first showed evidence of gypsy moth defoliation in 1984. Collection of tree crown condition data began in Virginia in 1991 and continues through the present, but because of the pattern of gypsy moth activity and sample size concerns, only data from the 1992–95 period were utilized. For each year, all phase 3 plots in Virginia were assigned to one of five gypsy moth activity categories: present, likely present, possibly present, not currently present

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but present in past, or absent. Each plot was assigned to one of these categories based on conditions recorded on the plot (tree notes, tree damage codes, percent basal area in oak, plot disturbance codes) and proximity of the plot to aerially sketch mapped areas of gypsy moth defoliation. Plots were assigned to the present category if the tree or plot notes recorded by the field crews specifically indicated gypsy moth activity or if the plots were within 1 km (0.62 mi) of a mapped area of defoliation and had a disturbance code indicating the presence of damaging insects or oak trees with damaged foliage, buds, or shoots. Assignment of a plot to the likely present, possibly present, or present in past category was based on the amount of oak basal area on the plot, plot-level disturbance codes, tree-level damage codes, and past gypsy moth activity. Any plot failing to meet the requirements for the present, likely present, possibly present, or present in past categories was assigned to the absent category. Only two of the five categories, present and absent, were used for this particular study. Though the gypsy moth feeds on a variety of species, oaks (*Quercus* spp.) are the preferred host; therefore, only data for oak trees on plots with five or more living oaks with diameter at breast height (d.b.h.) > 12.6 cm were utilized in the analyses.

Two sets of crown condition indicators were included in the analyses: those recorded by the field crews (absolute indicators) and those calculated from the field data (composite indicators). The following were the absolute crown condition indicators (USDA Forest Service 2004):

1. Crown density—the amount of crown branches, foliage, and reproductive structures that blocks light visibility through the projected crown outline.
2. Crown dieback—recent mortality of branches with fine twigs, which begins at the terminal portion of a branch and proceeds inward toward the trunk.
3. Foliage transparency—the amount of skylight visible through the live, normally foliated portion of the crown, excluding dieback, dead branches, and large gaps in the crown.

The absolute indicators are visually assessed by the field crews and are recorded in 5-percent increments from 0 to 100 percent. The composite crown indicators, composite crown volume (CCV) and composite crown surface area (CCSA), were calculated as

$$CCV = 0.5 \cdot \pi \cdot R^2 \cdot CL \cdot CD$$

and

$$CCSA = \frac{4\pi CL}{3R^2}\left[\left(R^2 + \frac{R^4}{4CL^2}\right)^{1.5} - \left(\frac{R^4}{4CL^2}\right)^{1.5}\right]CD$$

where:
R = crown diameter (meters)/2.
H = total tree height (meters).
CL = H*(live crown ratio)/100.
CD = crown density/100 (Zarnoch *et al.* 2004).

Crown diameter is the average of the greatest crown width and crown width measured along a line perpendicular to the axis of greatest crown width and live crown ratio is the percentage of the live tree height supporting live foliage. Crown diameter and live crown ratio were measured in the field; tree heights were not measured in the field and were predicted with FIA models. The use of predicted heights for calculating CCV and CCSA may mask some of the differences in crown size because trees undergoing stress would be expected to be shorter than trees free of stress. (Measurement of tree heights on the phase 3 plots began in 2000, but at the same time measurement of crown diameter was dropped. Hence, crown diameter is now predicted from models that have the potential to similarly mask tree crown condition. See Bechtold *et al.* [2002] for further discussion). Stem diameters, which were needed to predict tree height, were not measured between 1992 and 1994, and so CCV and CCSA were calculated for 1995 only.

To account for stem size, stand condition, and species impacts on crown condition, Zarnoch *et al.* (2004) recommend standardizing and residualizing the crown condition indicators so that trees may be combined or compared across species, or plots, or both. Their methods were employed in modeling CCV and CCSA for each year by species with the simple linear regression:

$$\beta_0 + \beta_1 \text{d.b.h.} + \beta_2 \text{ba}$$

where d.b.h. is diameter at breast height (cm) and ba is stand-level basal area (m^2) per hectare for all trees ≥ 2.5-cm d.b.h.

The residuals from the regression models were standardized by species. No single model form was found to be consistently adequate for predicting the absolute indicators across species and years; therefore, the absolute indicators were standardized by species only.

Means of the standardized and standardized-residualized crown condition indicators were calculated by year for the absent and present gypsy moth activity categories to test the hypothesis:

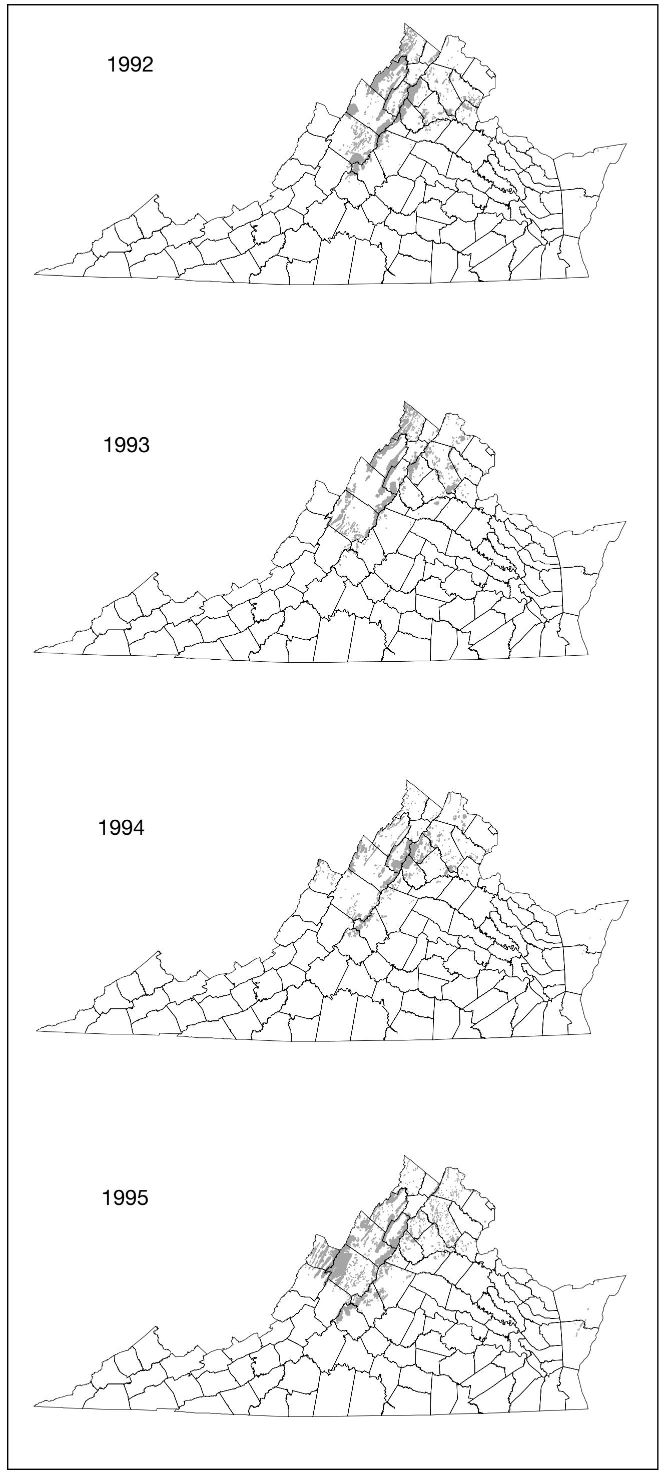
$$H_0: \mu_{absent} = \mu_{present}$$
$$H_1: \mu_{absent} \neq \mu_{present}.$$

Calculation of the standardized and standardized-residualized crown condition indicator means for both gypsy moth activity categories was performed with the SAS software procedure SURVEYMEANS (SAS 2001) because this procedure can make provision for the FIA sample survey design, which results in unequal-sized clusters of trees on the inventory plots. Given this survey design, it was simplest to test the null hypothesis given above via two-sided 95-percent confidence intervals for the difference (μ_{absent} - $\mu_{present}$). Two groups were declared significantly different at the 0.05 level of significance if the confidence interval for (μ_{absent} - $\mu_{present}$) did not include 0.

Results and Discussion

Gypsy moth defoliation in Virginia was most severe in 1992, when 748,100 acres were defoliated, and in 1995, when 849,584 acres were defoliated (fig. 1) (Virginia Department of Forestry 2005). In 1992 and 1994, six plots met the criteria for gypsy moth presence; five plots met the criteria in 1995 and three plots in 1993. The number of plots in the absent category ranged from 24 in 1992 to 37 in 1994 (table 1). Ten oak species were included in the analyses: *Quercus alba* L., *Q. coccinea* Muenchh., *Q. falcata* Michx. var *falcata*, *Q. marilandica* Muenchh., *Q. nigra* L., *Q. phellos* L., *Q. prinus* L., *Q. rubra* L., *Q. stellata* Wangenh., and *Q. velutina* Lam. Four of these species (*Q. marilandica*, *Q. nigra*, *Q. phellos*, and *Q. stellata*) had less than 30 observations each per year and were grouped together as one species for standardizing and standardizing-residualizing. The number of oak trees included in the analyses

Figure 1.—*Aerial sketch map areas of gypsy moth defoliation in Virginia, 1992–95.*



ranged from 73 to 103 for the present category and from 276 to 494 for the absent category (table 1).

Table 1.—*Number of plots and living oak trees in each gypsy moth activity category.*

Year	Gypsy moth		Gypsy moth	
	Absent	Present	Absent	Present
	(Number of plots)		(Number of oak)	
1992	24	6	276	90
1993	35	3	461	73
1994	37	6	494	103
1995	36	5	474	97

The standardized and standardized-residualized indicators describe deviation from the expected (average) crown conditions for a given population under typical conditions and are expressed in terms of standard deviation units from the mean. Trees with about average crown conditions will have standardized and standardized-residualized values near 0. Better or poorer than average crown conditions will be > or < 0, with the direction (positive or negative) depending on the nature of the crown condition indicator. For example, high crown dieback is indicative of poor crown condition and would correspond to positive standardized values. On the other hand, low crown density indicates poor crown condition and would correspond to negative standardized values. As expected, trees in the present category generally exhibited poorer than average crown conditions. Trees in the absent category generally exhibited average or better than average crown conditions; however, only a small number of the differences between the group means were significant: crown dieback in 1992, foliage transparency and crown dieback in 1994, and composite crown surface area in 1995 (table 2). Though significant differences were found between the crown conditions for trees on plots with and without the gypsy moth stress agent, no crown condition indicator was consistently different between the two groups.

Care was taken to assign plots to the present and absent categories correctly; thus, it was expected that the differences between the crown conditions in areas with and without gypsy moth activity would have been more extreme. Factors that may have impacted the hypothesis testing include the small sample size and inclusion of plots across the entire State. Given the sample survey design of the analysis, the confidence interval degrees of freedom were dependent on the number of plots in the gypsy moth activity categories. The small number of plots in the present category resulted in a larger t-value, and thus wider confidence intervals, which made it more difficult to declare differences significant than it would have been if the sample size had been larger. Plots from across the entire State, and not just in northern Virginia within the range of gypsy moth activity, were included in the absent category. Thus, the averages for the absent category may include some effects of geographic location.

The timing of plot assessment also may have contributed to the finding of only a few, small significant differences. Gypsy moth larvae typically feed from early May to late June (Coulson and Witter 1984), though the peak of defoliation may not occur until late July (Liebhold *et al.* 1997). Phase 3 plots are measured throughout the entire summer season (June through August), so some plots may be assessed before defoliation climaxes. This might have been the case with the three plots in the present category in 1993, because all of these plots were measured before June 18. For the other years, the plots in the present category were assessed as early as June 6 and as late as August 23: between July 22 and August 3 in 1992; between June 6 and June 29, and on August 23 in 1994; and between June 13 and July 28 in 1995. Even when measured late in the season, crown conditions may not show the effects of gypsy moth defoliation (or other defoliation events) because hardwood trees have the potential to produce a second flush of leaves if initial defoliation has been severe (USDA Forest Service 2005). Hence, the timing of plot assessment may affect the usefulness of the crown condition indicator for detecting forest health stressors, particularly if the impacts of the stressor are ephemeral or if they are manifested after the plot has been assessed.

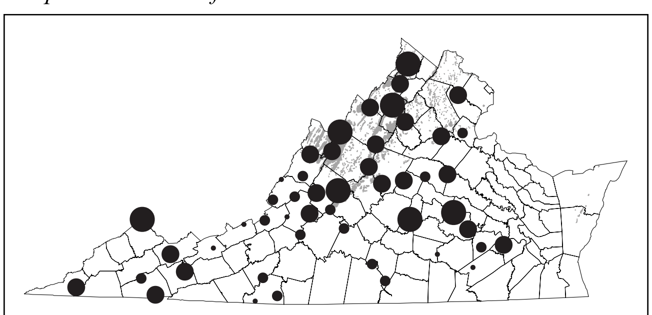
Overall, success in detecting differences in this study was due in part to *a priori* knowledge of where gypsy moth defoliation occurred (fig. 1). Consider the map in figure 2, which shows the 1995 plot averages for oak standardized-residualized CCSA. The size of the dot indicates the magnitude of deviation from the expected species averages, with the larger dots indicating a

Table 2.—*Average absolute and composite crown condition indicators by year and gypsy moth activity category (Absent, Present), and 95-percent CIs for the difference of the means (Absent – Present).*

Indicator	Year			
	1992	1993	1994	1995
Standardized crown density				
Absent	0.15	0.03	0.00	0.15
Present	– 0.12	– 0.32	– 0.24	– 0.54
95-percent CI	– 0.16, 0.70	– 0.34, 1.04	– 0.31, 0.78	– 0.20, 1.57
Standardized crown dieback				
Absent	– 0.13	0.01	– 0.02	– 0.06
Present	0.21	– 0.12	0.24	0.32
95-percent CI	– 0.62, – 0.04[a]	– 0.21, 0.47	– 0.35, – 0.18[a]	– 0.83, 0.07
Standardized foliage transparency				
Absent	0.04	– 0.09	– 0.09	– 0.06
Present	0.33	0.47	0.52	0.55
95-percent CI	– 0.66, 0.09	– 1.53, 0.41	– 1.00, – 0.23[a]	– 2.34, 1.12
Composite crown volume standardized residual				
Absent	—[b]	—	—	0.10
Present	—	—	—	– 0.10
95-percent CI	—	—	—	– 0.15, 0.55
Composite crown surface area standardized residual				
Absent	—	—	—	0.15
Present	—	—	—	– 0.31
95-percent CI	—	—	—	0.11, 0.80[a]

CI = confidence interval.
[a] Significant difference.
[b] Insufficient data to calculate the indicator for this year.

Figure 2.—*Plot averages for oak standardized-residualized composite crown surface area overlying the area of gypsy moth defoliation in Virginia in 1995. The size of the dot indicates the magnitude of deviation from the expected species averages with the larger dots indicating a deviation toward smaller (poorer) composite crown surface areas.*



deviation toward smaller (poorer) CCSA. While the dots in the area of gypsy moth defoliation are large, they are not clearly distinguishable from dots in other parts of the State; e.g., south-western and east central areas. Thus, unless one already knows where forests may be undergoing stress, comparing plot-level crown conditions may not pinpoint specific trouble spots, but may provide a starting point for further investigation.

Conclusions

The examination of crown conditions within and outside areas of known gypsy moth defoliation provided insight into the practicability of using the crown condition indicators to identify trees undergoing stress. Trees on plots in two categories of gypsy moth activity had significant differences in crown condition, but the differences were neither extensive nor consistently significant for an indicator over the time period examined. When considered alone, the crown condition indicators may help us identify the presence of a known stressor, but perhaps only if the general area undergoing stress is known already. The crown condition indicators may also provide a starting point for identifying unknown stressors, though forest health problems may be difficult to distinguish if their manifestation in crown condition is subtle. Ongoing research continues to examine the usefulness of the crown condition indicators as early signals of declining forest health. Besides the annually collected phase 3 survey data, designed experiments and studies examining the effect of assessment timing will refine our expectations for the crown condition indicators.

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Searching for American Chestnut: The Estimation of Rare Species Attributes in a National Forest Inventory

Francis A. Roesch[1] **and William H. McWilliams**[2]

Abstract.—American chestnut, once a dominant tree species in forests of the Northeastern United States, has become extremely rare. It is so rare, in fact, that on completion of 80 percent of the plot measurements of the U.S. Department of Agriculture Forest Service's most recent inventory in Pennsylvania, only 33 American chestnut trees with a diameter at breast height ≥ 1.0 in were found, out of 72,416 sampled trees. This paper discusses auxiliary sampling strategies that allow Forest Inventory and Analysis (FIA) units to estimate rare species in general as a first step in considering the especially difficult problems that American chestnut poses. The strategies involve (1) an increase of the initial plot size, (2) the use of adaptive cluster sampling, and (3) a combination of the first two. Adaptive cluster sampling was developed for the estimation of rare clustered events and is considered here because American chestnut is not only rare but also known to occur almost exclusively in clusters.

American chestnut (*Castanea dentata* (Marsh.) Borkh.), once a dominant tree species in Eastern U.S. forests, has become extremely rare in those same forests (McWilliams *et al*, 2006). It is so rare, in fact, that on completion of 80 percent of the plot measurements of the U.S. Department of Agriculture Forest Service's most recent inventory in Pennsylvania, only 33 American chestnut trees were found out of 72,416 sampled trees. This paper explores adaptations to the Forest Inventory and Analysis (FIA) sample design for estimating attributes of rare species in general as a first step in considering the especially difficult problems that American chestnut poses.

National inventories are best suited to (and funded for) small-scale problems such as the desire to estimate a level of X per million hectares. Related large-scale attributes and rare events, however, are often of disproportionate interest, which results in a general scale problem within the inventory because the rarer an event is, the greater its variance of observation will be and the higher the probability is that the event will be missed entirely by a small-scale inventory.

A few alternative approaches to detecting and estimating rare events would be to increase the sample size, increase the sample complexity (by adding a stage or phase, for example), proportionally or optimally allocate the sample, increase the size of the observation unit, or use adaptive cluster sampling. Here we consider the following options that are readily available to FIA for increasing the sample of American chestnut without increasing the number of sample points:

(1) Increase the size of the sample units utilizing the existing design features, and alter the size distributions selected by the components of FIA's tri-areal design within the natural range of American chestnut (fig. 1), to wit:
    a. Sample chestnut trees with diameter at breast height (d.b.h.) from 1.0 to 5.0 in on the subplot rather than the microplot.
    b. Use the existing design's previously developed macroplot to sample all chestnut trees larger than a breakpoint diameter.

(2) Use adaptive cluster sampling with search circles of a fixed size dependent upon the expected intra-cluster distribution (as in Roesch 1993).

(3) Some combination of options 1 and 2.

Although a detailed discussion of this point is beyond the scope of this article, a minor modification of option 3 could be used for increased efficiency in the estimation of American chestnut.

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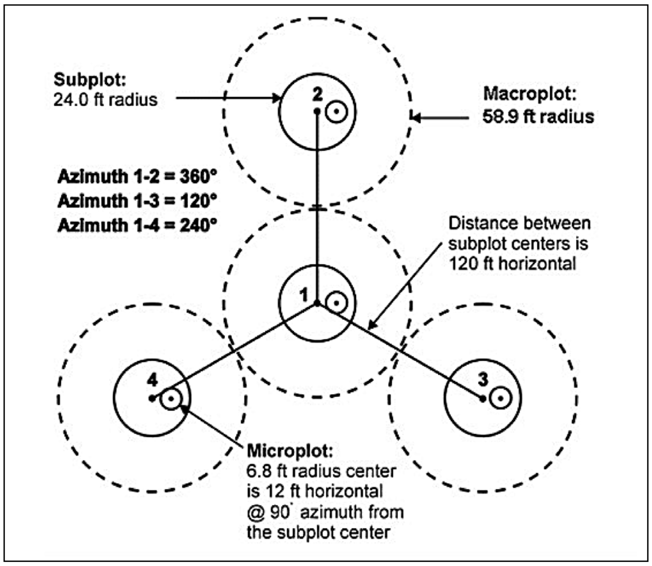
Figure 1.—*The FIA plot design. All trees greater than 5.0 in d.b.h. are measured on the subplot. Trees greater than 1.0 in d.b.h. are measured on the microplot. The macroplot is an optional feature currently used in the Pacific Northwest as an auxillary sample for large trees.*



FIA = Forest Inventory and Analysis.
Source: Bechtold and Patterson 2005.

That modification would be to extend the search area for the first member of the network (defined below) by a predetermined portion of the crew members' approach to the plot, thereby increasing the plot size exclusively for American chestnut. The extreme rareness of the American chestnut may warrant such an extended search area, and this extension of the search area would probably not substantially increase observation time because the crew is already traveling to the plot and American chestnut is distinctive enough to usually be recognized immediately. As long as the area of the extended search is known, unbiased estimators can be formed in the same way they are for the options we will consider in greater detail.

Alternatively, if one forsakes the desire for unbiased estimators in favor of any indicator of the presence of American chestnut, crew members could record any observation of the species during the course of their workday. The quality of the resulting information would be comparable to that obtained in almost all of the botanical studies conducted through the middle of the 20th century, and the information obtained could be used as a contemporary update to species distribution maps that were developed in the same way and are still relied on today.

The options considered here are described in detail below.

Option 1

Option 1 exploits an adaptable feature of the existing FIA design, first by employing the currently underutilized macroplot to sample this rare species and second by redefining the various plots within the tri-areal design for intensified observations on American chestnut. The macroplot, an optional feature in the FIA sample design, may be used to augment the sample for attributes of regional interest. This option has at least two advantages. First, it is somewhat efficient because increased selection areas could be limited to plots in areas with a high probability of containing the rare event of interest and to observations on the species of interest.

In addition, there would not be any further theoretical development or explanation needed for FIA practitioners and data users, other than a description of the larger selection areas for chestnut trees. The largest disadvantage is that additional costs of observation would be incurred on every plot in all areas of interest. Some potential also exists for field crew confusion with respect to the species-specific plot sizes and the identification of plots in high-probability areas.

Option 2

In option 2, the existing inventory is modified by adapting the field procedure when American chestnut is observed. Roesch (1993, 1994), following the work of Kalton and Anderson (1986), Levy (1977), Thompson (1990, 1991a, 1991b), and Wald (1947), showed how to do this for forest inventories using adaptive cluster sampling, in which unique networks of trees are sampled rather than unique trees.

Adaptive designs are usually described as being executed in two stages. First a probability sample of units in a population is taken and then additional units are selected near those units that display a specific condition of interest. Combining probability proportional to size sampling schemes common in forestry with an adaptive sampling scheme results in a system that can be applied to both equal and unequal probability forest inventory systems (Roesch 1993). In this article, the initial selection of trees by FIA's tri-areal design forms the basis of the first stage (Reams *et al.* 2005). In general, if a sample tree displays some rare condition of interest, (e.g., being an American chestnut), a specified area is examined for additional chestnut trees. This is repeated for every new chestnut found. The goal is to choose a distance rule that would identify a reasonable number of additional trees for the sample. Achievement of this goal is facilitated by a foreknowledge of the spatial distribution of the rare event of interest.

Further development assumes that the tree is the sampling unit and that there are N trees in the area of interest with labels 1,2,...,N. Associated with the N trees are values of interest $\mathbf{y} = \{y_1, y_2, ..., y_N\}$ and characteristics of interest $\mathbf{C} = \{C_1, C_2, ..., C_N\}$ (Roesch 1993). In this case, the species itself is the characteristic of interest; therefore, if tree i is an American chestnut tree, $C_i = 1$, and otherwise $C_i = 0$. This study was designed to determine an optimal adaptive sampling design and estimators for the presence, size, and fecundity of American chestnut within most of its natural range. As an example, suppose the variable of interest is total basal area of American chestnut trees. Let $x_i = C_i y_i$, so if tree i is an American chestnut tree, $x_i = C_i y_i = 1 * ba_i$.

The field crew would take the following steps:

(1) Conduct the initial sample.

(2) For all American chestnut trees conduct the adaptive part of the sample:

   (a) Measure all desired attributes y_i.

   (b) Observe all American chestnut trees that are within a circle of radius r from the center of tree i and have not already been sampled (i.e., ignore all new trees of other species).

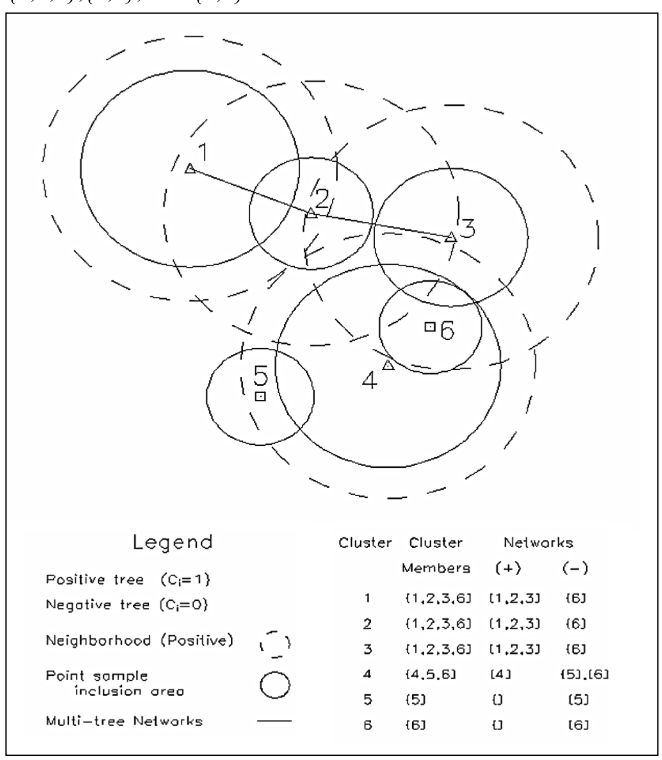
   (c) For all newly observed American chestnut trees, return to (a).

   (d) Stop when no new American chestnut trees are observed.

Similarly, the initial FIA design is extended to a network of chestnut trees. Each tree is surrounded by a circular area of selection. Options for definitions of the radius r are discussed below. These options attempt to determine a radius that would identify a reasonable number of additional trees for the sample—that is, enough additional trees to provide an estimation advantage and few enough to be considered during the measurement of the field inventory plot. This requires us to consider all of the available information on the spatial distribution of chestnut trees. It is clear that this extra effort in the design stage will be rewarded by the increased efficiency of a well-planned adaptive sampling survey.

A cluster is the set of all trees included in the sample as a result of the initial selection of tree i. A network is the subset of trees within a cluster such that selection of any tree within the network by the original sample (step 1 above) will lead to the selection of every other tree in the network. Because selection of trees for which $C_i = 0$ will not result in the selection of any other trees, these trees are networks of size 1. This procedure maps the population of N trees into a population of M networks, conditioned on C (fig. 2). Each network is sampled with known probability because the network population is mapped directly onto the tree population. We ignore trees not displaying the condition (i.e., for which $C_i = 0$) unless they are in the original estimators. This results in unbiased estimators (Thompson

Figure 2.—*Adaptive sampling attributes for a group of six trees in a population. A randomly placed point in the initial sample can select trees from the sets: {},{1},{2},{3},{4},{5},{1,2},{3,4},{3,4,6},{4,5}, and {4,6}.*



Source: Roesch 1993.

1990). The probability (p_i) of using tree i in an estimator is equal to the union of the selection areas of each tree in the network (a_i) to which it belongs, divided by the area of the forest (L_F).

Estimator of the Population Total

Thompson (1990) showed that an unbiased estimator can be formed by modifying the Horvitz-Thompson estimator (Horvitz and Thompson 1952) to use observations not satisfying the condition only when they are part of the initial sample. We can calculate the probability that a tree is used in the estimator even though its probability of being observed in the sample is unknown. The probability of tree k, in network K, being included in the sample from at least one of m plots is:

$$\alpha_k = \alpha_K = 1 - \left(1 - \frac{a_k}{L_F}\right)^m$$

where:

a_K = union of the inclusion areas for the trees in network K to which tree k belongs.

L_F = the total area of the forest.

For the HT estimator, let:

$$J_k = \begin{cases} 0 & \text{if the kth tree does not satisfy the condition and is not selected in the} \\ 1 & \text{sample, otherwise} \end{cases}$$

Then sum over the v distinct trees in the sample:

$$t_{HT} = \left(\frac{1}{L_F}\right) \sum_{k=1}^{v} \left(\frac{y_k J_k}{\alpha_k}\right)$$

The statistical properties of t_{HT} and other adaptive sampling estimators are discussed in Roesch (1993).

As its name implies, adaptive cluster sampling can be very efficient if the rare condition is distributed in clusters. In adaptive cluster sample designs, a compromise must be found between the level of new knowledge attained and survey cost. Adaptive sampling has at least three advantages: (1) it is efficient because only the presence of American chestnut triggers additional effort and cost; (2) it can be used on an attribute by attribute basis, so adapting the sample for estimation of American chestnut does not affect the cost of other estimates; and (3) it nullifies the weakness of the existing FIA design for the estimation of rare events. Its disadvantages include the potential for field crew confusion with respect to species-specific search rules and the identification of plots in high-probability areas, and the necessity for additional theoretical development and explanation for FIA practitioners and data users.

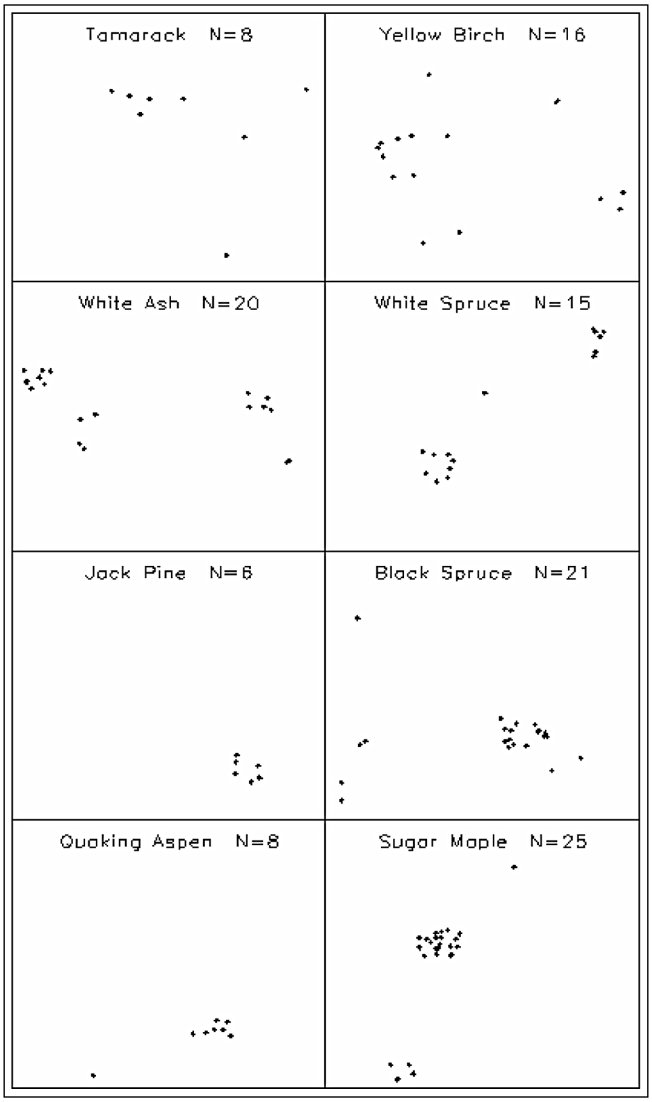
Simulation

To illustrate the considerations that must be taken into account when choosing between these options for sampling rare events, a simulation utilizing the same population described in Roesch (1993) was conducted. In brief, the simulated population was built using the coalesced 1981 FIA plot data from Hancock County, ME, as seed data. The data were chosen because they were conveniently on hand and were sufficient to illustrate the attributes of these sampling options. Ten sample points were applied to the population 1,000 times and the following four sample designs for eight rare tree distributions within the population were compared:

(1) Bi-areal design.
    Microplot: d.b.h. < 5.0 in
    Subplot: d.b.h. ≥ = 5.0 in
(2) Tri-areal design—breakpoint diameter (9, 12, 15, and 18 in).
    Microplot: d.b.h. < 5.0 in
    Subplot: 5.0 in ≤ = d.b.h. < breakpoint diameter
    Macroplot: d.b.h. ≥ = breakpoint diameter
(3) Adapted bi-areal design.
    Search radii of 20, 30, 40, 50, and 60 ft
(4) Adapted tri-areal design.
    Search radii of 20, 30, 40, 50, and 60 ft

We estimated total basal area and mean squared error (MSE) for the eight rare species whose spatial distributions are plotted individually in figure 3 for each variation of each design. Design 1 is the default design that would be used if no special consideration were given to the rare species. The varying breakpoint diameters affect designs 2 and 4 while the varying search radii affect designs 3 and 4.

Figure 3.—*The spatial locations of the eight rare species in the simulated population described in Roesch (1993).*



Results

Figures 4 through 7 show the simulation's calculated ratios of the MSEs of designs 2, 3, and 4 to design 1 for breakpoint diameters 9, 12, 15, and 18 in, respectively.

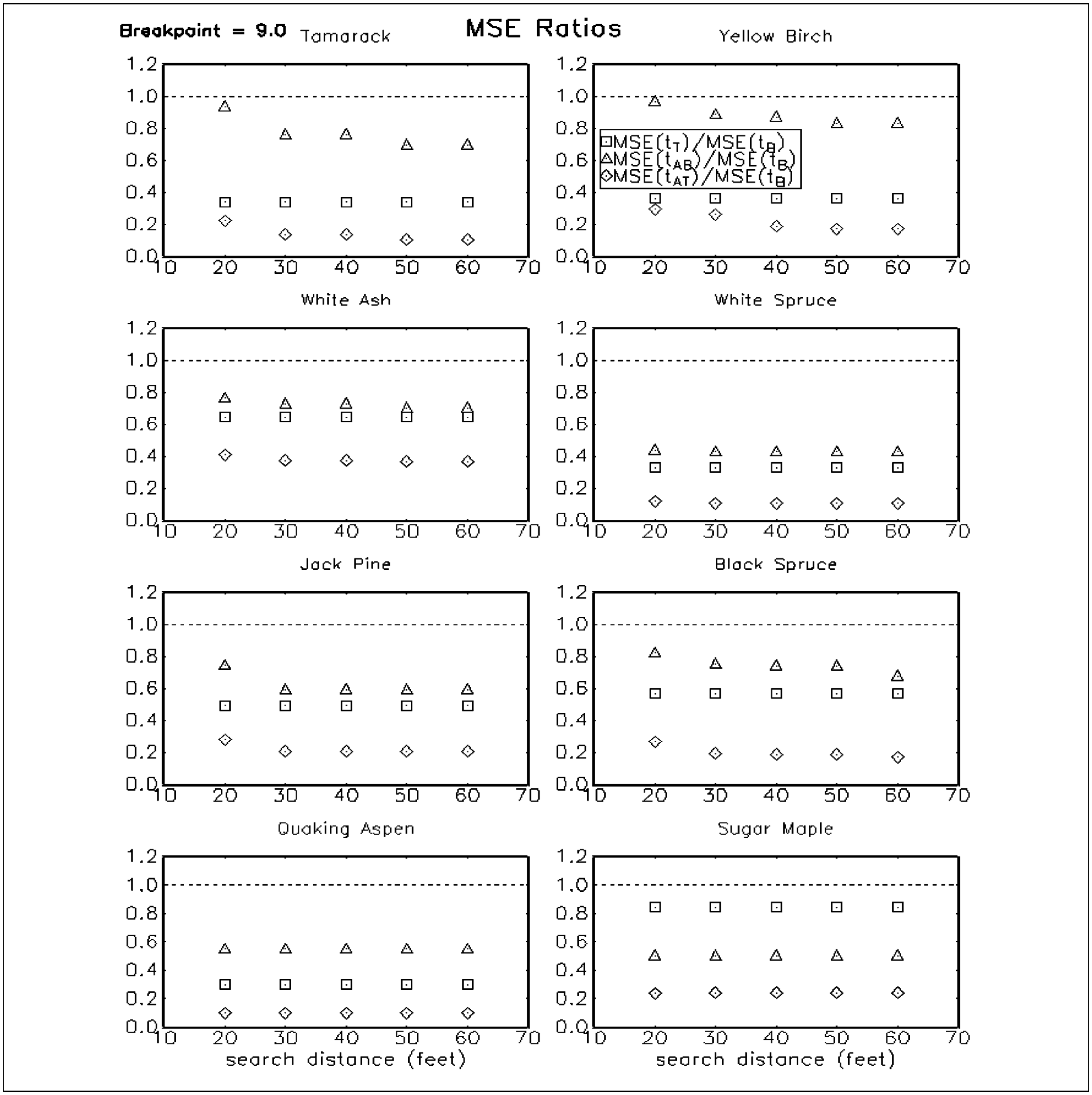
Figure 4 represents the heaviest investment in additional observations on the macroplots for designs 2 and 4 of those studied with a breakpoint diameter of 9 in. For four of the eight distributions (tamarack, yellow birch, white spruce, and quaking aspen), the reduction in MSE for the tri-areal design relative to the bi-areal design is greater than 60 percent; that is, the ratios are less than 40 percent. The tri-areal design has the least advantage over the bi-areal design in the case of the highly clumped sugar maple distribution, with MSE ratios greater than 80 percent. In all instances, the plots for the adapted bi-areal and adapted tri-areal designs show some advantage over their nonadapted counterparts. In all graphs but the sugar maple graph, the tri-areal design shows a greater reduction in MSE over the bi-areal design than does the adapted bi-areal design. The difference is very small in three of the graphs (white ash, white spruce, and jack pine) and fairly small in a fourth (black spruce). The adapted tri-areal in all cases shows the greatest overall reduction in MSE ratios. Note that in most cases a threshold can be discerned, beyond which an increase in search distance for the adapted designs yields little additional MSE reduction. With tamarack and jack pine for example, this appears to happen between search distances of 20 and 30 feet. With quaking aspen and sugar maple, this threshold appears to have occurred before the shortest distance simulated, 20 ft.

Figure 5 represents a smaller investment in additional observations on the macroplots for designs 2 and 4 than did figure 4 with an increased breakpoint diameter of 12 in. For six of the eight distributions, the ratio of tri-areal design MSE to the bi-areal design MSE exceeds the ratio of adapted bi-areal design MSE to MSE for the nonadapted bi-areal design. No advantage can be discerned for the tri-areal design over the bi-areal design for two species (jack pine and quaking aspen). The miniscule advantage noted for sugar maple could hardly be justified by the six-fold increase in plot size. For the remaining species, the tri-areal designs still show a significant advantage over their respective bi-areal counterparts. In all instances the adapted designs outperform their nonadapted counterparts.

The results in figure 6, for the breakpoint diameter of 15 in, show that the diameter distributions of five of the species are such that the tri-areal design provides no advantage. It is at this breakpoint diameter that an advantage of the adapted bi-areal over the unadapted tri-areal is first observed for white spruce.

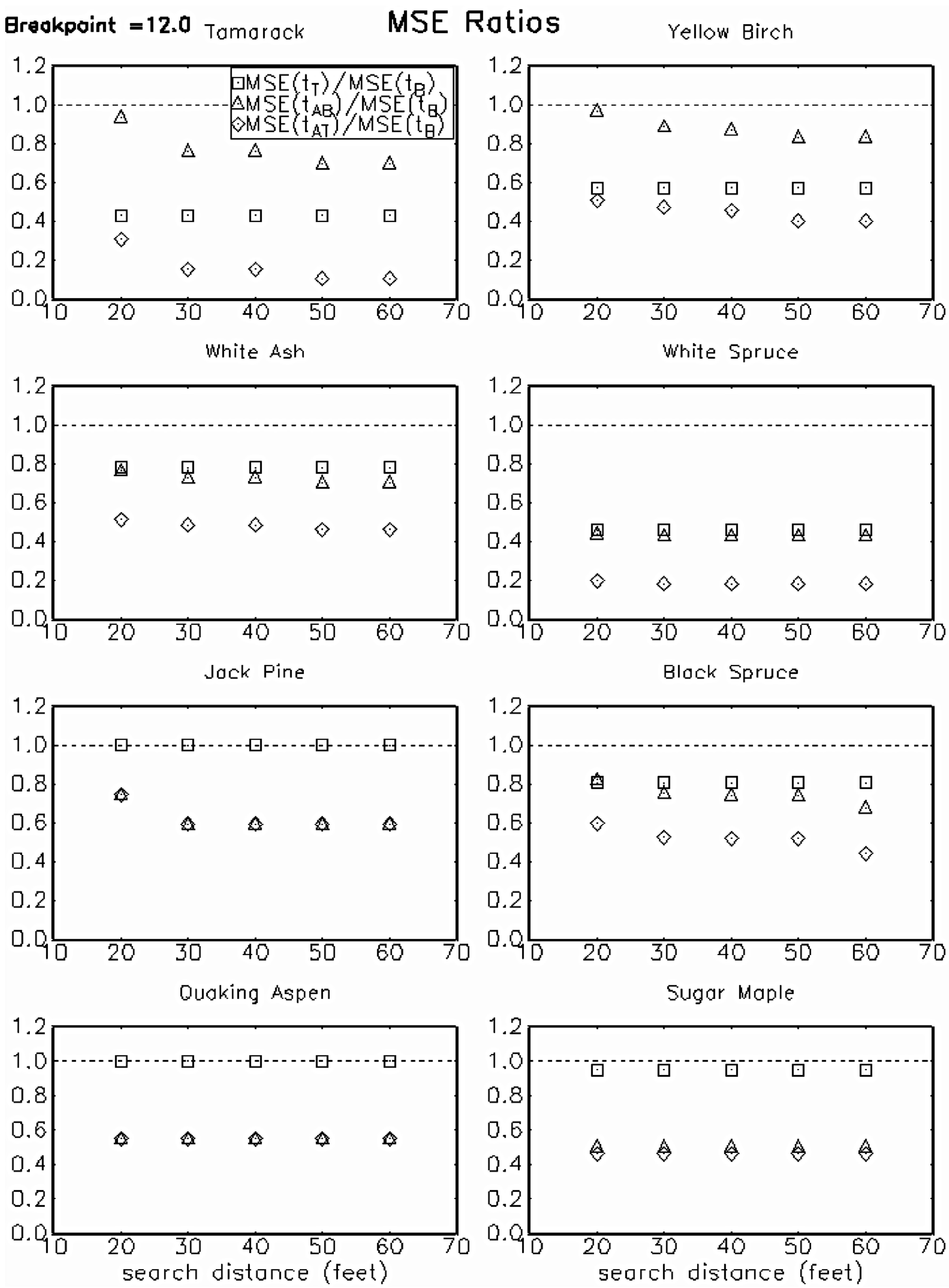
Figure 7 shows that none of the diameter distributions supports an argument for a breakpoint diameter of 18 in or larger.

Figure 4.—*Plots from 1,000 simulations for each species of three mean square error ratios using a breakpoint diameter of 9 in. The denominator in each case is the mean square error of the total basal area estimator from the bi-areal design (t_B). The numerators are (1) the mean square error of the total basal area estimator from the tri-areal design (t_T), (2) the mean square error of the total basal area estimator from the adapted bi-areal design (t_{AB}), and (3) the mean square error of the total basal area estimator from the adapted tri-areal design (t_{AT}).*



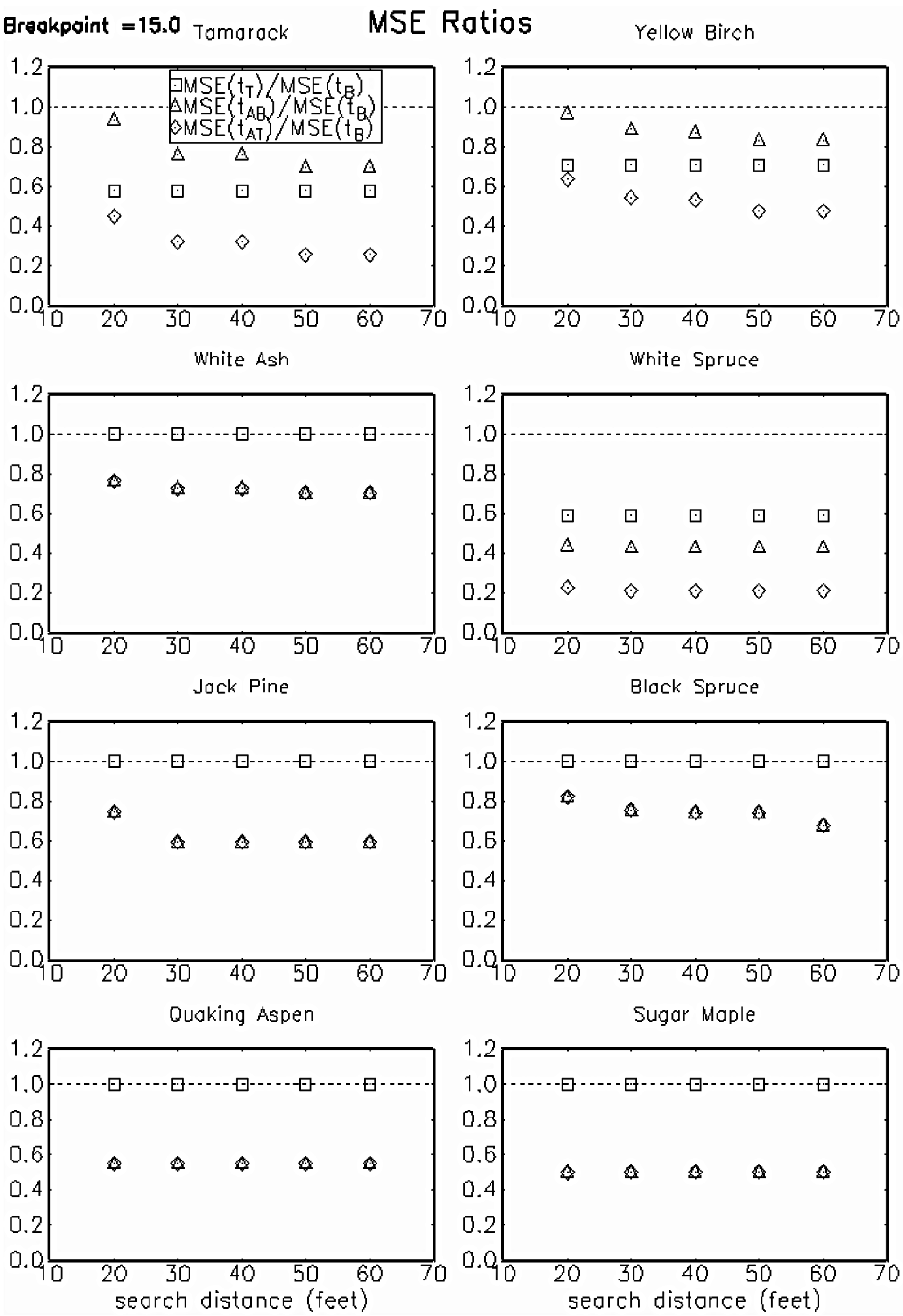
MSE = mean square error.

Figure 5.—*Plots from 1,000 simulations for each species of three mean square error ratios using a breakpoint diameter of 12 in. The denominator in each case is the mean square error of the total basal area estimator from the bi-areal design (t_B). The numerators are (1) the mean square error of the total basal area estimator from the tri-areal design (t_T), (2) the mean square error of the total basal area estimator from the adapted bi-areal design (t_{AB}), and (3) the mean square error of the total basal area estimator from the adapted tri-areal design (t_{AT}).*



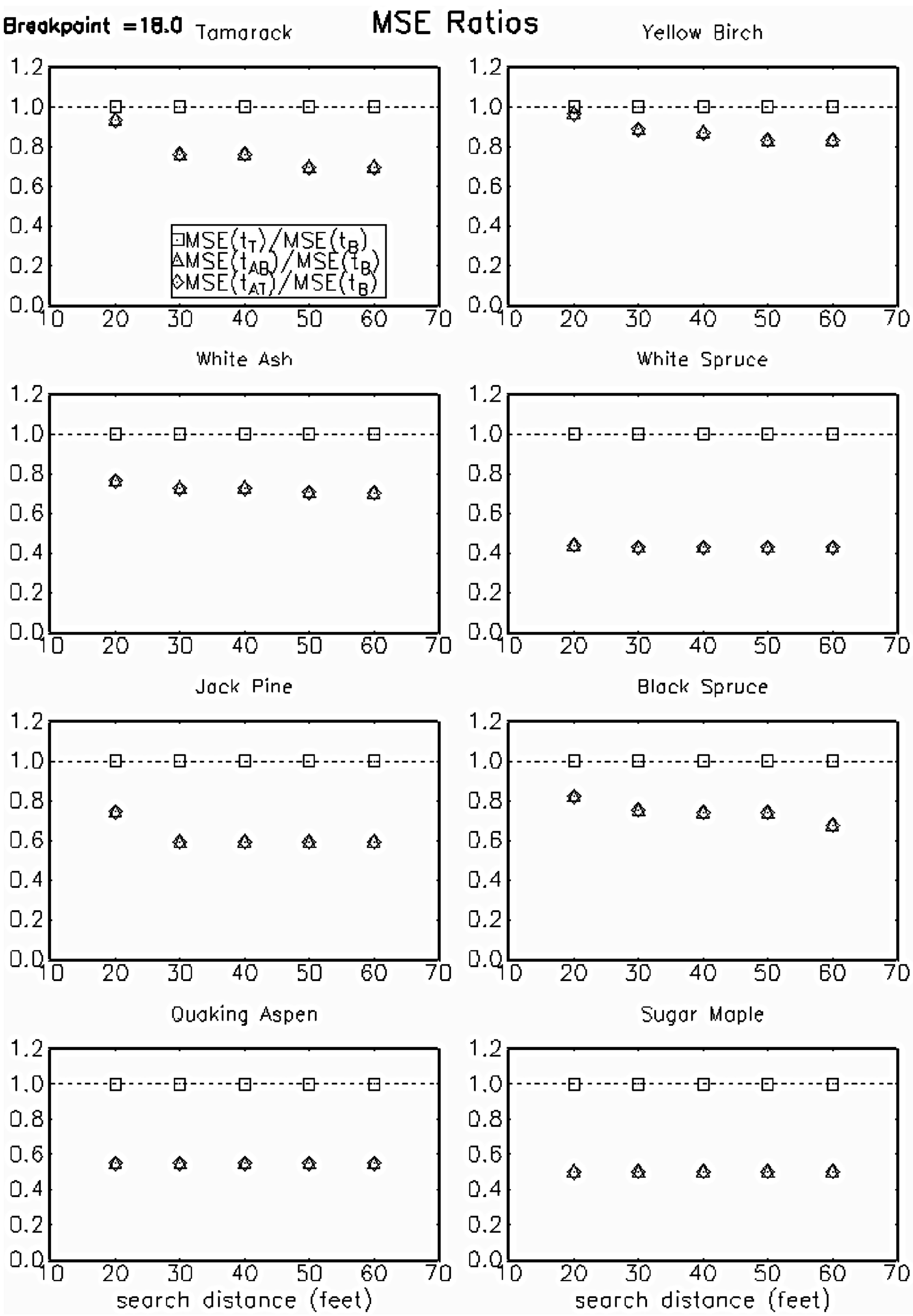
MSE = mean square error.

Figure 6.—*Plots from 1,000 simulations for each species of three mean square error ratios using a breakpoint diameter of 15 in. The denominator in each case is the mean square error of the total basal area estimator from the bi-areal design (t_B). The numerators are (1) the mean square error of the total basal area estimator from the tri-areal design (t_T), (2) the mean square error of the total basal area estimator from the adapted bi-areal design (t_{AB}), and (3) the mean square error of the total basal area estimator from the adapted tri-areal design (t_{AT}).*



MSE = mean square error.

Figure 7.—*Plots from 1,000 simulations for each species of three mean square error ratios using a breakpoint diameter of 18 in. The denominator in each case is the mean square error of the total basal area estimator from the bi-areal design (t_B). The numerators are (1) the mean square error of the total basal area estimator from the tri-areal design (t_T), (2) the mean square error of the total basal area estimator from the adapted bi-areal design (t_{AB}), and (3) the mean square error of the total basal area estimator from the adapted tri-areal design (t_{AT}).*



MSE = mean square error.

Discussion

Estimation of American chestnut attributes is ideal as a test case of adaptive sampling for FIA because the species is so rare, in stark contrast to its previous abundance, and because there is intense scientific interest in the species. A significant advantage of the FIA design for estimation of well-dispersed forest attributes is the intentionally thorough dispersion of the sample plots through the spatial-temporal cube, while this very aspect constitutes a significant weakness for estimation of forest attributes that occur in rare clusters within the cube. An adaptive sampling design laid on top of the FIA design in targeted areas could nullify this weakness of the existing design for the estimation of this rare event.

Relative cost is a major concern when choosing between sampling strategies. The additional monetary cost of the adaptive strategy for a particular application depends on relative cluster size and occurrence in the sample. These factors can be predicted given adequate previous knowledge of the population. In the example in Roesch (1994), the additional cost of including extra trees was shown to be controllable by the distance examined. Within this distance, the species of each tree must be determined and if any tree is an American chestnut, its d.b.h., and location must be recorded. Because American chestnut trees are truly rare and found in clusters, the additional cost will be small and the estimate of the per-tree attributes will be improved. The size of the search area determines the size of the networks of interest found as well as the number of additional other trees encountered. Therefore, for any other specific attribute one would want to select a minimally sized search area dependent on the expected proximity of the target trees to each other.

Adaptive cluster sampling provides a way for FIA to monitor rare events at a relatively small cost. It also allows flexibility in the inventory in that once a particular condition becomes less rare, the adaptive sampling procedure can be dropped for that condition, and other conditions can be added to the list of those adapted for.

This direct application of adaptive sampling should yield much-improved estimates of American chestnut attributes; however, it appears that this method could be used even more efficiently for American chestnut with a minor modification. That is, the extreme rareness of the American chestnut may warrant an extended search area for the first member of the network. This is a viable option not discussed in the Roesch or Thompson papers cited. The search area would be extended by a defined portion of the crew members' approach to the plot. This would increase the plot size for American chestnut only, without substantially increasing observation time. That is, the crew is already traveling to the plot, and they generally look around while they are doing that. American chestnut is so distinctive that it is usually recognized immediately. At any rate, the relative advantage of the extended plot may be evaluated in a future study.

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Rapid Forest Change in the Interior West Presents Analysis Opportunities and Challenges

John D. Shaw[1]

Abstract.—A recent drought has caused compositional and structural changes in Interior West forests. Recent periodic and annual inventory data provide an opportunity to analyze forest changes on a grand scale. This "natural experiment" also provides opportunities to test the effectiveness of Forest Inventory and Analysis (FIA) methodologies. It also presents some analysis challenges, because analysts must evaluate the relative contributions of data obtained on phase 2 and phase 3 (i.e., Forest Health Monitoring) plots. In the case of the latter, some variables may reveal less-than-catastrophic changes. Evaluation of available data may allow FIA analysts to answer several longstanding, fundamental questions.

Introduction

Early in 2003, scientists and managers from universities and government agencies approached the Interior West Forest Inventory and Analysis (IW-FIA) program with questions about a widespread episode of drought-related mortality they were observing in pinyon-juniper woodlands (primarily common pinyon [*Pinus edulis* Engelm.] or singleleaf pinyon [*P. monophylla* Torr. & Frem.] in combination with any of several *Juniperus* spp.). In response, IW-FIA analysts began to follow the progression of mortality in States where annual inventory had recently started (Shaw 2005, Shaw *et al.* 2005). FIA annual data revealed an ecosystem-wide mortality episode that varied regionally in its intensity. In addition, FIA data showed that population-wide mortality, which ranged between 3 and 14 percent of pinyon basal area at the State scale, was considerably lower than suggested by anecdotal reports and ad-hoc surveys, some of which suggested 40 to 100 percent mortality of pinyon basal area.

The IW-FIA experience with this "natural experiment" revealed some important facts, perhaps the most important being that the annual inventory system can provide important information about forest change not obtainable from traditional, periodic inventories. At the same time, the event raised questions as to whether the same analysis could be repeated for other types of disturbances and other forest types (Shaw 2005). These questions relate not only to events that result in considerable mortality, but also events that produce widespread nonlethal effects—for example, crown dieback. A more general approach to these questions might be "How sensitive to forest change is the FIA sample for a given forest type (or species) and type of disturbance?" or, to state the issue another way, "We know it's happening, but can FIA see it?"

These concerns are not unique to IW-FIA, but apply to the FIA program in a broad way. In his introductory talk at this symposium, Reams raised three relevant points: (1) FIA is in the business of quantifying trends, (2) FIA analysis and reporting have an increasingly ecological emphasis, and (3) it has been difficult for FIA to anticipate the "next big issue" in forest management. To that list, Guldin added the point that consumers of FIA data were not only interested in what is happening to the forest, but also where it is happening. In this paper, selected data from 16 western species (table 1) are explored with the intent of developing an approach for a priori sensitivity analysis of FIA data.

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Table 1.—*Selected species and distribution by State in the Interior West.*

FIA Code	Species name	Range in Interior West*
15	white fir (*Abies concolor* (Gord. & Glend.) Lindl. ex Hildebr.)	AZ, CO, ID, NV, NM, UT
19	subalpine fir (*A. lasiocarpa* (Hook.) Nutt.)	All IW-FIA States
63	alligator juniper (*Juniperus deppeana* Steud.)	AZ, NM
65	Utah juniper (*J. osteosperma* (Torr.) Little)	All IW-FIA States
66	Rocky mountain juniper (*J. scopulorum* Sarg.)	All IW-FIA States
69	oneseed juniper (*J. monosperma* (Engelm.) Sarg.)	AZ, CO, NM
93	Engelmann spruce (*Picea engelmannii* Parry ex Engelm.)	All IW-FIA States
106	common pinyon (*Pinus edulis* Engelm.)	AZ, CO, ID, NV, NM, UT, WY
108	lodgepole pine (*P. contorta* Dougl. ex. Loud.)	CO, ID, MT, NV, UT, WY
113	limber pine (*P. flexilis* James)	All IW-FIA States
122	ponderosa pine (*P. ponderosa* Dougl. ex Laws.)	All IW-FIA States
202	Douglas-fir (*Pseusotsuga menziesii* (Mirb.) Franco)	All IW-FIA States
321	Rocky Mountain maple (*Acer glabrum* Torr.)	All IW-FIA States
322	bigtooth maple (*A. grandidentatum* Nutt.)	AZ, CO, ID, NM, UT, WY
746	aspen (*Populus tremuloides* Michx.)	All IW-FIA States
814	Gambel oak (*Quercus gambellii* Nutt.)	AZ, CO, NV, NM, UT, WY

IW-FIA = Interior West-Forest Inventory and Analysis.

** Ranges based on Little (1971, 1976); IW-FIA States include Arizona (AZ), Colorado (CO), Idaho (ID), Montana (MT), Nevada (NV), New Mexico (NM), Utah (UT), and Wyoming (WY).*

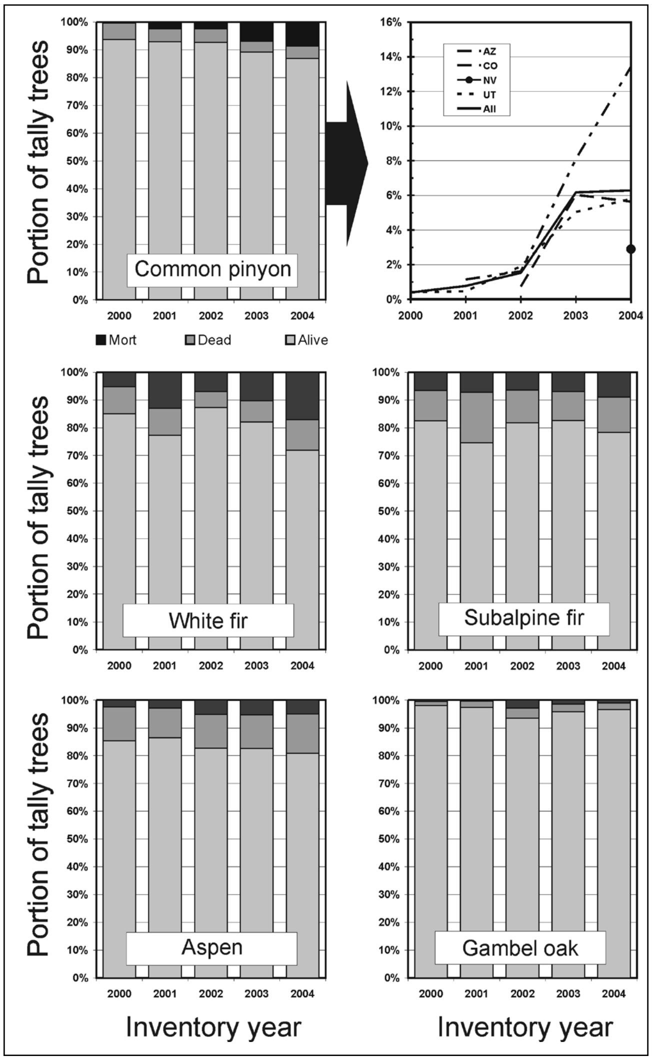
Analysis Approach

Detailed description of disturbances that affect western forests is beyond the scope of this article, but we know that landscape-scale phenomena occur in many forest types—for example, bark beetle outbreaks occur in pinyon pines, lodgepole pine, and Engelmann spruce, and aspen has been declining due to a wide variety of factors. These events are commonly related to drought and other stressors. Because the recent drought is thought to have caused mortality in forest types other than pinyon-juniper, FIA data are analyzed here under the assumption that the recent period of drought has caused at least some change in other forest types in the past 5 years. Qualitative comparisons are made here using the response of pinyon-juniper woodlands as a reference (fig. 1).

Several key characteristics of the pinyon-juniper mortality event affect our expectations for other species. Most importantly, pinyon-juniper woodlands are the most common type in the Southwest, comprising approximately 50 percent of FIA plots in the States of Arizona, Colorado, Nevada, New Mexico, and Utah. This suggests that, in terms of sample size, pinyon-juniper may provide the best-case scenario with respect to the possibility of detecting forest change. FIA has long recognized limitations to analysis of rare types because of low sample size; all types that remain are "in betweeners" for which the adequacy of the samples remain to be assessed.

Another key aspect of the pinyon-juniper type is that background mortality is known to be relatively low for species that occur in the type, based on results of periodic inventories. For example, annual mortality, on a volume basis, was estimated at 0.08 to 0.23 percent for common pinyon and 0.14 percent for singleleaf pinyon, and even lower (< 0.10 percent) for juniper species. In contrast, for example, estimates of annual mortality for ponderosa pine ranged from 0.21 to 0.48 percent in the same inventories (Shaw 2005). At least some of the differences among species are likely to be because stand density tends to be an accretion process in pinyon-juniper stands, whereas stands of most other forest types tend to become established with an overabundance of seedlings (or sprouts) and undergo self thinning over most of the life in the stand. Therefore, capturing episodic mortality becomes an issue of separation of "unusual" mortality from background mortality.

Figure 1.—*Samples from 2000–04, showing relative number of live, dead, and mortality trees. Graph shows resulting pinyon mortality estimate over time. Species selected for comparison show increasing mortality trends (white fir and subalpine fir) or lack of clear trends (aspen and Gambel oak).*



Because FIA now uses a single fixed-plot design for all forest types and pinyon-juniper woodlands tend to have relatively low stem density, plots in most other forest types are expected to have more tally trees per plot than plots in the pinyon-juniper type. This may mitigate the fact that fewer plots are likely to be located in other types than in the pinyon-juniper type. The actual effect, however, may depend on the nature of the disturbance (for example, whether trees are affected singly or in patches). On a related note, the typical number of tally trees found on an FIA plot is expected to vary according to the range of mixtures in which a species may be found. For example, in the last periodic inventory of Nevada, which is dominated by pinyon-juniper woodland, 590 plots had only one tree species present (usually singleleaf pinyon) and 920 plots had two tree species present. Only 138 plots included three or more tree species. In contrast, aspen has more than 70 associated tree species in the West, 45 of which are relatively common and many of which occur together. Hence, the abundance of any given species on a plot can range from a small fraction of basal area to 100 percent. These contrasts suggest that sensitivity to forest change may be different for species that occur in mixed stands compared with species that are most common in monotypic stands.

Finally, species-specific responses to type and severity of disturbance may affect the ability to detect change with FIA inventories. Although not yet confirmed by remeasurement data, it is thought that many of the pinyon trees on which drought symptoms (e.g., faded foliage and branch dieback) were observed in the past 5 years eventually succumbed. Some damage responses are relatively rare in the data because the time span between when a tree appears healthy and when it can be reasonably judged as dead can be relatively short compared with the 5-year window for being considered "recent" mortality. As a result, the probability of recording drought-related damage on live trees may be relatively low. In effect, this produces a binary response—live or dead—for most of the individuals that are measured. In contrast, it is common for juniper species, which are typically multistemmed, to suffer dieback in a few stems, thereby reducing live crown volume. Dead stems persist for some time, increasing the probability that a live juniper is observed with damage while it is still alive. Hypothetically, at least, this situation suggests that junipers may be more likely to exhibit a wider range of responses to drought than pinyons.

For other species, the drought response may resemble that of the pinyons, with mortality being the primary detectable response in most drought-affected trees and little damage evident on survivors, or it may resemble the response of the junipers, where mortality is low but damage is common. For any given species, the expected response will depend on the species' ecology and the type and severity of disturbance.

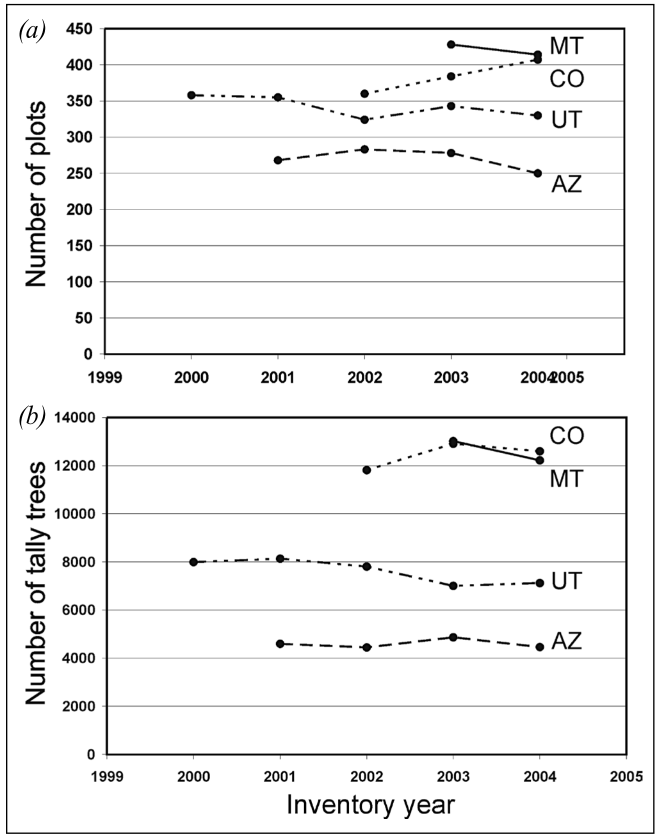
Looking for Consistency and Trends

In a first attempt to assess the sensitivity of FIA data to mortality and damage, 16 species (table 1) were selected for comparison and contrast in terms of their relative abundance on the landscape and the distribution of values recorded for selected variables. Ranges of the selected species vary from limited local or regional distributions to common occurrence throughout the IW-FIA States. Plot data used in this analysis come from a combination of annual and periodic inventories conducted from 2000 to 2004. Annual inventory was implemented in most of the IW-FIA states during this period (table 2), resulting in uneven (although generally increasing) geographic coverage in any given year. For this reason, the analysis presented here is primarily qualitative.

If FIA data are expected to reveal trends with annual resolution, there should be annual consistency in basic characteristics of the inventory, such as number of plots visited per year or number of plots occurring annually in a given forest type. Similarly, the sample should include relatively consistent distributions of trees by species and size over time. Consistency of the sample is important in light of the fact that nonoverlapping sets of plots are measured in successive annual panels. Some annual variation in the sample is inevitable, so the issue is primarily a matter of how much noise is introduced by sample size variation as compared with the magnitude of the signal caused by forest changes.

It is currently impossible to evaluate consistency of sample size for all eight IW-FIA States because annual inventory has not yet been implemented in all States and in some of those only one annual panel has been completed. For the four States with 2 or more complete years of annual data, annual variation in the number of plots and number of trees differs by State (fig. 2). Annual variation in number of plots is usually within 5 percent of the 5-year State average (fig. 2a), and variation in the number

Figure 2.—*Annual variation in number of plots and number of tally trees for Interior West-FIA States with two or more complete years of annual inventory data.*



AZ = Arizona; CO = Colorado; MT = Montana; UT = Utah.

Table 2.—*Type, year, and location of FIA surveys used in this study.*

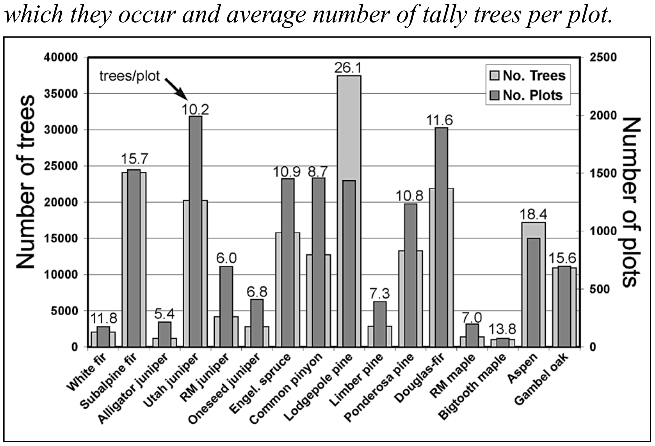
State	Inventory year				
	2000	2001	2002	2003	2004
AZ	none	annual (10%)	annual (10%)	annual (10%)	annual (10%)
CO	none	none	annual (10%)	annual (10%)	annual (10%)
ID	periodic	periodic	periodic	annual (10%)	annual (10%)
MT	none	none	none	annual (10%)	annual (10%)
NV	none	none	none	none	annual (10%)
NM	periodic	none	none	none	none
UT	annual (10%)	annual (10%)	annual (10%)	annual (10%)	annual (10%)
WY	periodic	periodic	periodic	none	none

AZ = Arizona; CO = Colorado; ID = Idaho; MT = Montana; NV = Nevada; NM = New Mexico; UT = Utah; WY = Wyoming.

of tally trees is usually within 7 percent of average (fig. 2b). This includes plots found to be inaccessible, plots to which access has been denied, and plots missed due to fire, weather, or other logistical limitations. Some of the annual variation may be expected to decrease over time once annual inventory is fully implemented and logistical issues are resolved. The remainder of variation, partly due to annual panel shift of the phase 2 grid and partly due to other causes, is likely to exist after full implementation.

Species varied widely in the number of plots on which they occurred and the average number of individuals found on a plot (fig. 3). As expected, timber species were usually represented by more trees per plot than woodland species. Among timber species, shade intolerant species known to regenerate in high numbers, such as aspen and lodgepole pine, tended to have higher numbers of trees per plot than late successional species such as subalpine fir and Engelmann spruce. Interestingly, of the 16 species examined, 6 were found on a number of plots comparable to or greater than the number on which common pinyon was found. These species were relatively common in the northern IW-FIA states, where pinyon-juniper woodlands do not occur. While sample sizes are not exactly comparable due to the mixture of annual and periodic plots, it appears that rangewide sample sizes of at least some species are comparable to that of pinyon-juniper and should be adequate to determine rangewide trends.

Figure 3.— *Select tree species showing number of plots on which they occur and average number of tally trees per plot.*



RM = Rocky Mountain.

Detecting Nonlethal Effects

Preliminary analysis of drought-related effects in pinyon-juniper woodland showed that there was relatively little mortality in the juniper component (Shaw *et al.* 2005). It is possible, however, that the drought caused sublethal damage to juniper species—e.g., death of some stems in multistemmed trees. As a result, it is reasonable to expect that there is a "drought signature" in live junipers and, perhaps, for other species in which relatively little mortality was observed. Two phase 3 indicator variables, crown density and crown dieback, were examined for possible trends over the time that most of the mortality was observed. It was expected that at least some of the species should have experienced changes in crown volume during the drought period, and that the changes should be reflected as decreases in mean crown density or increases on crown dieback over time.

The number of trees with crown density and dieback observations (i.e., trees located on phase 3 plots) was relatively small compared to the number of tally trees on phase 2 plots over the same time period. This difference is expected because there are approximately one-sixteenth the number of phase 3 plots as phase 2 plots. In 2003 and 2004, the years during which the highest number of phase 3 plots was measured, the number of crown observations ranged from less than 20 to just more than 300 for most species. The small number of trees with crown measurements suggests that it may be difficult to generalize about rangewide trends for some species, especially considering the large geographic ranges that are typical of Western species.

Mean crown density ranged between 30 and 60 percent, and in any year it was usually within 5 percentage points of the 5-year mean for most species (fig. 4a). There appeared to be a slight downward trend in mean crown density for many species over the 5-year period, although year-to-year variation was high compared to the magnitude of the overall trend. Interestingly, the rank of mean crown density among species appeared as might be expected from general knowledge of crown characteristics. The junipers, firs, and spruces tended to be in the upper ranges of density, whereas aspen and Gambel oak usually ranked lowest.

Mean crown dieback values tended to be low (< 8 percent), in part because no dieback was recorded on many trees in the sample (fig. 4b). Interannual variation in mean dieback values tended to be approximately 2 percentage points, but variation was much higher for some species. Variation appears to mask any existing trends, with the exception of Gambel oak, which appears to have suffered increasing dieback between 2001 and 2004. Although changes in mean values are highly variable, distributions of responses appear more informative. In all years, the vast majority of dieback observations are in the 0 and 5 percent categories for all species, with very few observations of dieback > 15 percent (fig. 5a). The few observations of high dieback tend to occur in 2002 or later, suggesting that there may be a "drought signature" in the data. Gambel oak is the only species that clearly shows the expected pattern, which is not only an increasing mean dieback value, but a shifting distribution of values over time (fig. 5b). Similar patterns might be observable in other species given larger samples.

Figure 4.—*Mean responses for crown variables by species, 2000–04. Trends of selected species are highlighted.*

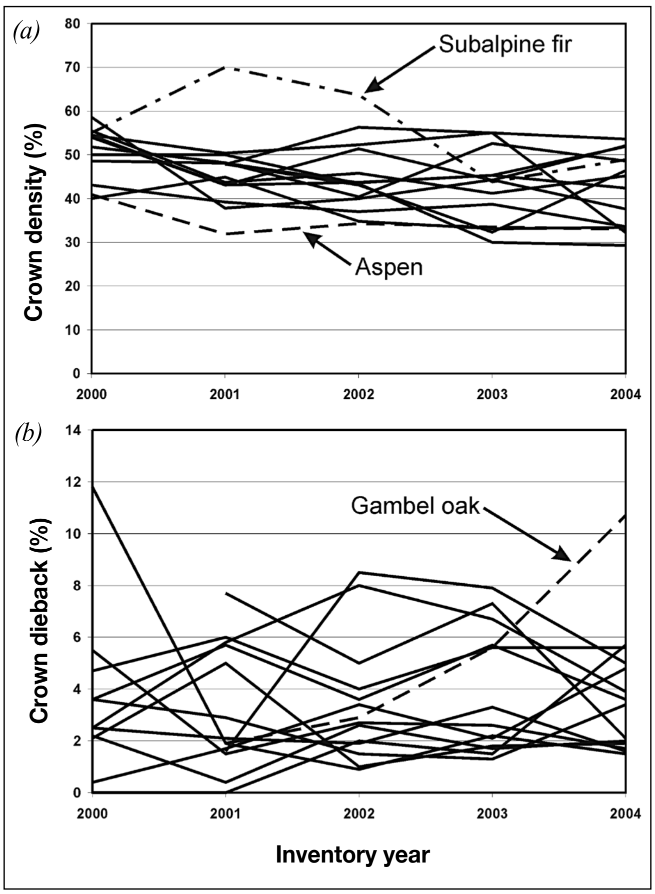
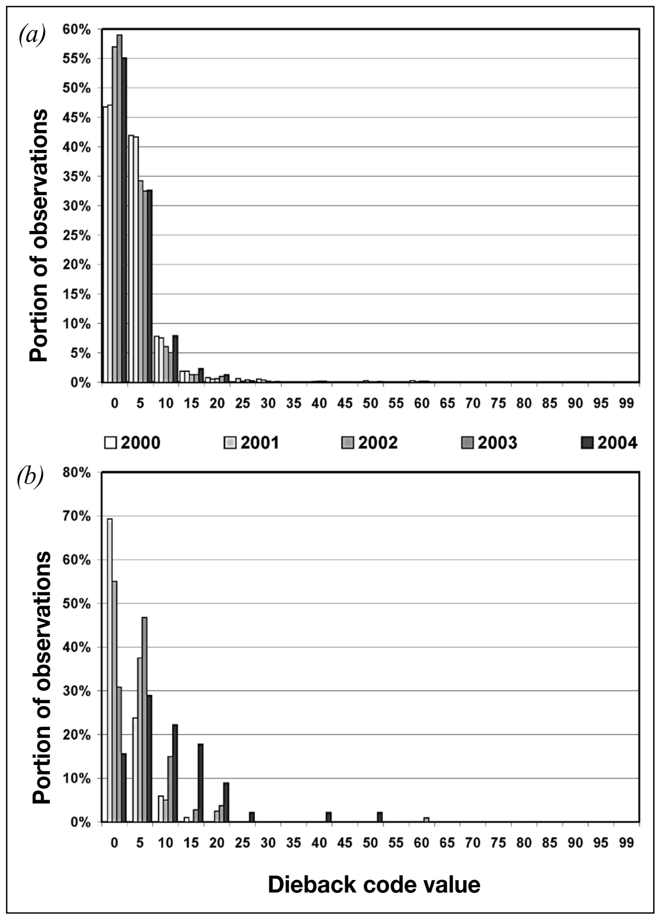


Figure 5.—*Distribution of crown dieback observations for all species (a) and Gambel oak (b), 2000–04.*



Conclusions

The IW-FIA experience with drought-related mortality in pinyon-juniper woodlands suggests a need to produce similar analyses for other species and forest types. Opportunities to track trends by species or forest types will depend on the magnitude and type of forest change, as well as the effects on individual trees (mortality vs. damage) and the representation of the species in the sample. Currently, complete sensitivity analysis is challenging because plot coverage in the Interior West is uneven in time and space. Analysis opportunities should improve with time, however, as annual inventory is implemented in all states.

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Forests on the Edge: Evaluating Contributions of and Threats to America's Private Forest Lands

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Abstract.—The Forests on the Edge project, sponsored by the U.S. Department of Agriculture Forest Service, uses geographic information systems to construct and analyze maps depicting ecological, social, and economic contributions of America's private forest lands and threats to those contributions. Watersheds across the conterminous United States are ranked relative to the amount of their private forest land, relative to the contributions of their private forest lands to water quality and timber supply, and relative to threats from development, wildfire, and ozone. In addition, development and wildfire threats to private forest land contributions to water quality and timber supply are assessed. The results indicate that private forest lands are concentrated in the Eastern and Southeastern United States and that threats to the contributions of private forest lands are also concentrated in the same regions. Threats also are distributed throughout the North Central, Central Hardwoods, and Pacific Northwest regions. The maps may be used to focus additional studies on watersheds of particular concern.

Introduction

America's forest lands contribute in a myriad of ways to the economic, ecological, and social well-being of the Nation. Increasingly, however, forest lands are threatened from a variety of sources including urbanization, climate change, invasive flora and fauna, wildfire, pollution, fragmentation, and parcelization. The increasing emphasis on sustainable forest management requires quantitative and spatial assessments of the impacts of these threats to forest lands and forest land contributions. The Forests on the Edge (FOTE) project, sponsored by State and Private Forestry, U.S. Department of Agriculture Forest Service, conducts map-based assessments of threats to the Nation's private forest lands using spatial data layers and geographic information systems. The Montreal Process criteria and indicators provide an appropriate context for framing and conducting these assessments (McRoberts *et al.* 2004). For example, Criterion 2, Maintenance of the Productive Capacity of Forest Ecosystems, includes indicators related to forest area and timber production; Criterion 3, Maintenance of Forest Ecosystem Health and Vitality, includes indicators related to fire, wind, disease, and insects; and Criterion 4, Conservation and Maintenance of Soil and Water Resources, includes indicators related to the contributions of forests to water quality.

The objectives of FOTE are threefold: (1) to construct nationally consistent data layers depicting the spatial location of

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private forest lands and their contributions such as water quality and timber supply; (2) to construct similar layers depicting threats to the contributions of private forest land from sources such as conversion to urban and exurban uses, wildfire, and pollution; and (3) to identify watersheds whose private forest lands simultaneously make the most important contributions and face the greatest threats.

Methods

Data Layers

All data layers were obtained as or constructed to be nationally consistent and were summarized at the spatial scale of fourth-level watersheds (Steeves and Nebert 1994). Watersheds were selected as the analytical units because they highlight the important connections between private forests and ecological processes. Only watersheds with at least 10 percent forest cover of which at least 50 percent is in private ownership were considered for the study.

Area of Private Forest Land

A 100-m resolution forest ownership layer was constructed by aggregating the classes of the National Land Cover Dataset (Vogelmann *et al.* 2001) into forest and nonforest classes and using the Protected Areas Database (PAD) (DellaSalla *et al.* 2001) to distinguish ownership and protection categories. The emphasis for this study was private forest land, which includes tribal, forest industry, and nonindustrial ownerships. Stein *et al.* (2005) provide detailed information on this layer.

Water Quality

Private forest lands provide nearly 60 percent of all water flow from forests in the United States and nearly 50 percent of the water flow originating on land in the conterminous 48 States. Water flow from private forests is generally considered clean relative to water flow from other land uses and, therefore, makes a positive contribution to water quality. The water quality layer depicts the contribution of private forest land to the production of clean water and is based on three underlying assumptions: (1) water bodies near the heads of hydrologic networks are more sensitive to the loss of forest buffers than water bodies near the bases of the networks, (2) the presence or absence of upstream forest buffers influences water quality downstream in the networks, and (3) forest land throughout watersheds better indicates the contributions of private forest land to water quality than does forest land only in the immediate vicinity of water bodies (FitzHugh 2001).

The water quality layer was constructed from two underlying layers: the forest ownership layer and the National Hydrography Dataset (USGS 2000), which depicts water bodies in the 48 contiguous States. The layer was constructed in four steps: (1) a 30-m buffer was constructed around all water bodies, (2) the buffers were intersected with the private forest land class of the forest ownership layer to quantify the amount of private forest land in close proximity to water bodies, (3) each buffer segment was assigned to one of four categories based on the relative position of the segment to the head of its hydrologic network, and (4) for each watershed, the percentage of the total buffer area in each of the four categories was determined. Water quality index (WQI) was then calculated for each watershed as

$$WQI = 0.6*(A_1+A_1*A_2)+0.4*(0.53*B_1+0.27*B_2+0.13*B_3+0.07*B_4)$$

where:

A_1 = percent of watershed in private forest land.

A_2 = percent of total forest land in watershed that is privately owned.

B_1 = percent of private forest land buffer in the first category (nearer head of hydrologic network headwater).

B_2 = percent of buffer in the second category.

B_3 = percent of buffer in third category.

B_4 = percent of buffer in fourth category (farthest downstream from the head of hydrologic network).

The 0.6 and 0.4 weightings of the A and B variable components, respectively, reflect the third assumption above. The relative weightings of the B variables among themselves reflect the assumption that each category of buffer is twice as important as the following category.

Timber Supply Layer

Private forest lands make a substantial contribution to America's timber resources, accounting for 92 percent of all timber harvested in the United States in 2001 (Smith *et al.* 2004). The timber supply layer depicts the ranking of watersheds relative to an index of their private forest land contributions to timber supplies and is based on Forest Inventory and Analysis (FIA) plot data (http://ncrs2.fs.fed.us/4801/fiadb/) and Timber Products Output data (http://www.ncrs.fs.fed.us/4801/regional-programs/tpo/). The timber supply index (TSI) is based on four subindexes of timber contributions of the timberland component of private forest land. Timberland is defined by the FIA program as forest land that has not been withdrawn from production and that is capable of producing 20 ft^3/yr of industrial wood. For each watershed, the four subindexes are calculated as follows: (1) growth index (GI) is the average growing stock volume growth rate on private timberland in the watershed relative to the average for private timberland in all watersheds, (2) volume index (VI) is the average net growing stock volume per acre on private timberland in the watershed relative to the net volume for private timberland in all watersheds, (3) area index (AI) is the ratio of private timberland and total private land for the watershed relative to the same ratio for all watersheds, and (4) private area index (PI) is the ratio of private timberland area and total area in the watershed. TSI was calculated for each watershed as

$$TSI = PI*(GI+VI+AI).$$

Development

The development layer depicts predicted threats to private forest lands resulting from conversion to urban or exurban uses. The layer is based on estimates of current population and housing density data obtained from the 2000 Census and predictions of housing density increases. A spatially explicit model was used to predict the full urban-to-rural spectrum of housing densities (Theobald 2005). The model uses a supply-demand-allocation approach and is based on the assumption that future growth patterns will be similar to those in the past decade. Future patterns are forecast on a decadal basis in four steps: (1) the number of new housing units in the next decade was forced to meet the demands of the predicted populations; (2) a location-specific average population growth rate from the previous to current time step was computed for each of three density classes: urban, exurban, and rural; (3) the spatial distribution of predicted new housing units was adjusted with respect to accessibility to the nearest urban core area; and (4) predicted new housing density was added to the current housing density under the assumption that housing densities do not decline over time. For these analyses, predicted new housing was not permitted to occur on protected private land as indicated by PAD (DellaSalla *et al.* 2001). The spatially explicit housing density predictions were combined with the forest ownership layer to identify watersheds with the greatest predicted conversion of private forest land to urban and exurban uses. Stein *et al.* (2005) provide detailed information on this layer.

Wildfire

Although wildfire is one of the most compelling threats to forest land, particularly in the Western United States, predicting wildfire risk is extremely complex and relies on a variety of regional models using regional variables. Further, even if the models could be readily used to construct a national layer, the geographic consistency of the layer would be questionable. Therefore, as a surrogate for wildfire risk, FOTE used the 1-km by 1-km resolution current fire condition class (CFCC) data which depict deviations of fire incidence from historic natural fire regimes and estimated efforts necessary to restore stands to historic regimes (Schmidt *et al.* 2002). All private forest lands in each watershed were assigned to one of three CFCC classes: (1) $CFCC_1$, forest lands with fire regimes that are within or near historical ranges and that can be maintained by treatments such as prescribed fire or fire use; (2) $CFCC_2$, forest lands with fire regimes that have been moderately altered from historical ranges and that may require moderate levels of prescribed fire, fire use, hand or mechanical treatment, or a combination to be restore the historical fire regime; and (3) $CFCC_3$, forest lands with fire regimes that have been substantially altered from historical ranges and that may need high levels of hand or mechanical treatment before fire is used to restore historical fire regimes. For each watershed, an index was calculated as

$$CC = CC_1 + 2*CC_2 + 4*CC_3$$

where CC_i is the area of private forest land in class $CFCC_i$. The weights associated with each class in the calculation of CC reflect the assumption that each class is twice as important as the next class. The wildfire layer depicts the ranking of watersheds relative to their CC index values.

Ozone

Ozone affects forest ecosystems by causing foliar lesions and rapid leaf aging, altering species compositions, and weakening pest resistance (Chappelka *et al.* 1997, Miller 1996). It is the only gaseous air pollutant that has been measured at known phytotoxic levels at both remote and urbanized forest locations (EPA 1996). The ozone layer depicts private forest land threatened by ground level ozone and was based on late summer observations by FIA field crews of ozone damage to bioindicator species known to be sensitive to ground level ozone. Data for more than 2,500 FIA plots were available for the study. Each plot was assigned a biosite value based on a subjective assessment by trained observers of the quantity and severity of damages (Coulston *et al.* 2003, Smith *et al.* 2003). Inverse distance weighted interpolation was used to create a map of ozone damage. This map was then combined with the forest ownership layer to identify private forest land with elevated levels of ozone damage. For each watershed, the percentage of private forest land in moderate or high damage categories was calculated.

Analyses

For each contribution and threat layer, with the exception of ozone, the distribution of watershed values was determined, and a percentile ranking was assigned to each watershed. Because only approximately 10 percent of watersheds satisfying the 10 percent forest cover and 50 percent private ownership criteria had elevated levels of ozone damage, no percentile ranking was constructed. For each watershed, development and wildfire threats to water quality and timber supply contributions were assessed using the average of the watershed's percentile rankings for the contribution and the threat. The results are depicted using percentile-based categories of the average of the contribution and threat percentiles.

Results

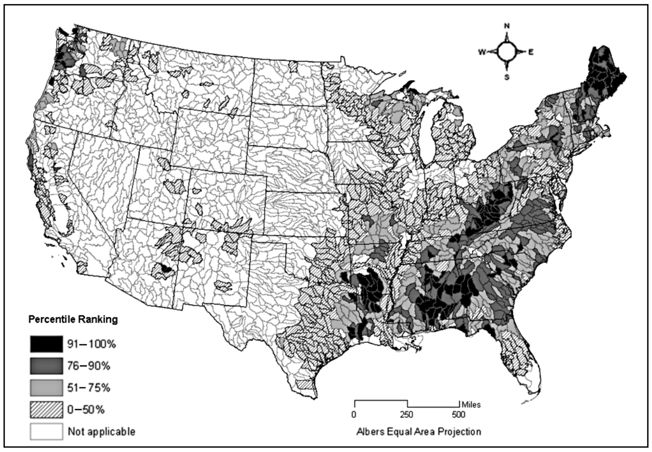
The results are briefly discussed and maps are presented for percent private forest land area, water quality and timber supply contributions, and development, wildfire, and ozone threats. Maps of the threats from development and wildfire to water quality and timber supply are also presented and discussed. No assessments of threats of ozone to water quality or timber supply were made, because so few watersheds had elevated levels of ozone damage.

Watersheds with the greatest percentage of private forest land are generally in New England, the Southeast, and the Pacific Northwest (fig. 1). The concentration in the East is not surprising, because much of the forest land in the West is in public ownership. Watersheds whose private forests make the greatest contributions to water quality and timber supply align closely with the watersheds with greatest amounts of private forest land (figs. 2 and 3).

Development threats to private forest land area are concentrated in southern New England and the Southeast, although some are also found in the Pacific Northwest (fig. 4). Wildfire threats to private forest land, as indicated by the surrogate CC layer, are primarily in the northeastern quadrant of the country (fig. 5). The two Midwestern areas in this northeastern quadrant, however, are characterized by low percentages of private forest land (fig. 1). With only a few exceptions, watersheds with elevated levels of ozone damage were in the east-central portion of the country (fig. 6).

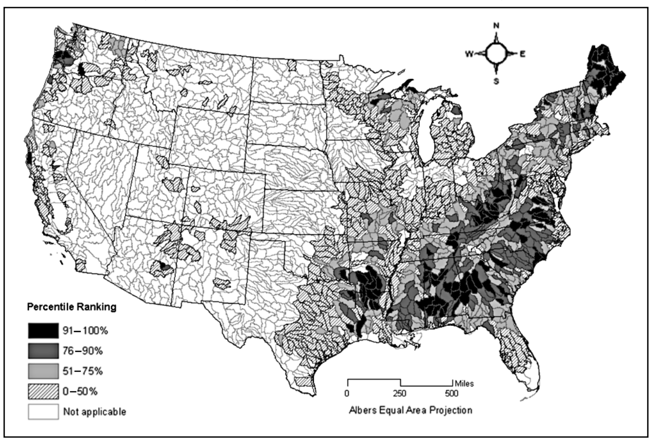
Development threats to the contributions of private forest land to both water quality and timber supply are concentrated in southern New England and the Southeast (figs. 7 and 8). These results are as expected, because higher percentile watersheds for all three underlying layers are also in southern New England and the Southeast. Wildfire threats, as indicated by the surrogate CC layer, to both water quality and timber supply contributions are distributed throughout the East and Southeast, the Lakes States, the Central Hardwoods region, and the Pacific Northwest (figs. 9 and 10).

Figure 1.—*Percentile rankings of watersheds with respect to percent of private forest land.*



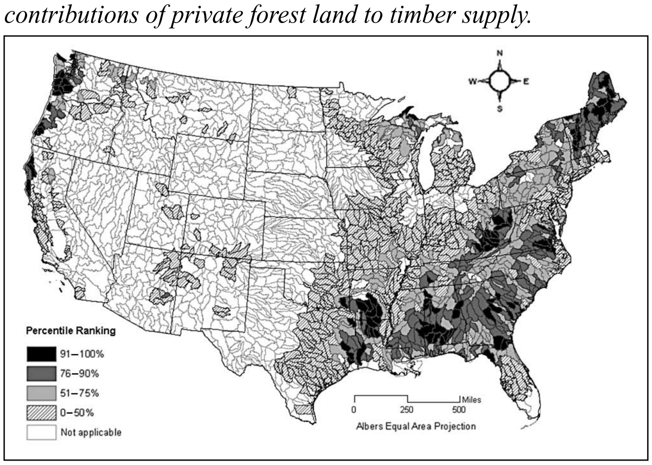
Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 2.—*Percentile rankings of watersheds with respect to contribution of private forest land to water quality.*



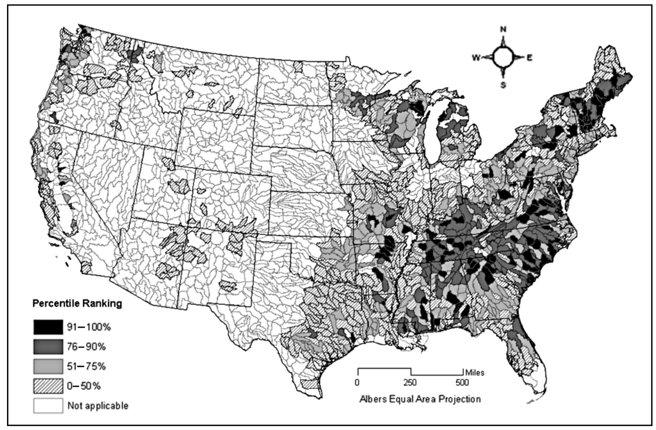
Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 3.—*Percentile rankings of watersheds with respect to contributions of private forest land to timber supply.*



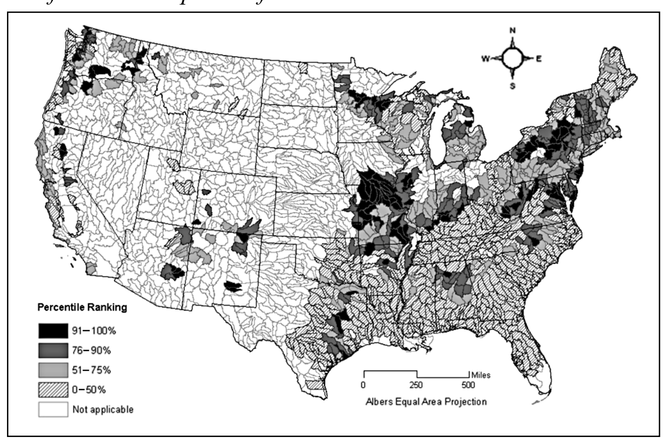
Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 4.—*Percentile rankings of watersheds with respect to percent of private forest land predicted to convert to exurban or urban uses by 2030.*



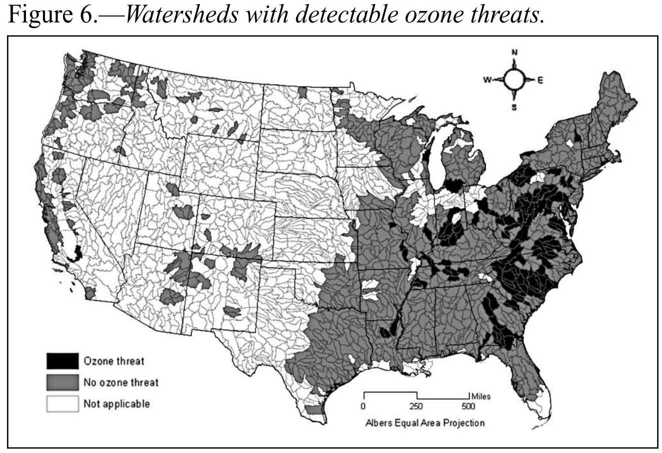
Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 5.—*Percentile rankings of watersheds with respect to wildfire threat to private forest land.*



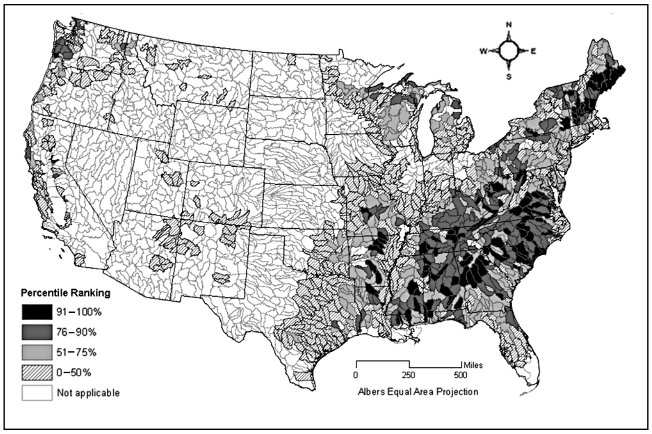
Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 6.—*Watersheds with detectable ozone threats.*



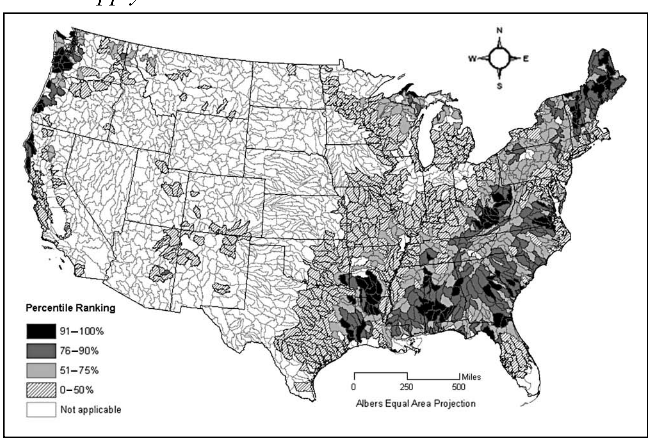
Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 7.—*Percentile rankings of watersheds with respect to development threat to the contributions of private forest land to water quality.*



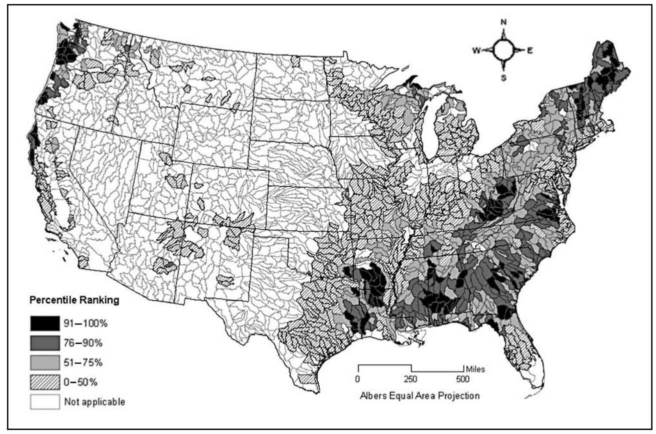
Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 8.—*Percentile rankings of watersheds with respect to development threat to contribution of private forest land to timber supply.*



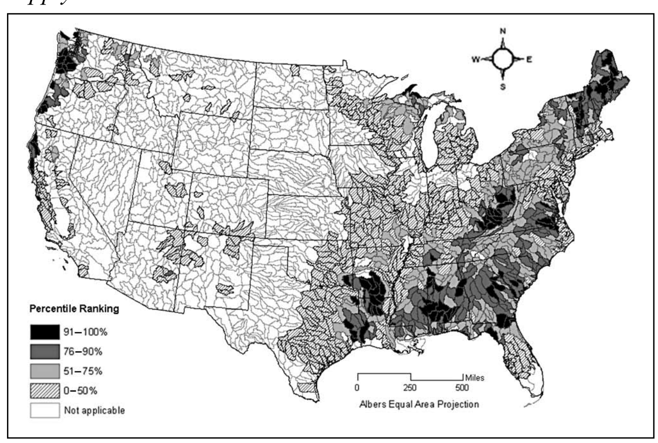
Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 9.—*Percentile rankings of watersheds with respect to wildfire threat to contribution of private forest land to water quality.*



Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Figure 10.—*Percentile rankings of watersheds with respect to wildfire threat to contribution of private forest land to timber supply.*



Forests on the Edge. Map produced by Forest Inventory and Analysis, Northern Research Station, USDA Forest Service.

Conclusions

Several conclusions may be drawn from this study. First, private forest land is located mostly in the Eastern United States, particularly New England and the Southeast, although there are also concentrations in the Pacific Northwest. Second, the watersheds making the greatest private forest contributions to water quality and timber supply are generally the watersheds with the greatest percentages of private forest land. Third, the watersheds with the greatest private forest land contributions to water quality and timber supply are also the watersheds most threatened by development. Fourth, the CC surrogate for wildfire depicts the greatest threats to watersheds in the central part of the Eastern United States and the Pacific Northwest. Watersheds depicted by this layer in the central part of the United States have relatively small percentages of private forest land. Fifth, the FOTE spatial approach to assessing threats to the contributions of private forest lands produces useful, visual information that is relatively easy to obtain and interpret. The only serious impediment associated with this approach is the difficulty in obtaining or constructing nationally consistent data layers that depict the contributions and threats of interest.

Future work will include assessment of additional contributions such as at-risk species and interior forest and threats such as insects, disease, and additional pollutants. In addition, work has begun on construction of an Internet-based system that permits users to select particular contribution and threat layers, options for combining them, and options for depicting the results.

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Relationships Between the Attributes of Standing Live and Dead Down Trees in Forests of the Lake States

Christopher W. Woodall[1] **and Linda Nagel**[2]

Abstract.—Refining the understanding of the relationship between a stand's standing live and down dead trees in terms of size, density, and biomass attributes may aid efforts to predict fuel loadings based on standing tree attributes. Therefore, the objective of this study was to compare down dead and standing live tree attributes (size, density, and biomass) for inventory plots and identify any possible relationships. Study results indicate no relationship between down woody material biomass and trees per ha, stand basal area, or a stand mean diameter. There appears to be a defined limit, however, to maximum observed down woody biomass in relation to stand density attributes (basal area and trees per ha). This study suggests that down woody accumulation dynamics result from sudden stand-level disturbances (e.g., blowdowns) and infrequent mortality from gradual stand development obscures and complicates attempts to broadly summarize relationships between a stand's standing live and down dead attributes in forests of the Lake States.

Fuel Prediction

Following the fire season of 2000 in the United States, forest fuel loadings were identified as a knowledge gap in both strategic-scale fire hazard management efforts and small-scale fire incident management activities. Consequently, tremendous effort has been expended to estimate fuel loadings across the United States. Unfortunately, fuel loadings are sampled in most forests only at very low sample intensities. This fact, in combination with the heterogeneous spatial distribution of fuels, results in a relatively insufficient fuel loading dataset with which to estimate fuels at small scales across the Nation. Therefore, efforts have been focused on developing methodologies to predict the fuel loadings for any forest location based on nonfuel attributes such as remotely sensed canopy cover information, digital elevation models, climate data, and standing live tree attributes. Biophysical gradient models (LANDFIRE; www.landfire.gov) (Rollins *et al.* 2004) have enabled the prediction of fuels at finer resolutions; however, the variance associated with these fine-scale estimates may be rather large.

Despite the development of models to estimate relationships between down woody fuels and stand/site attributes, there remains a sizeable knowledge gap in fundamental relationships between down woody fuel loadings and basic stand attributes. How do down woody fuel loadings vary by stage of stand development? How do down woody fuels vary by levels of standing live tree density? How do fuels vary by standing live tree size/density relationships? The inclusion of more fundamental models of stand dynamics and fuel loadings may aid in the construction of sophisticated biophysical models. Therefore, the goal of this study was to refine understanding of the relationship between down woody fuel loadings and stand attributes in forests of the Lake States with specific objectives including (1) to correlate down woody fuel loadings with the number of live trees per acre, live basal area per acre, latitude, and live tree tons per acre, (2) to determine the relationship between the number of down dead and standing live trees per acre with respect to tree size class, and (3) to evaluate the relationship between the number of live trees per acre and total down woody fuel loadings in terms of outliers defining the relationship (99th percentile).

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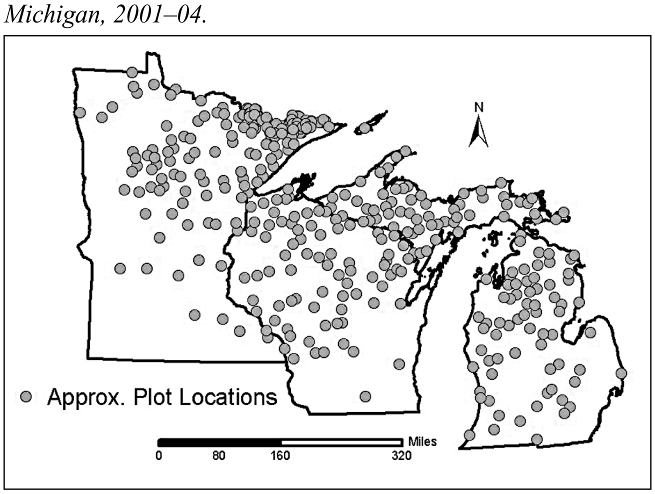
Data/Analysis

Standing tree and down woody fuel data were acquired from the Forest Inventory and Analysis program (FIA) of the U.S. Department of Agriculture Forest Service. The FIA program is responsible for inventorying the forests of the United States, including both standing trees and down woody materials on permanent sample plots established across the study area (Bechtold and Patterson 2005). In the FIA inventory, 378 plots were sampled in forests of the upper Great Lakes States (Minnesota, Wisconsin, and Michigan) from 2001 to 2004 (fig. 1). Both standing live and down dead woody materials attributes were measured on these inventory plots. For details on the establishment and sampling of standing trees by the FIA program, see Bechtold and Patterson (2005). Down woody material sampling methods on FIA plots are detailed by Woodall and Williams (2005). The largest fuels (more than 1,000-hr fuels), with a transect diameter greater than 3.0 in., were sampled on each of three 24-ft horizontal distance transects radiating from each FIA subplot center at 30, 150, and 270 degrees. Data collected for every more than 1,000-hr piece include transect diameter, length, small-end diameter, large-end diameter, decay class, and species. Fine woody debris (FWD) (1-, 10-, and 100-hr fuels) was sampled on the 150-degree transect on each subplot. Fine woody debris with transect diameters less than 0.25 in. and 0.25 in. to 1.00 in (1- and 10-hr, respectively) were tallied separately on a 6-ft slope-distance transect (14 ft to 20 ft on the 150-degree transect). Fine woody debris with transect diameters of 1.00 to 2.99 in (100-hr) were tallied on a 10-ft slope-distance transect (14 ft to 24 ft on the 150-degree transect) (for more information on fuel class definitions, see Deeming *et al.* 1977). Per unit area estimates (tons/acre) for the fuel hour classes followed Brown's (1974) estimation procedures (for further information see Woodall and Williams 2005). Total down woody fuels was a summation of both FWD and coarse woody debris (CWD). Logs per acre estimates were determined using DeVries (1986) estimation procedures.

Figure 1.—*Study plot locations in Minnesota, Wisconsin, and Michigan, 2001–04.*



Pearson's correlation coefficients and associated p-values were estimated between the following plot-level estimates: total woody fuels, live trees per acre, live basal area per acre, latitude, live tree tons per acre, and site index. The means and associated standard errors were estimated for the variables of number of live and down dead trees per acre by standing live tree mean diameter class. Finally, the relationship between the number of live trees per acre and total woody fuel loadings was evaluated by determining the 99th percentile of total woody fuels by live tree biomass classes (10 tons/acre class widths). The relationship between the 99th percentile of woody fuels and midpoint of the live tonnage class was modeled using a linear regression model: $\log_{10}$ (live tree tons) = $\log_{10}$ (total woody fuels).

Stand and Site Correlations

Total woody fuels per acre were not strongly correlated with any stand or site attributes. Pearson's correlation coefficients between total fuels and stand/site attributes were live trees per acre -0.10 (p-value = 0.05), live tons/acre -0.08 (p-value = 0.14), live basal area -0.09 (p-value=0.08), site index 0.03 (p-value = 0.60), and latitude 0.08 (p-value = 0.13). These correlations weakly indicate that (1) forests with larger amounts of standing live biomass might have less down dead biomass, and (2) forests on higher quality sites and in higher latitudes with slower decay rates might have higher amounts of dead biomass. More definitive conclusions cannot be made, however, given the weak correlation coefficients and predominantly nonsignificant p-values.

Size/Density Relationships

Standing live trees often exhibit a strong relationship between the maximum number of trees that may occupy a unit area and the average size of those constituent trees (Reineke 1933, Long 1985). As individual trees grow in size, the total number of trees per unit area must decrease to accommodate the growing trees—a process known as self-thinning. The observations in this study exhibited an obvious self-thinning trend: as the mean diameter at breast height of stands increased, the mean number of trees per acre decreased (fig. 2). How does the mean number of CWD pieces per acre change as these stands experience mortality due to self-thinning? Results from this study indicate very little change in the number of CWD pieces per acre as stands progress through stand development (fig. 2). For Lake States forests, the decay rate of fallen trees and the mortality rate (or CWD input rate) may be in equilibrium when viewed in terms of number of trees and CWD pieces. If decay was slowed by colder temperatures, then one might expect more CWD pieces in stands in advanced stages of stand development due to CWD piece accumulation over time. We found this result when we looked at size/density relationships in Lake States forests above and below the 45.5 degree latitude. Given the nearly zero slope of the CWD pieces per acre by standing live tree size, size density relationships of standing live trees may not indicate dead and downed wood resources.

Live Versus Dead Biomass

There appears to be no relationship between the number of standing live trees per acre and the total woody fuels in study stands (fig. 3). When examined by classes of standing live tree biomass (tons/acre), mean total woody fuels still shows no relationship with a stand's standing live tree density (table 1). There appears to be no practical way to predict total woody fuels based on the standing live tree density for Lake State forests. One relationship, however, is overlooked: the maximum potential amount of fuels appears to be determined by the amount of standing live biomass. When we compare total woody fuels to the number of live trees per acre, there appears to be an outer limit with the maximum amount of fuels negatively related to the number of standing live trees per acre (fig. 3). The 99th percentile of total woody fuels per acre decreases as classes of standing live biomass increase (table 1). A linear regression between the log of 99th percentile of fuels and the log of the midpoint of the standing live tree biomass class had an r-squared of 0.65 with an approximate slope of -1.0. This negative relationship may be viewed conceptually as driven by stand development processes (fig. 4). The left side of this relationship may be occupied by stands that have had recent disturbances that have reduced the amount of standing live tree biomass and greatly increased woody fuels. Conversely, logging or flood events might have reduced both the biomass of standing live and down dead biomass. The right side of this relationship

Figure 2.—*Number of trees/logs per acre by mean standing live tree diameter at breast height.*

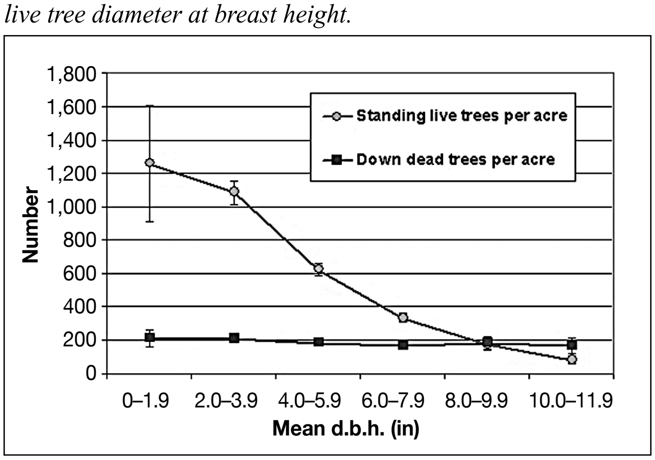


Figure 3.—*Total woody fuels (coarse and fine woody debris, tons/acre) by number of standing live trees per acre.*

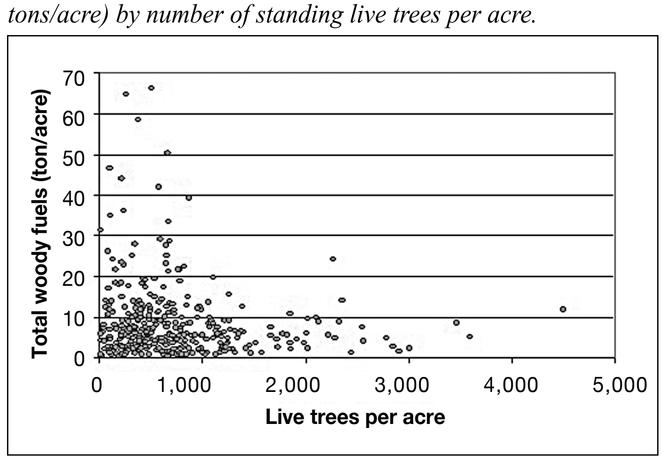
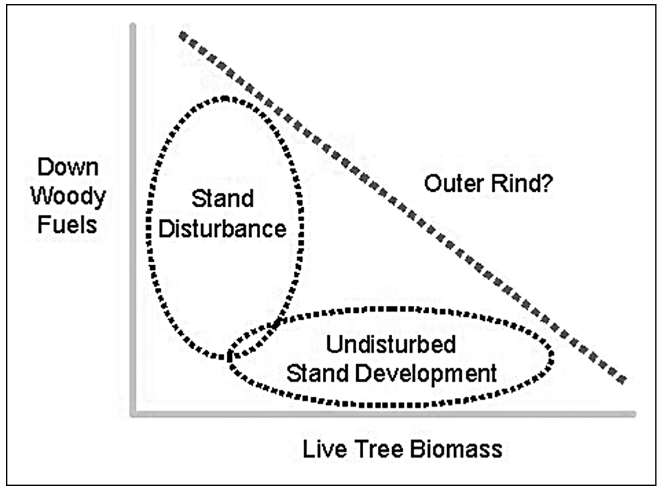


Table 1.—*Mean and 99th percentile of woody fuels (tons/acre) by classes of standing live tree biomass (tons/acre).*

Standing live tree biomass (tons/acre)	Total woody fuels (tons/acre)	
	Mean	99th Percentile
0.0–9.9	8.3	33.4
10.0–19.9	10.1	64.8
20.0–29.9	8.8	66.2
30.0–39.9	7.2	22.4
40.0–49.9	8.6	58.4
50.0–59.9	11.8	46.3
60.0–69.9	8.0	21.6
70.0–79.9	6.7	18.2
80.0–89.9	6.7	10.2
90.0–99.9	9.7	24.1
100.0–109.9	5.2	11.9
110.0–119.9	4.1	5.9

Figure 4.—*Theoretical relationship between standing live tree biomass and down dead fuels in forests of the Lake States.*



may be occupied by stands that have experienced very little disturbance mortality, but rather have density-induced mortality fuel input through stand development processes. These stands may demonstrate a balance between the decay and input of fuels through time as evidenced earlier in this study. Overall, the range in fuel loadings appears to decrease as the standing live tree density increases.

Conclusions

Relationships between standing live and down dead tree attributes in forests of the Lake States are often not statistically significant. Stand and site attributes, such as tree density and site quality, are not strong predictors of any stand's down and dead woody biomass at the stand level. Furthermore, the density of CWD pieces does not follow the same trajectory as the density of standing live trees as mean live tree size at the stand level increases. Despite the lack of live and dead/down tree relationships, standing live tree density may indicate maximum fuel loadings in Lake State forests. This study found a negative relationship between the 99th percentile of woody fuel biomass by classes of live tree biomass. Although the amount of fuels may not be estimated using live tree biomass as an independent variable, live tree biomass may indicate the range of possible fuel loadings—a range possibly driven by stand disturbance and development processes.

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Thematic and Positional Accuracy Assessment of Digital Remotely Sensed Data

Russell G. Congalton[1]

Abstract.—Accuracy assessment or validation has become a standard component of any land cover or vegetation map derived from remotely sensed data. Knowing the accuracy of the map is vital to any decisionmaking performed using that map. The process of assessing the map accuracy is time consuming and expensive. It is very important that the procedure be well thought out and carefully planned to be as efficient as possible. This paper presents a brief review of the current methods used in thematic map accuracy assessment. A discussion of positional error is included as it is impossible to assess thematic accuracy without carefully considering positional accuracy.

Introduction

Assessing the accuracy of thematic maps generated from remotely sensed data has become a required component of most mapping projects. Researchers assess their maps because they wish to determine if a newly developed technique or algorithm produces better results than an established method. Government agencies often require a measure of accuracy to meet the standards set up in the contract for the work. Many will use the map as part of a decisionmaking process, while others use map accuracy as a guide throughout the mapping project to evaluate the accuracy of each stage of the mapping process and to improve the map.

Errors come from many sources when generating a thematic map from remotely sensed data. Congalton and Green (1993) provide a good discussion of the errors that can result if the classification scheme is not well understood or if the reference data are poorly collected. Lunetta *et al.* (1991) present a very effective diagram and discussion of the various sources of error that can accumulate from the beginning of a mapping project through to the end. These sources include sensor issues, geometric registration, errors introduced by the classification process, assumptions made in the accuracy assessment, and limitations in the map output, to name just a few. Careful consideration of the entire mapping project before it is begun can go a long way toward reducing these errors.

Accuracy

Assessing the accuracy of maps generated from remotely sensed data requires evaluating both positional accuracy and thematic accuracy. While these two accuracies can be assessed separately, they are very much interrelated and failure to consider both of them is a serious mistake.

Positional Accuracy

Positional accuracy, a measure of how closely the imagery fits the ground, is the most common measure of map accuracy. In other words, positional accuracy is the accuracy of the location of a point in the imagery with reference to its physical location on the ground. It is imperative for any accuracy comparison that the same exact location can be determined both on the image and on the ground. The major factor influencing positional accuracy is topography, while sensor characteristics and viewing angles can also have some affect. It is commonly accepted that a positional accuracy of half a pixel is sufficient for sensors such as Landsat Thematic Mapper and SPOT. As sensors increase in spatial resolution, such as the 4-m multispectral IKONOS data, positional accuracy increases in importance and new standards need to be established. These standards need to be based on current ability to locate the chosen location (sample site) on both the image and the ground.

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Positional accuracy is an integral part of thematic accuracy. If an image is registered to the ground to within half a pixel and a Global Positioning System (GPS) unit is used to locate the place on the ground to within about 15 meters, then it is impossible to use a single pixel as the sampling unit for assessing the thematic accuracy of the map. If positional accuracy is not up to the standard or a GPS is not used to precisely locate the point on the ground, then these factors increase in importance and can significantly affect the thematic accuracy assessment.

Figure 1 shows an example of positional accuracy. In this figure, the digital image is not exactly registered to the Geographic Information System (GIS) road layer. Therefore, the road layer does not line up exactly on top of the roads in the imagery. Positional accuracy has historically been based on National Map Accuracy Standards and measured in terms of root mean square error (RMSE). Most often, the RMSE is computed as the sum of the square of the differences between the position of the point on one data layer as compared to the position of the same point on another data layer (often the ground) using the same data that were used to register the layers together. This measure is, therefore, not an independent measure of positional accuracy. Instead, it would be more useful and more indicative of the true accuracy to collect an independent sample of points from which to compute the RMSE.

Thematic Accuracy

Thematic accuracy refers to the accuracy of a mapped land cover category at a particular time compared to what was actually on the ground at that time. Clearly, to perform a meaningful assessment of accuracy, land cover classifications must be assessed using data that are believed to be correct. Thus, it is vital to have at least some knowledge of the accuracy of the reference data before using it for comparison against the remotely sensed map. Congalton (1991: 42) points out that, "Although no reference data set may be completely accurate, it is important that the reference data have high accuracy or else it is not a fair assessment. Therefore, it is critical that the ground or reference data collection be carefully considered in any accuracy assessment."

Accuracy assessment begins with the generation of an error matrix (fig. 2), a square array of numbers or cells set out in rows and columns, which expresses the number of sample units assigned to each land cover type as compared to the reference data. The columns in the matrix represent the reference data (actual land cover) and the rows represent assigned (mapped) land cover types. The major diagonal of the matrix indicates agreement between the reference data and the interpreted land cover types.

Figure 1.—*Example of positional accuracy.*

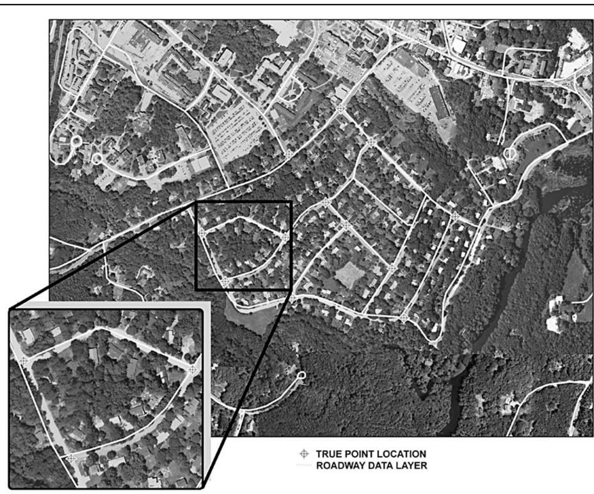

Figure 2.—*Example error matrix showing overall, producer's, and user's accuracies.*

		Reference Data V	W	U	row total
Classified Data	V	43	10	6	59
	W	3	23	5	31
	U	2	1	30	33
column total		48	34	41	123

Land Cover Categories

V = Vegetation

W = Water

U = Urban

OVERALL ACCURACY
= 96/123 = 78%

PRODUCER'S ACCURACY

V = 43/48 = 90%
W = 23/34 = 68%
U = 30/41 = 73%

USER'S ACCURACY

V = 43/59 = 73%
W = 23/31 = 74%
U = 30/33 = 91%

The error matrix is useful for both visualizing image classification results and for statistically measuring the results. The error matrix is the only way to effectively compare two maps *quantitatively*. A measure of overall accuracy can be calculated by dividing the sum of all the entries in the major diagonal of the matrix by the total number of sample units in the matrix (Story and Congalton 1986). In the ideal situation, all the nonmajor diagonal elements of the error matrix would be zero, indicating that no area had been misclassified and that the map was 100 percent correct (Congalton *et al.* 1983). The error matrix also provides accuracies for each land cover category as well as both errors of exclusion (omission errors) and errors of inclusion (commission errors) present in the classification (Card 1982, Congalton 1991, Congalton and Green 1999).

Omission errors can be calculated by dividing the total number of correctly classified sample units in a category by the total number of sample units in that category from the reference data (the column total) (Congalton 1991, Story and Congalton 1986). This measure is often called the "producer's accuracy," because from this measurement the producer of the classification will know how well a certain area was classified (Congalton 1991). For example, the producer may be interested in knowing how many times vegetation was in fact classified as vegetation (and not, say, urban). To determine this, the 43 correctly classified vegetation samples (fig. 2) would be divided by the total 48 units of vegetation from the reference data, for a producer's accuracy of 90 percent. In other words, vegetation was correctly identified as vegetation 90 percent of the time.

Commission errors, on the other hand, are calculated by dividing the number of correctly classified sample units for a category by the total number of sample units that were classified in that category (Congalton 1991, Congalton and Green 1999, Story and Congalton 1986). This measure is also called "user's accuracy," indicating for the user of the map the probability that a sample unit classified on the map actually represents that category on the ground (Congalton and Green 1999, Story and Congalton 1986). In figure 2, while the producer's accuracy for the vegetation category is 90 percent, the user's accuracy is only 73 percent. That is, only 73 percent of the areas mapped as vegetation are actually vegetation on the ground. However, because each omission from the correct category is a commission to the wrong category, it is critical that both producer's and user's accuracies are considered, since reporting only one value can be misleading.

It is vital that the error matrix generated for the accuracy assessment be valid. An improperly generated error matrix may not be truly representative of the thematic map and, therefore, meaningless. The following factors must be considered to generate a valid error matrix (Congalton 1991):

1. Reference data collection.
2. Classification scheme.
3. Sampling scheme (Congalton 1988b, Hay 1979, Stehman 1992, van Genderen and Lock 1977).
4. Spatial autocorrelation (Campbell 1981, Congalton 1988a).
5. Sample size and sample unit (Congalton 1988b, Congalton and Green 1999, Hay 1979, van Genderen and Lock 1977).

Failure to consider even one of these factors could lead to significant shortcomings in the accuracy assessment process.

Reference Data Collection

Reference data collection is the first step in any assessment procedure, and may be the single most important factor in accuracy assessment, since an assessment will be meaningless if the reference data cannot be trusted. Reference data can be collected in many ways, including photo interpretation, aerial reconnaissance with a helicopter or airplane, video, drive-by surveys, and visiting the area of interest on the ground (Congalton and Biging 1992). Not all of these approaches are valid in every situation and great care needs to be taken to make sure that the reference data are accurate.

A key factor in reference data collection is the separation of training data from accuracy assessment data. In the not-too-distant past, many assessments of remotely sensed maps were conducted using the same data set used to train the classifier (Congalton 1991). This training and testing on the same data set resulted in an improperly generated error matrix that clearly overestimated classification accuracy. For accuracy assessment procedures to be valid and truly representative of the thematic map, data used to train the image processing system should not be used for accuracy assessment. These data sets must be independent.

Finally, the information used to assess the accuracy of remotely sensed maps should be of the same general vintage as those originally used in map classification. The greater the time period between the imagery used in map classification and the data used in assessing map accuracy, the greater the likelihood that differences are due to change in vegetation (from harvesting, land use changes, etc.) rather than misclassification. Therefore, ground data collection should occur as close as possible to the date of the remotely sensed data.

Classification Scheme

A classification scheme categorizes remotely sensed map information into a meaningful and useful format. The rules used to label the map must be rigorous and well defined. An effective means of ensuring these requirements are met is to define a classification system that is totally exhaustive, mutually exclusive, and hierarchical (Congalton and Green 1999). A totally exhaustive classification scheme guarantees that *everything* in the image falls into a category; i.e., nothing is left unclassified. A mutually exclusive classification scheme means that everything in the image fits into one *and only one* category; i.e., an object in an image can be labeled only one category. Total exhaustion and mutual exclusivity rely on two critical components: (1) a set of labels (e.g., white pine forest, oak forest, nonforest, etc.), and (2) a set of rules (e.g., white pine forest must comprise at least 70 percent of the stand). Without these components, the image classification would be arbitrary and inconsistent. Finally, hierarchical classification schemes—those that can be collapsed from specific categories into more general categories—can be advantageous. For example, if it is discovered that white pine, red pine, and hemlock forest cannot be reliably mapped, these three categories could be collapsed into one general category called coniferous forest.

Sampling Scheme

An accuracy assessment very rarely involves a complete census or total enumeration of the classified image, since this data set is too large to be practical (Hay 1979, Stehman 1996, van Genderen and Lock 1977). Creating an error matrix to evaluate the accuracy of a remotely sensed map therefore requires sampling to determine if the mapped categories agree with the reference data (Rosenfield *et al.* 1982).

To select an appropriate sampling scheme for accuracy assessment, some knowledge of the distribution of the vegetation/land cover classes should be known. Stratified random sampling has historically prevailed for assessing the accuracy of remotely sensed maps. Stratified sampling has been shown to be useful for adequately sampling important minor categories, whereas simple random sampling or systematic sampling tended to oversample categories of high frequency and undersample categories of low frequency (Card 1982, van Genderen *et al.* 1978).

Spatial Autocorrelation

Because of sensor resolution, landscape variability, and other factors, remotely sensed data are often spatially autocorrelated (Congalton 1988a). Spatial autocorrelation involves a dependency between neighboring pixels such that a certain quality or characteristic at one location has an effect on that same quality or characteristic at neighboring locations (Cliff and Ord 1973, Congalton 1988a). Spatial autocorrelation can affect the result of an accuracy assessment if an error in a certain location can be found to positively or negatively influence errors in surrounding locations. The best way to minimize spatial autocorrelation is to impose some minimum distance between sample units.

Sample Size and Sample Unit

An appropriate sample size is essential to derive any meaningful estimates from the error matrix. In particular, small sample sizes can produce misleading results. Sample sizes can be calculated using the equation from the multinomial distribution, ensuring that a sample of appropriate size is obtained (Tortora 1978). Some researchers have suggested using the binomial equation to compute sample size. Given the need to create an error matrix, however, the binomial equation is inappropriate. A general rule of thumb developed from many projects shows that sample sizes of 50 to 100 for each map category are recommended, so that each category can be assessed individually (Congalton and Green 1999).

In addition to determining appropriate sample size, an appropriate sample unit must be chosen. Historically, the sample units chosen have been a single pixel, a cluster of pixels, a polygon, or a cluster of polygons. A single pixel is a poor choice of sample unit (Congalton and Green 1999), since it is an arbitrary delineation of the land cover and may have little relation to the actual land cover delineation. Further, it is nearly impossible to align one pixel in an image to the exact same area in the reference data. In many cases involving single pixel accuracy assessment, the positional accuracy of the data dictates a very low thematic accuracy. A cluster of pixels (e.g., a 3 by 3 pixel square) is always a better choice for the sample unit, since it minimizes registration problems. A good rule of thumb is to choose a sample unit whose area most closely matches the minimum mapping unit of the reference data. For example, if the reference data have been collected in 2-hectare minimum mapping units, then an appropriate sample unit may be a 2-hectare polygon.

Analysis Techniques

Once an error matrix has been properly generated, it can be used as a starting point to calculate various measures of accuracy in addition to overall, producer's, and user's accuracies. Two techniques have been found to be extremely useful. The first is a discrete multivariate technique called Kappa (Bishop *et al.* 1975), which can be used to statistically determine (1) if the remotely sensed classification is better than a random classification, and (2) if two or more error matrices are significantly different from each other. Kappa calculates a KHAT value (Cohen 1960), which is a measure of the *actual* agreement of the cell values minus the *chance* (i.e., random) agreement (Congalton and Mead 1983, Rosenfield and Fitzpatrick-Lins 1986) and can be viewed as a measure of accuracy. The KHAT value can be used to determine whether the results in the error matrix are significantly better than a random result (Congalton 1991). The KHAT accuracy value inherently includes more information than the overall accuracy measure since it indirectly incorporates the error (off-diagonal elements) from the error matrix. In addition, confidence limits can be calculated for the KHAT statistic, which allows for an evaluation of significant differences between KHAT values (Congalton and Green 1999).

Secondly, the analysis of the error matrix can be taken yet another step further by normalizing the cell values. An iterative proportional fitting technique, called *Margfit*, can be used to perform this normalization. Because the cell values in each row and column in the matrix are forced to sum to one, each cell value becomes a proportion of one, which can easily be multiplied by 100 to obtain percentages. Consequently, producer's and user's accuracies are not needed because the cell values along the major diagonal represent the proportions correctly mapped. Congalton *et al.* (1983) argue that the normalized accuracy is a more inclusive measure of accuracy than either KHAT or overall accuracy because it *directly* includes the information in the off-diagonal element of the error matrix. Because each row and column sums to the same value, different cell values (e.g., different forest cover classes) within an error matrix and among different error matrices can be compared despite differences in sample sizes. The software for performing both the Kappa and Margfit analyses is available from the author.

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The Spatial Distribution of Riparian Ash: Implications for the Dispersal of the Emerald Ash Borer

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Abstract.—A pilot study to assess riparian ash connectivity and its implications for emerald ash borer dispersal was conducted in three subbasins in Michigan's Southern Lower Peninsula. Forest Inventory and Analysis data were used to estimate ash biomass. The nineteen percent of plots in riparian physiographic classes contained 40 percent of ash biomass. Connectivity of riparian and upland ash was assessed using the spatial pattern analysis program FRAGSTATS. Higher mean proximity and patch cohesion was found among riparian patches. Greater connectivity and high ash biomass in riparian patches may facilitate spread of this insect.

Introduction

The emerald ash borer (EAB) (*Agrilus planipennis* Fairmaire, Coleoptera: Buprestidae), a native of Asia, was initially discovered in the United States in May 2002. Although the method of introduction is unknown, it is believed that EAB arrived in solid wood packing material (i.e., crates and wood pallets) transported to Detroit, Michigan (Haack *et al.* 2002). The extent of its damage and its life history traits indicate that EAB has been established in the United States since the early 1990s (Herms *et al.* 2004). Although the majority of devastation has affected ash trees in southeastern Michigan, EAB has dispersed throughout Michigan's Lower Peninsula and into Indiana, Ohio, and Windsor, Ontario. In addition, isolated EAB-positive locations have been identified in Michigan's Upper Peninsula (Michigan Department of Agriculture 2005), Maryland, and Virginia (Herms *et al.* 2004).

In the United States, EAB is known only as a pest to ash (*Fraxinus* spp.). Although EAB is a threat to all ecosystems where ash is found, EAB poses a substantial risk to riparian forests. Riparian forests tend to have high biodiversity (Goforth *et al.* 2002) and serve ecologically important roles in forest ecosystems, which enhance their value and vulnerability. Throughout Michigan, ash, particularly black and green ash, is a dominant overstory component of riparian forests (Tepley *et al.* 2004). White ash, largely an upland species, is typically found on dry to dry-mesic sites; however, in the Southern Lower Peninsula (SLP), white ash is often found growing along the margins of wet-mesic deciduous swamps (Barnes and Wagner 2004). Because ash species occupy different sites, it is important to understand how the spatial arrangement of ash may influence EAB dispersal patterns.

Not only are riparian ash at risk for EAB infestation, they may serve as EAB dispersal conduits. Preliminary research from a case study at an infestation site in Tipton, MI, offers evidence that riparian forests may facilitate EAB dispersal by channeling the direction of movement (McCullough *et al*. 2004). This study found that larval gallery density decreased with increasing distance from the source of infestation and that EAB seemed to display directional dispersal, as the majority of infested trees followed the path of a drainage ditch (McCullough *et al*. 2004). Therefore, presence of ash in riparian forests creates potential corridors of available habitat that may direct the course of dispersal into uninfested areas.

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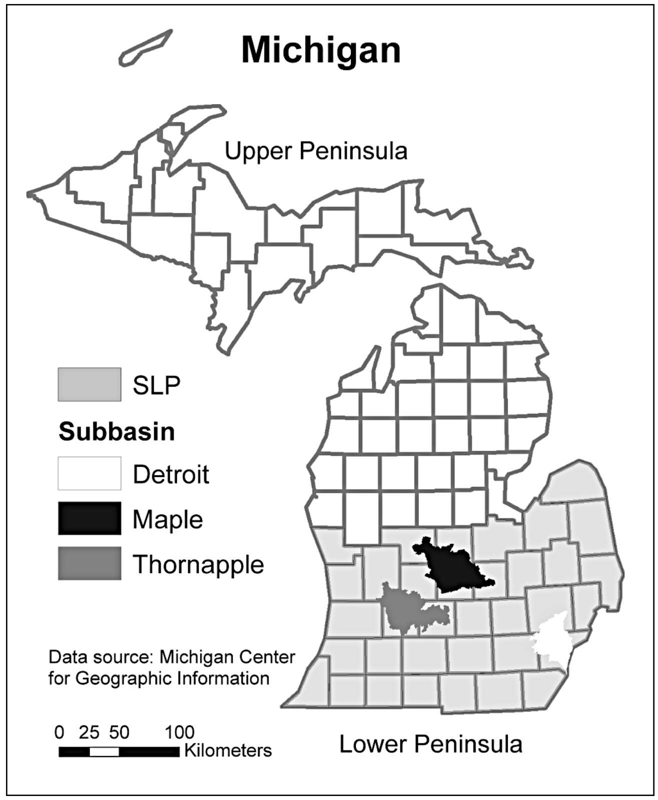
It is widely believed that corridors connecting similar patches of habitat facilitate the movement of organisms (Tewksbury *et al*. 2002). Haddad and Baum (1999) found that a contrast between corridor and surrounding habitat enhanced the effectiveness of corridors in increasing butterfly density within suitable corridor-linked patches. These studies suggest that ash patches with high connectivity may facilitate dispersal along connected corridors and have higher EAB densities. In addition, if corridors of ash habitat are bordered by contrasting or unsuitable habitats, especially in the fragmented SLP, these areas may be more susceptible and have higher rates of spread. Therefore, assessments of the spatial distribution of riparian ash may help predict directionality of dispersal.

The purpose of this study is to evaluate the spatial arrangement of ash habitat patches and assess the connectivity of riparian ash. To accomplish this goal, we will (1) map ash biomass and riparian ash distribution for the entire Lower Peninsula, (2) compare ash abundance in the SLP by physiographic class, and (3) calculate connectivity indexes for riparian and upland ash forest patches for three subbasins in the SLP. Our motivation is to identify the importance of riparian ash as it relates to the direction and rate of EAB dispersal, and provide information that may help mitigate the rapid spread of this insect.

Figure 1.—*Study area. The Southern Lower Peninsula and the Detroit, Maple, and Thornapple subbasins.*



SLP = Southern Lower Peninsula.

Methods

Study Area

Ash biomass was mapped for the entire Lower Peninsula (fig. 1); however, specific analysis of FIA plots was conducted only in the SLP. The SLP includes Allegan, Barry, Berrien, Branch, Calhoun, Cass, Clinton, Eaton, Genesee, Gratiot, Hillsdale, Huron, Ingham, Ionia, Jackson, Kalamazoo, Kent, Lapeer, Lenawee, Livingston, Macomb, Monroe, Montcalm, Muskegon, Oakland, Ottawa, Saginaw, St. Clair, St. Joseph, Sanilac, Shiawassee, Tuscola, Van Buren, Washtenaw, and Wayne Counties (fig. 1).

The study area for the connectivity analysis included three subbasins (classified by the Natural Resources Conservation Service and U.S. Geological Survey) located in the SLP: Detroit, Maple, and Thornapple (fig. 1). Subbasins are defined by the Watershed Boundary Dataset as eight-digit hydrologic unit codes (HUCs), formerly the lowest watershed accounting unit. Each eight-digit HUC represents approximately 448,000 acres (Laitta *et al.* 2004).

Mapping Ash Distribution

Forest inventory data were obtained from all FIA plots measured in the Lower Peninsula between 2000 and 2005. Forested plots were brought into Arc Map 9.0 and were used to create an interpolated surface of ash biomass using the ordinary cokriging method (ESRI 2004); log transformed biomass of all ash species and log transformed biomass of all tree species were used as covariates. Once the predicted surface of ash biomass was created, nonforest areas were masked using a land cover dataset for the Lower Peninsula, developed by the Integrated Forest Monitoring Assessment and Prescription (IFMAP) project, to reveal predicted ash biomass on forested land area only. Riparian ash forest types were mapped for the Lower Peninsula. These forest types were selected from (1) wetland vector polygons mapped from aerial photographs by the U.S. Fish & Wildlife Service during an inventory of national wetlands (National Wetlands Inventory [NWI]) data), and (2) pixels from the IFMAP land cover dataset that were classified as lowland deciduous (IFMAP land cover classification is derived from Landsat Thematic Mapper satellite imagery). Riparian ash forest types from NWI data are defined as Palustrine system, forested or scrub-shrub class, with the subclass or secondary subclass equal to the broadleaf deciduous category (in which ashes, among others, are canopy dominants).

Estimates of Ash Abundance

Total ash biomass was calculated for all FIA plots in the SLP measured between 2000 and 2005 by multiplying oven-dry tree biomass and the current number of trees per acre, then decoding by all species of ash. Ash biomass was summarized by physiographic class code, and estimates were compared by riparian and upland site. Physiographic classes—narrow floodplains/bottomlands, broad floodplains/bottomlands—and all hydric classes were defined as riparian; all other physiographic classes were considered upland.

Fragmentation Analysis

An IFMAP raster image file was extracted using a mask for each of the three subbasins. Three separate raster grids containing only those land cover/land use pixels within the boundary of each subbasin were created. The grids were then input into the spatial pattern analysis program for categorical maps, FRAGSTATS, in which landscape connectivity metrics were calculated for riparian and upland ash patches (McGarigal *et al*. 2002). Under IFMAP forest type classification, lowland deciduous and northern hardwood cover types represented riparian and upland ash patches, respectively. For estimates of fragmentation, the mean proximity index (McGarigal *et al*. 2002) was used and is defined as

$$\text{PROX\_MN} = \frac{\sum_{j=1}^{n} \sum_{s=1}^{n} \frac{a_{ijs}}{h_{ijs}^2}}{n_i} \qquad (1)$$

where:

a_{ijs} is the area of patch i of patch type j within specified distance s of patch ij (the focal patch); h_{ijs} is the distance between patch ijs and the focal patch (based on patch edge-to-edge distance, computed from cell center to cell center); and n_i is the total number of patches in class i. The patch cohesion index was calculated as an estimate of connectivity and is defined as

$$\text{COHESION} = \left[1 - \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{ij}\sqrt{a_{ij}}}\right]\left[1 - \frac{1}{\sqrt{A}}\right]^{-1} \bullet (100) \qquad (2)$$

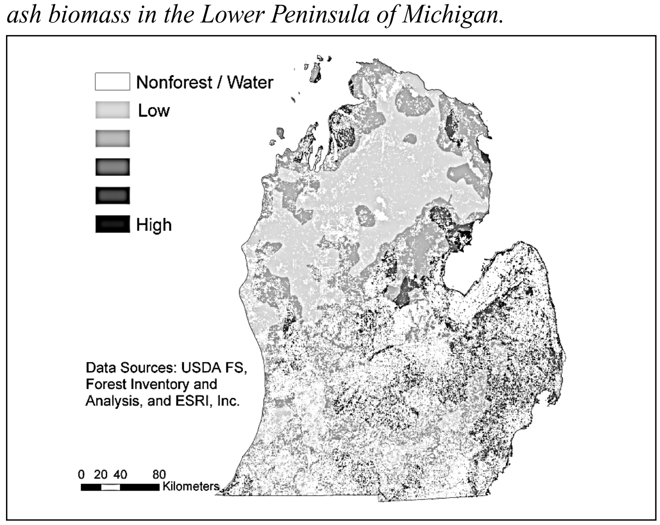
where:

p_{ij} is the perimeter of patch i of patch type j in terms of number of cell surfaces, a_{ij} is the area of patch ij in terms of number of cells and A is the total number of cells in the landscape (McGarigal *et al.* 2002).

Results

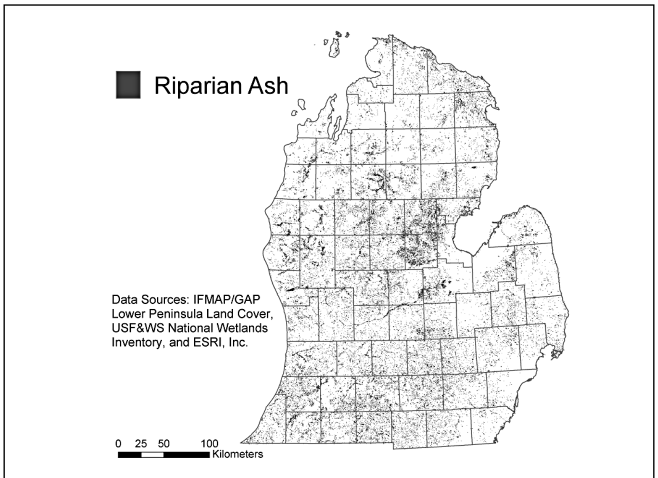
A map of log transformed ash biomass for all ash species in the Lower Peninsula was created (fig. 2). Ash biomass is relatively low throughout much of the Northern Lower Peninsula. In contrast, high proportions of ash biomass are found in the SLP. Although forests in the SLP tend to have higher ash biomass,

Figure 2.—*Ordinary cokriged interpolation of log transformed ash biomass in the Lower Peninsula of Michigan.*



the forests are made up of smaller parcels, as the degree of forest fragmentation decreases from south to north. Riparian ash forest types are distributed throughout the Lower Peninsula (fig. 3). Though concentrated in the central portion of the Lower Peninsula, riparian ash forest types make up much of the ash biomass in the SLP. Throughout the Lower Peninsula, riparian ash forest types form narrow, sinuous bands and tend to be clustered around watercourses.

Figure 3.—*Distribution of riparian ash forest types in the Lower Peninsula of Michigan.*



The majority of forest area in the SLP is classified as uplands (table 1). A total of 1,714 plots were sampled and 19 percent were in riparian physiographic classes. Although making up less than a quarter percent of total area, plots in riparian physiographic classes held 40 percent of ash biomass. Mean ash biomass was higher in riparian plots at 17,546 pounds per acre; upland plots had a mean ash biomass of 6,290 pounds per acre (table 1). Twenty-four percent of plots in riparian physiographic classes (or riparian plots) had no ash biomass; 55 percent of plots in upland physiographic classes (or upland plots) had no ash biomass.

The mean proximity index for riparian forest type patches was greater than upland patches in two of the three subbasins (table 2). Lowland deciduous forest type patches in the

Table 1.—*Analysis of FIA plots by physiographic class code, Southern Lower Peninsula of Michigan, 2000–05.*

	Floodplain physiographic class	Upland physiographic class
Total number of plots	327	1,387
Total ash biomass (lbs/acre)	5,737,567	8,724,879
Mean ash biomass/plot (lbs/acre)	17,546	6,290
Standard deviation	24,463	13,461
Number of plots with no ash	80	760

FIA = Forest Inventory and Analysis.

Table 2.—*Landscape metrics for lowland deciduous and northern hardwood forest types in three subbasins in the Southern Lower Peninsula of Michigan.*

			Subbasin		
			Detroit	Maple	Thornapple
Forest type	Lowland deciduous	Total area (acres)	7,112.92	27,726.92	23,052.28
		Percentage of landscape (%)	1.90	4.58	4.25
		Number of patches	5,323.00	14,422.00	17,022.00
		Mean patch area (acres)	1.34	1.92	1.35
		Mean proximity index (MPI)	4.98	19.43	6.98
		Standard deviation of MPI	19.28	86.43	28.20
		Connectance index	0.39	0.22	0.23
		Patch cohesion index	82.46	89.39	82.19
	Northern hardwood	Total area (acres)	20,449.21	12,579.94	29,452.22
		Percentage of landscape (%)	5.45	2.08	5.42
		Number of patches	21,299.00	10,625.00	16,471.00
		Mean patch area (acres)	0.96	1.18	1.79
		MPI	2.75	1.73	9.27
		Standard deviation of MPI	4.30	4.15	57.28
		Connectance index	0.25	0.18	0.18
		Patch cohesion index	67.81	70.62	85.59

Detroit, Maple, and Thornapple subbasins had mean proximity index values of 4.98, 19.42, and 6.98, respectively. Northern hardwood forest type patches had mean proximity indices of 2.75, 1.73, and 9.27 in the Detroit, Maple, and Thornapple subbasins, respectively. Patch cohesion had greater variability for northern hardwood forest patches than for lowland deciduous patches. In northern hardwood forest patches, the patch cohesion index was 67.81 in the Detroit subbasin, 70.62 in the Maple subbasin, and 85.59 in the Thornapple subbasin (table 2). On average, the patch cohesion index was higher in lowland deciduous patches and was more stable, ranging from 82.46 to 89.39 to 82.19 in the Detroit, Maple, and Thornapple subbasins, respectively. Average landscape area is 3.58 percent in riparian plots and 4.32 percent in upland plots. Northern hardwood patches occupied an average of 20,827 acres per subbasin, while lowland deciduous patches contained an average of 19,297 acres per subbasin.

Discussion

Riparian forests are associated with many types of surface waters (Palik *et al.* 2004), including rivers and streams. As a result of this association, riparian forest types often have a linear, sinuous pattern that is influenced by stream flow. This pattern of distribution is suitable for guiding EAB dispersal and maximizing the distance an insect will travel. Therefore, the spatial distribution of riparian ash may be important in facilitating long-distance dispersal of EAB in the SLP by funneling EAB movement along corridors of suitable ash habitat, particularly in areas bordered by unsuitable or non-ash environments. Although riparian ash forests do not account for a total area greater than upland ash forests, average ash biomass is higher in riparian forest types. The damage potential and potential capacity for supporting EAB density is therefore higher in riparian ash forest types. EAB represents a substantial risk to riparian forests in the highly fragmented SLP because riparian ash forest types create corridors of potential EAB habitat and contain a high proportion of ash. These factors increase the vulnerability of riparian forests to EAB and enhance the ability to direct dispersal.

The ability to direct dispersal is related to spatial arrangement. The mean proximity index measures the relative fragmentation and isolation of similar patch types (McGarigal *et al*. 2002). Higher mean proximity values for riparian forest patches indicate that riparian patches were surrounded by a higher number of similar patch types than were upland patches. Similar to the mean proximity index, the patch cohesion index is a measure of the physical connectedness of corresponding patch types (McGarigal *et al*. 2002). Patch cohesion was higher in lowland deciduous patches, which is an indication that riparian forest patches offer greater connectivity between patches relative to upland, northern hardwood forest types. Higher connectivity between riparian ash patches increases the likelihood of stronger EAB travel along riparian corridors.

Although this study is preliminary, initial results suggest that (1) the forests in the SLP, where the distribution of riparian ash is great, are highly fragmented; (2) riparian ash forest types make up a small percentage of total area but contain a large amount of ash biomass; and (3) riparian ash forest types are more highly connected to patches of similar forest type than are upland ash forest types. Thus, the spatial distribution and pattern of riparian ash abundance in the SLP may influence the direction and rate of EAB spread by allowing EAB to quickly increase radial dispersal along narrow, connected corridors.

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The Investigation of Classification Methods of High-Resolution Imagery

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Abstract.—As remote-sensing technology advances, high-resolution imagery, such as Quickbird and photography from the National Agriculture Imagery Program (NAIP), is becoming more readily available for use in forestry applications. Quickbird imagery is currently the highest resolution imagery commercially available. It consists of 2.44-m (8-ft) resolution multispectral bands ranging from blue to near infrared and a panchromatic band acquired simultaneously at 0.61-m (2-ft) resolution. In the near future, NAIP will provide annually updated, orthorectified, natural color, aerial photography at 1-m resolution across the continental United States. Our objective was to investigate two classification methods: an individual tree crown delineation and classification procedure and a technique using Feature Analyst software for classifying high-resolution Quickbird and NAIP photography. Both methods were found to be effective for discriminating different vegetation types using Quickbird and NAIP photography, although the Quickbird imagery proved to be superior to the NAIP photography according to visual and numerical assessments.

The numerical accuracy of the resulting maps ranged from 48 percent to 63 percent at the Level II classification, in which a class was determined based on the plurality of the species within approximately a hectare of the point. At the Level III forest and nonforest classification, the numerical accuracies ranged from 89 percent to 94 percent. The visual assessments revealed good results, especially at Level III forest and nonforest classifications. We believe that these assessments show strong potential for their use as ancillary products in Interior West FIA's forest resource estimation procedures and should be further pursued.

Introduction

The U.S. Department of Agriculture (USDA) Forest Inventory and Analysis Program (FIA) strives to produce better information with lower costs and increased frequency. The objective of FIA is to estimate broad-scale forest population totals and to track trends and detect changes in our Nation's forests. In the past, inventories were conducted and estimates produced on a periodic basis (every 5 to 20 years). The 1998 Farm Bill, however, requires a proportion of all field plots to be measured (1 out of 10 in the Western United States and 1 out of 5 in the East) *each* year on *all* lands in the United States, and forest population estimates must be updated. In an effort to become more efficient, the Interior West (IW) region of FIA is investigating high-resolution remotely sensed products to assist in obtaining the information requirements of this legislation while reducing inventory costs.

With the technological advancement of satellite systems, high-resolution satellite imagery, such as Quickbird, is becoming more readily available for use in forestry applications. Currently, Quickbird imagery has the highest resolution commercially available. It consists of 2.4-m (7.9-ft) resolution multispectral bands ranging from blue to near infrared and a panchromatic band acquired simultaneously at 0.6-m (2.0-ft) resolution. The Quickbird satellite was launched in October

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2001 and is owned and operated by DigitalGlobe (http://www.digitalglobe.com). Quickbird has a geolocational accuracy within 23 meters, an imaging swath 16.5-km (10.2-mile) wide, 128 gbits image storage capacity onboard, and an off-axis unobscured design telescope with an 11-bit dynamic range (DigitalGlobe 2005). These characteristics present an opportunity to identify individual crowns of vegetation.

In addition to Quickbird, another high-resolution product we examined is aerial photography from the National Agricultural Imagery Program (NAIP), which is available for download from the Internet (http://www.apfo.usda.gov). The NAIP acquires digital ortho imagery during the agricultural growing season of the continental United States. The photography is orthorectified, natural color, 1-m resolution photography with a horizontal spatial accuracy matching within 3 m of an orthorectified reference digital ortho quarter quad (DOQQ). With resolution, timely acquisitions, and availability, this product is very desirable as a modeling tool or for identifying/locating vegetative features on the ground.

Numerous algorithms are being developed for delineating individual tree crowns (Culvenor 2002, Definiens 2003, Leckie *et al.* 2003, Pouliot *et al.* 2002). CLC-Camint, Inc., uses its own proprietary methodology for delineating and classifying tree crowns using Quickbird imagery. This methodology uses an automated individual tree crown (ITC) classification and object-based segmentation procedure (Gougeon 1995, Gougeon 1997) to generate a digital map of tree crowns integrated into a Geographical Information System. The ITC algorithm uses a valley-following approach (Gougeon 1995) to delineate unique tree crowns. This approach searches for the shaded areas between crowns and removes (masks out) these areas, leaving objects representing the crown of a tree. The method uses the Quickbird imagery to create a digital layer depicting each unique tree crown. These delineated crowns are further classified by species type based on identified training sites (or trees), along with multispectral, textural, structural, and contextual analysis tools. Signatures are developed for each individual tree crown, and a maximum likelihood decision rule assigns it to a species type class.

An alternative automated procedure for extracting features is implemented in Feature Analyst, software developed by Visual Learning Systems, Inc. (http://www.vls-inc.com). Feature Analyst is a user-friendly, automated machine learning approach for extracting land cover features, or objects based on user-specified examples. Feature Analyst uses spectral and spatial pattern recognition techniques to extract features from high-resolution digital imagery. Where traditional classifiers use color and tone to extract features, Feature Analyst uses characteristics such as size, shape, color, texture, shadow, association, and pattern to extract features of interest. Although Feature Analyst has the functionality of delineating individual tree crowns, only stand-level classifications were generated for this study.

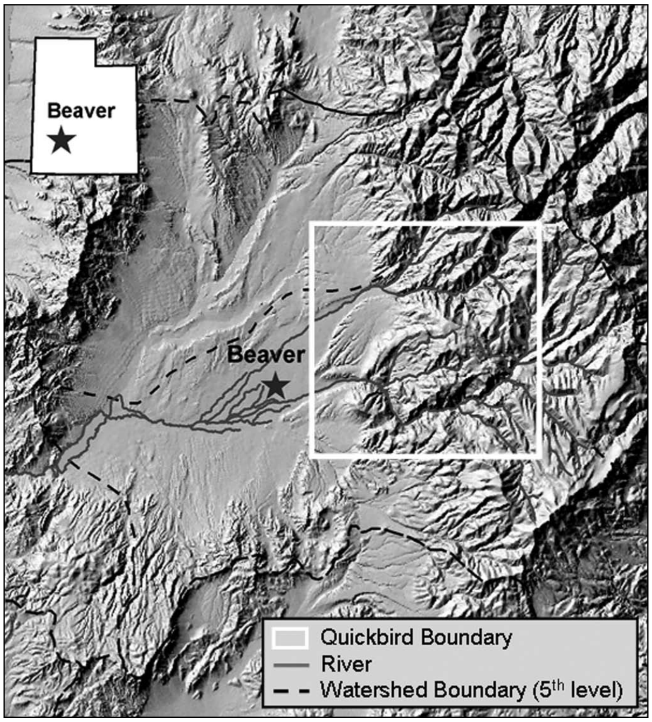
Our interest for this study was to investigate the capabilities of Feature Analyst and how it compares with CLC-Camint's ITC process for producing map products using high-resolution Quickbird imagery and high-resolution NAIP photography. Three analyses were conducted in this study. First, we tested the accuracy of the ITC algorithm for delineating and classifying crowns in a diverse forest area in the southern Rocky Mountains of Utah using Quickbird imagery. Second, we tested the accuracy of Feature Analyst for classifying forest stands in the same area applied to Quickbird imagery. Third, we once again tested the accuracy for classifying forest stands using Feature Analyst, but this time applied to NAIP photography.

Methods

Area of Interest

IW-FIA staff identified a 100 km^2 area of interest (AOI) within the southern Rocky Mountains of Utah that represented a diverse number of forest and species types. The AOI is east of Beaver, UT, within the Fishlake National Forest (fig. 1). The area was selected for its diversity of species types and altitudinal range with the intent to examine the performance of the ITC and Feature Analyst methods across multiple ecosystems that occur in the Western States. Within this area, elevation values range from 1,920 m (6,298 ft) to more than 3,000 m (9,840 ft). The species types reflect this elevational gradient with pinyon pine and juniper species at the lower

Figure 1.—*The AOI in the southern Rocky Mountains of Utah.*



AOI = area of interest.

elevations, oak and mahogany hardwood species at mid ranges, and aspen, Douglas fir, subalpine fir, and Engelmann spruce at higher elevations. The area also encompasses the Beaver River, which typically includes riparian vegetation types.

ITC Delineation and Classification/Quickbird

A map of individual tree crowns, with species identified, was produced using the ITC process over the AOI. The process of producing this map involved multiple steps carried out by staff at IW-FIA and CLC-Camint, as outlined in table 1.

The Quickbird imagery for the AOI was provided as courtesy of DigitalGlobe CLC-Camint defined the specifications of the Quickbird scene and preprocessed the imagery. The acquired scene was approximately 300 km^2 in size, surrounding the AOI. This scene increased the range of altitudinal gradient to more than 1630 m (5,346 ft), from approximately 1,815 m (5,953 ft) to more than 3,450 (11,316 ft) at Mount Baldy Peak. The scene was received from DigitalGlobe radiometrically calibrated and corrected for sensor- and platform-induced distortions. CLC-Camint performed an orthorectification procedure based on a 1:24,000 map and mapped the scene.

At this stage, CLC-Camint applied an initial unsupervised classification technique to delineate sites with unique, homogenous signatures occurring on the image, with the help of aerial photographs. These areas were identified as potential training sites, which were delineated by a georeferenced point shapefile. A total of 170 training sites were identified. These sites were then located by IW-FIA on aerial photographs and labeled according to nine classes (table 2) of homogenous species or predominant mix of species based on the area around the sites. Each label was then given a number ranging from 0 to 100, indicating the percent confidence of the interpretation. The 170 labeled training sites were sent back to CLC-Camint for use in their ITC delineation and classification procedures.

CLC-Camint next performed the automated ITC delineation and classification procedure. The ITC valley-following algorithm does not work well in areas with sparse crowns (i.e.,

Table 1.—*The process between IW-FIA and CLC-Camint to develop a map product delineating individual tree crowns.*

Main activities	Group in charge
Acquire Quickbird scene	CLC-Camint
Unsupervised classification, identify training sites	CLC-Camint
Assign labels to training sites	IW-FIA
ITC delineation and classification	CLC-Camint
Review results and field check training sites	IW-FIA
Refine classification	CLC-Camint
Accuracy assessment	CLC-Camint/IW-FIA
Delineate stands	CLC-Camint
Accuracy assessment	CLC-Camint/IW-FIA
Cost assessment	CLC-Camint/FS-RMRS

FS-RMRS = Forest Service, Rocky Mountain Research Station; ITC = individual tree crown; IW-FIA = Interior West-Forest Inventory and Analysis.

Table 2.—*The list of classes used for classification in the individual tree crown process.*

Code	Species type
1	Spruce/fir
2	White fir
3	Aspen
4	Mahogany
5	Pinyon
6	Juniper
7	Oak/maple
8	Other hardwoods
9	Nonforest

pinyon and juniper species types) where there are no shadows between the trees (Gougeon and Leckie 2001). Consequently, an eCognition (Definiens 2003) procedure was applied to these areas prior to running the ITC algorithm. The ITC classification process involved two steps: a first-run classification based on the 170 training sites, and a second-run classification performed after reviewing the results of the first classification. For the second classification, ancillary information and/or new training information may be added in areas having many misclassifications. The results for this paper include output from the first classification. Currently, we are running the second classification, after reviewing the results of the first classification, field checking the original set of training sites, and identifying and labeling 130 additional training sites. The second classification will therefore use 300 correctly identified training sites along with ancillary data from a 10-m digital elevation model.

Feature Analyst/Quickbird

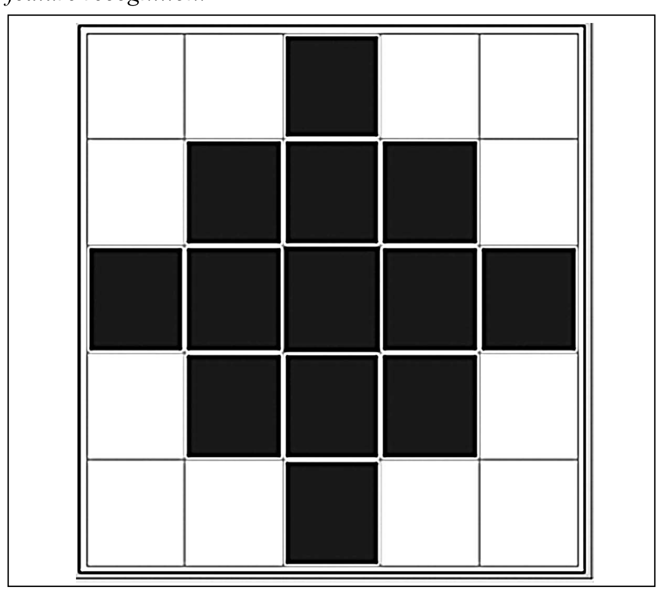
A map of forest stands, with forest types identified, was produced using Feature Analyst over the same area of the Quickbird image. This process was carried out by IW-FIA staff. Although the same point training sites as the ITC procedure were used, we created polygons surrounding these points for use as training sites in the Feature Analyst classification because Feature Analyst uses characteristics such as shape, texture, association, and pattern. Additional training polygons, determined from our field visit, were also delineated and resulted in a total of 300 sites for classification. Labels were assigned at a stand level based on Level I class assignments representing the dominant species, the dominant species associations, or a nonforest type (table 3).

The color infrared Quickbird imagery was used, including green, red, and near infrared bands as well as a 10-mr, U.S. Geological Survey digital elevation model (DEM) obtained from the Automated Geographic Reference Center Web site (http://agrc.its.state.ut.us/). All bands were resampled to a pixel size of 4.8 m, the smallest pixel size. For feature recognition, we set the pixel search pattern to a "Manhattan" style with a width of five pixels (fig. 2). Feature Analyst was set to run a wall-to-wall classification of the Level I classes resulting in a map with a minimum map unit size of 24 pixels (about 1 hectare).

Table 3.—*The list of Level I classes used for Feature Analyst classification and for assessing accuracy.*

Code	Species type	Number of training sites
1	Spruce-fir	8
2	Spruce-fir/aspen	9
3	Aspen/spruce-fir	15
4	Aspen	20
5	Aspen/white fir	9
6	White fir/aspen	3
7	White fir	16
8	White fir/mahogany	9
9	Mixed conifer	9
10	Cottonwood	9
11	Mahogany	18
12	Mahogany/pinyon-juniper	10
13	Pinyon-juniper/mahogany	11
14	Pinyon-juniper	19
15	Pinyon-juniper/oak	12
16	Oak/pinyon-juniper	12
17	Oak	19
18	Oak/mahogany	9
19	Chained woodland	14
20	Nonstocked timberland	11
21	Meadow	18
22	Agriculture	7
23	Road	10
24	Water	6
25	Barren	7
26	Shadow	10

Figure 2.—*The five-pixel, Manhattan search pattern used for feature recognition.*



Feature Analyst/NAIP

A map of forest stands, with forest types identified, was produced with Feature Analyst using NAIP photography within the study area. This process was also carried out by IW-FIA staff. The same 300 polygon training sites as the Feature Analyst/Quickbird process were used, but because of the misregistration between the NAIP photography and the Quickbird imagery, all polygon training sites were individually shifted to match the corresponding area.

The natural color NAIP photography was used, including blue, green, and red bands, as well as the 10-m USGS DEM. All bands were resampled to a pixel size of 1.0 m, the smallest pixel size. We set the pixel search pattern to a “Manhattan” style with a width of five pixels (fig. 2) for feature selection. Feature Analyst was set to run a wall-to-wall classification resulting in a map with a minimum map unit of 24 pixels (about 1 hectare).

Accuracy Assessment

Map accuracy and map comparisons were based on visual and numerical assessments at a stand level. A visual assessment was performed for each map to determine the reliability of the results of the ITC crown delineation and classification and the Feature Analyst results using Quickbird imagery and NAIP photography. For the ITC procedure, the visual assessment was based on the accuracy of the crown delineation and the classification of each crown. For the results of the Feature Analyst stand classifications using Quickbird and NAIP products, visual assessments were examined at three class levels: Level I included all 26 classes that were used for training (table 3); Level II included nine classes based on the plurality of species including one class with all nonforest classes (table 4); and Level III included two classes representing forest and nonforest.

For a more objective, numerical assessment and comparison of the three maps, an independent test set of 100 points was randomly selected within the extent of the Quickbird image and applied to each map. The points were assigned classes based on interpretation of 1:16,000 stereo aerial photographs and expert knowledge. These classes were compared to the maps based on the three class levels mentioned above for the visual assessment of the Feature Analyst classifications. For the maps generated using Feature Analyst, the test points were compared directly to the intercepted pixel class of the map. The ITC map involved two steps. First, the individual tree crowns were evaluated at each point and a stand-level class was assigned based on approximately a hectare or more area surrounding the point. Then, these class assignments were compared to the class assignment of the test set.

Table 4.—*The list of Level II classes used for Feature Analyst classification and for assessing accuracy.*

Code	Species type	Number of training sites
1	Spruce-fir	17
2	Aspen	44
3	White fir	25
4	Mixed conifer	9
5	Cottonwood	9
6	Mahogany	28
7	Pinyon-juniper	42
8	Oak	40
9	Chained woodland	14
10	Nonstocked timberland	11
11	Nonforest	58

Error matrices were generated for each map and a percent correctly classified (PCC) and a Kappa statistic were calculated to provide a numerical statistic of accuracy. The accuracy and comparisons were evaluated at the three different class levels.

Results

ITC Delineation and Classification/Quickbird

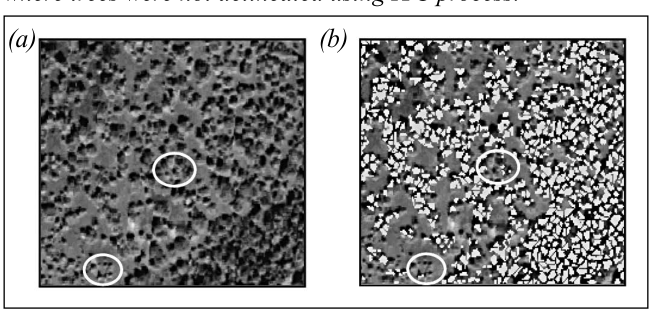
Based on a visual evaluation of the ITC product compared to the panchromatic Quickbird image, the ITC procedure performed fairly well delineating individual tree crowns. In areas of low crown densities with pinyon and juniper species, the delineation process generally picked up most of the tree crowns (fig. 3). In some of these areas, though, it seemed like larger pinyons and junipers were split into more than one crown and smaller trees were not captured at all (e.g., the gray circles in fig. 3). These conditions were a result of the eCognition procedure completed on the lower density areas prior to the ITC valley-following approach. The ITC valley-following algorithm performed adequately in depicting changes in stand densities, such as the different aspen stands shown in figure 4. This process did not perform well in areas having steep terrain, where tree shadows were long and narrow and/or there were many downed trees. For both of these conditions, the ITC algorithm placed trees incorrectly (fig. 5).

Although the ITC classification performed well in some areas, overall it needs improvement. Most of the classification difficulties were related to changes in elevation and aspect. For example, pinyon and juniper species on northern slopes were typically misclassified as spruce/fir and white fir species. Also, in the higher elevations, spruce/fir and aspen species tended to be misclassified as pinyon, juniper, and mahogany species.

The results of the numerical assessment for each class level are shown in table 5. When comparing the Level I class values interpreted from the first iteration ITC product to the 100 randomly selected test point values, 32 percent of the points were correctly classified with a Kappa value of 0.25. For the Level II class values, 48 percent of the points were correctly classified with a Kappa of 0.37. For the Level III classes, 90 percent of the points were correctly classified and a Kappa of 0.56.

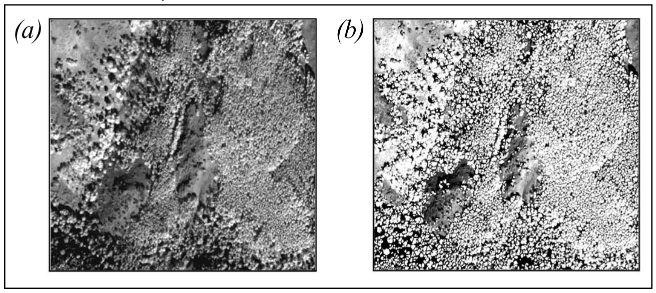
Feature Analyst/Quickbird

Figure 3.—*Visual comparison of ITC product with Quickbird panchromatic image in a pinyon-juniper forest type. (a) Panchromatic image. (b) Panchromatic image with crown delineation product overlayed. The circles show examples where trees were not delineated using ITC process.*



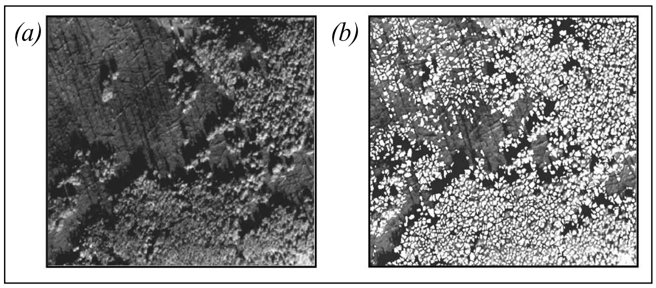
ITC = individual tree crown.

Figure 4.—*Visual comparison of ITC product with Quickbird panchromatic image in an aspen forest type with different densities. (a) Panchromatic image. (b) Panchromatic image with ITC overlay.*



ITC = individual tree crown.

Figure 5.—*Visual comparison of ITC product with Quickbird panchromatic image in a mixed aspen-conifer forest type. (a) Panchromatic image. (b) Panchromatic image with ITC overlay.*



ITC = individual tree crown.

Table 5.—*Numerical assessment of ITC process, Feature Analyst using Quickbird imagery, and Feature Analyst using NAIP photography including PCC and Kappa.*

Classification process	Statistic	26 classes	11 classes	2 classes
ITC/Quickbird	PCC	32	48	90
	Kappa	0.25	0.37	0.56
Feature Analyst/ Quickbird	PCC	41	63	94
	Kappa	0.37	0.57	0.69
Feature Analyst/ NAIP	PCC	23	51	89
	Kappa	0.19	0.43	0.50

ITC = individual tree crown; NAIP = National Agricultural Imagery Program; PCC = percent correctly classified.

The visual evaluation of the Feature Analyst classification of the Quickbird image compared to the color infrared Quickbird image indicated fairly good results. Figure 6 shows an area with aspen and mixed white fir/aspen stands. In this example, the classification performed relatively well in distinguishing aspen and white fir/aspen stands but confused mahogany with some of the more dense white fir areas (figs. 6b, 6c). At the Level III forest and nonforest classification (fig. 6d), Feature Analyst performed very well.

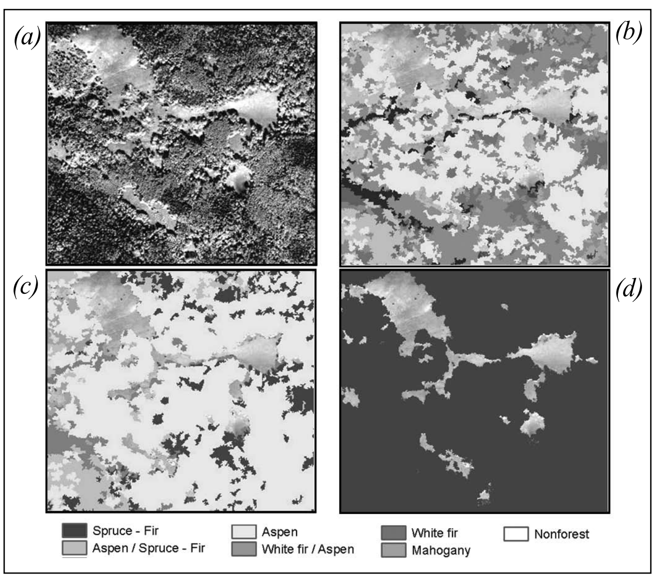
The results of the numerical assessment are shown in table 5. For the Level I class, the PCC of the Feature Analyst map using Quickbird imagery was 41 percent with a Kappa value of 0.37. The Level II class had a PCC of 63 percent and a Kappa of 0.57 while the Level III class had a PCC of 94 percent and a Kappa of 0.69.

Feature Analyst/NAIP

Figure 7 shows an example of the Feature Analyst classification of the NAIP photograph compared to the color infrared Quickbird image for the same area in Figure 6. Although the visual assessment of the results of the classification looks very different than that of the Feature Analyst classification of the Quickbird image, the results from the numerical assessment are fairly good. At the Level I classification, the PCC was only 23 percent with a Kappa at 0.19 (table 5). For the Level II classification, the PCC was much higher at 51 percent with a 0.43 Kappa value. The Level III class had a PCC of 89 percent with a Kappa of 0.50 (table 5). This increasing accuracy is noticeable visually as well.

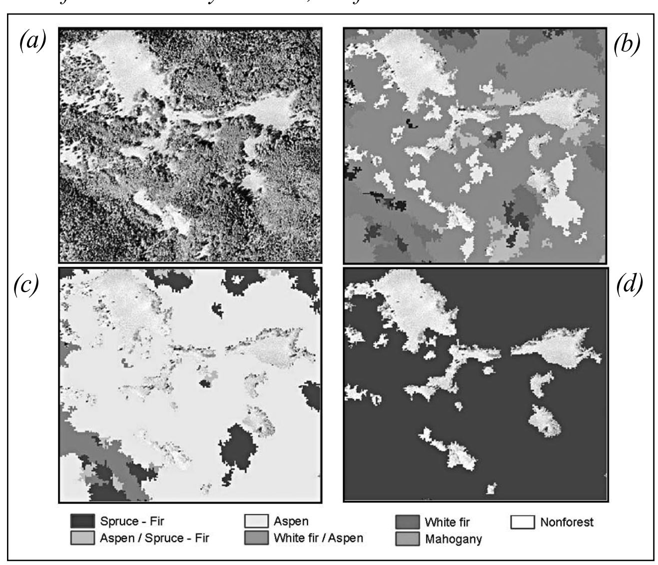
The PCC and Kappa values of the Feature Analyst map using NAIP photography were generally lower than the map using Quickbird imagery. With many classes (Level I) the PCC and Kappa of the NAIP map were much lower than the Quickbird

Figure 6.—*An example of the Feature Analyst classification using Quickbird imagery in aspen and mixed aspen/white fir stands. (a) Quickbird color IR image, (b) Quickbird color IR image with Level I classification overlayed, (c) Quickbird color IR image with Level II classification overlayed, and (d) Quickbird color IR image with Level III classification overlayed. Here, the forest class is colored black.*



IR = infrared.

Figure 7.—*An example of the Feature Analyst classification using NAIP photography in aspen and mixed aspen/white fir stands. (a) NAIP natural color image, (b) NAIP image with Level I classification overlayed, (c) NAIP image with Level II classification overlayed, and (d) NAIP image with Level III classification overlayed. Here, the forest class is colored black.*



NAIP = National Agricultural Imagery Program.

map at 18 percent and 0.18, respectively. With fewer classes (Level II), however, the PCC and Kappa of the NAIP map were only 12 percent and 0.14 lower, respectively, than the Quickbird map.

Discussion

Our investigation of high-resolution products was an initial test of the usefulness of the resulting map products in providing ancillary information to IW-FIA's forest resource estimation process. We based this investigation on both visual observations and numerical accuracy of the resulting map products as well as the time and costs devoted to the methods used to generate the products.

The visual evaluation of the map products revealed the conformity of the maps to expert knowledge and highlighted specific areas of concern. For the ITC delineation and classification product, most of the concerns were related to the species classification. As mentioned previously, the assessments were based on the first iteration of the classification effort. The final classification will most likely improve with the addition of the new training sites and ancillary information, such as elevation and aspect. Another issue discovered through the visual assessment was the consequences of long shadows in the areas of steep terrain and where there were many downed trees. These issues will need resolution within the valley-following algorithm.

Feature Analyst performed successfully as an alternative automated procedure for classification at a stand level, using both Quickbird imagery and NAIP photography. Most of the issues involved sensitivity of the classes defined, the number of classes, and the training samples used for classification. We created a fairly comprehensive list of classes based on the species occurring in the area and common associations that occurred in a stand. Common types with many training sites, such as aspen and pinyon and juniper, were well classified, but less common types, such as cottonwood and water, were overestimated. One characteristic of Feature Analyst that was not explored in this study was its learning ability. Classifications can be refined by delineating areas that were misclassified or classified correctly and rerunning the algorithm. This process is more time consuming but may be worth pursuing, especially for classes that are less common.

The numerical assessment showed that the Feature Analyst classification using Quickbird imagery had the highest percentage of correctly classified points and the highest Kappa at all class levels. Again, these were preliminary comparisons to the first iteration classification of the ITC process including fewer training sites and no ancillary data. Also, the stand-level comparisons were based on visual interpretations of classes defined by individual crown delineations, not the automated stand delineation process included with the ITC product. Still, Feature Analyst proved to be competitive with the ITC process at a stand level. Further investigations at a crown level are necessary.

The Quickbird imagery proved to be superior to the NAIP photography both visually and numerically, most likely because of its availability at a higher resolution, as color infrared, and at a higher bit size. Notably, the characteristics of NAIP including accessibility, resolution, and acquisition frequency make NAIP more appealing than Quickbird imagery for future analyses.

Although the ITC process and Feature Analyst are automated procedures, the generation of training sites is not yet automated. Defining the classes and delineating training sites is a tedious and time-consuming step that is essential for high-quality classifications. The level of detail and number of classes needed should be considered when defining the classes. Time allocated to photo interpretation and field visitation should be considered when delineating the training sites. The accuracy and experience of the photo interpreters should also be considered when delineating the training sites.

Conclusions

The objective of this study was to evaluate CLC-Camint's automated ITC delineation and classification approach and to investigate and compare two alternative automated methods for classifying stands within a diverse forested area near Beaver, UT. The numerical accuracy of the resulting maps ranged from 48 percent to 63 percent at the Level II classification, in which a class was determined based on the plurality of the species within approximately a hectare of the point. At the Level III forest and nonforest classification, the numerical accuracies ranged from 89 percent to 94 percent. The visual assessments revealed good results, especially at Level III. We believe that these assessments show strong potential for their use as ancillary products in IW-FIA's forest resource estimation procedures and should be further pursued.

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Measurement of Forest Disturbance and Regrowth With Landsat and Forest Inventory and Analysis Data: Anticipated Benefits From Forest and Inventory Analysis' Collaboration With the National Aeronautics and Space Administration and University Partners

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Abstract.—The Forest Inventory and Analysis (FIA) program has partnered with researchers from the National Aeronautics and Space Administration, the University of Maryland, and other U.S. Department of Agriculture Forest Service units to identify disturbance patterns across the United States using FIA plot data and time series of Landsat satellite images. Spatially explicit predictions of biomass loss and gain from 1972 to 2002 will be produced in 2-year intervals using 25 Landsat scenes distributed throughout the country. The map-based analyses that will be made possible through this collaboration will complement FIA's current ability to track disturbances at the county and State level.

Overview of the Collaboration

The Forest Inventory and Analysis (FIA) program has entered into a collaborative agreement with a diverse team of scientists for the purpose of using historical Landsat data to measure forest disturbance and regrowth since 1972. FIA analysts across the country are working with other U.S. Department of Agriculture (USDA) Forest Service scientists and collaborators from the National Aeronautics and Space Administration (NASA), the University of Maryland, and Oregon State University to create biennial maps of forest biomass change. The project has the following three stated goals:

1. To characterize disturbance regimes for forests across the United States and portions of Canada.
2. To evaluate the variability of post-disturbance forest regrowth.
3. To develop techniques that enable FIA analysts to study the disturbance history of any forested area in the country.

This collaboration has the potential to significantly improve FIA's capacity to monitor the forest changes resulting from disturbance. Historical Landsat imagery has been used to map the occurrence of several types of forest disturbances,

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including harvest (e.g., Cohen *et al.* 2002, Healey *et al.* 2005, Sader 1995), fire (e.g., Cocke *et al.* 2005), insect activity (e.g., Skakun *et al.* 2003), and storm events (e.g., McMaster 2005). In addition to mapping the occurrence and extent of disturbances, a few studies have attempted to measure their effect, either in general classes of tree mortality (Franklin *et al.* 2000, Jin and Sader 2005, Skakun *et al.* 2003) or as continuous variables representing change in an element of forest structure (Collins and Woodcock 1996, Healey *et al.* 2006b, Olsson 1994). The scope and precision of the maps to be produced through the current collaboration are unique. Biennial estimates of biomass loss and gain will be produced for areas across the continental United States and portions of Canada at the resolution of the Landsat pixel (~ 30 m). This production of highly specific (in time, space, and degree) estimates of change over an area of almost 1 million square km is only possible through the combined expertise of the assembled partners. The following section describes the relevant capacities of each of the partners and the contributions they are expected to make. The final section of this paper contains a discussion of the possible benefits to FIA of the products and techniques resulting from this effort.

Collaborators

NASA

The Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) is a NASA-funded program based at the Goddard Space Flight Center. The goal of this program (http://ledaps.nascom.nasa.gov/ledaps/ledaps_NorthAmerica.html) is to map forest disturbance and regrowth across the North American continent using three dates of Landsat imagery (1975, 1990, 2000). In meeting the significant logistical challenges of processing such a large number of images, LEDAPS has developed several automated algorithms for critical tasks such as removal of atmospheric effects, radiometric normalization, orthorectification, and disturbance detection (table 1). These algorithms will support not only the processing of the imagery needed in this project, but will also, once validated, be available to FIA for use in other projects.

The LEDAPS continentwide disturbance maps will be available by mid 2006. Because of the decadal sampling interval for these maps, it is likely that a portion of disturbances will not be detected. Vegetation regrowth following a disturbance can mask the disturbance's spectral signal if the sampling frequency is low (Healey *et al.* 2005, Jin and Sader 2005). Through the current collaboration, disturbance rates will be identified in more than 25 Landsat scenes across the country with imagery acquired at 2-year intervals from 1972 to the present using methods discussed below. These scenes will be chosen in a national-scale sampling framework so that the resultant disturbance maps may be used in concert with the LEDAPS product to improve national-level estimates of forest disturbance rates.

FIA

The national network of inventory plots maintained by FIA has a sampling intensity of at least one plot per 6,000 acres (approximately 1,400 plots per Landsat scene). In addition to measuring biometric characteristics such as biomass and basal

Table 1.—*Relevant processing algorithms under development by Landset Ecosystem Disturbance Adaptive Processing System.*

Algorithm name	Description	Current status
lndcal	Landsat-5 and Landsat-7 calibration and conversion to top-of-atmosphere reflectance	Operational
lndsr	Aerosol retrieval, atmospheric correction, conversion to surface reflectance	Operational/still in testing
lndcsm	Create cloud/shadow/snow mask	Prototype exists
lndreg	Precision image-to-image matching via Ground Control Points and orthorectification	Operational/still in testing
lnddm	Disturbance mapping using Disturbance Index (Healey *et al.* 2005)	Operational/still in testing
lndcom	Direct surface reflectance compositing across multiple acquisitions without Bidirectional Reflectance Distribution Function adjustment	Prototype exists

area at each plot, FIA records the likely cause and estimated year of forest disturbances occurring at each plot between measurements. FIA's plot data may be used in several ways to train and validate satellite-based forest change detection algorithms. A plot may be viewed categorically according to its binary FIA plot-level disturbance attribute, in which case it could be used to support the mapping of the location, but not the intensity, of disturbances. If a plot has been measured both before and after the identified disturbance, then the degree of damage may be assessed in terms of change in a stand attribute such as live volume or biomass. In this case, predictive models of disturbance intensity may be built using the relationship between the degree of measured physical change and the spectral differences seen in pre- and post-disturbance imagery. Plots that have not been revisited may still support efforts to map disturbance intensity. Measurements of attributes such as biomass from any date may be associated with contemporaneous imagery, and, if there is adequate radiometric normalization among images across time, a date-invariant predictive spectral model for that attribute may be produced. If that model is uniformly applied to normalized imagery from different dates, differences in predicted conditions may contain significant information about the intensity of local disturbances (Healey *et al.* 2006b).

FIA scientists, having long had access to the spatial coordinates of the Nation's largest forest inventory, have made important strides both in the modeling of biophysical variables using remotely sensed data (e.g., Blackard *et al.* 2006, Frescino *et al.* 2001, Lister *et al.* 2004, McRoberts *et al.* 2002, Moisen and Frescino 2002) and in the assessment of those models (Czaplewski and Patterson 2001, Edwards *et al.* 1998, Patterson and Williams 2003). In this respect, it is likely that FIA personnel will be instrumental both in interpreting information from FIA plot records and in modeling that information. FIA analysts will also be instrumental at the local level in helping identify the causes of mapped disturbances. Finally, FIA will have a role in communicating the results of this project as disturbance trends are included in regional and national reports.

Other USDA Forest Service and University Partners

While FIA's scientists have used satellite imagery and plot data to map forest conditions across large areas, the program has little experience in mapping forest changes. In contrast, other USDA Forest Service collaborators and those from the University of Maryland and Oregon State University have a good deal of experience in developing (Cohen *et al.* 1998, Huang *et al.* 2000, Powell 2004), testing (Cohen and Fiorella 1998, Healey *et al.* 2005), and applying (Cohen *et al.* 2002) Landsat-based change detection algorithms. Because of this experience, USDA Forest Service and university partners will have a leading role in developing methods for mapping change. As stated earlier, these methods will use historical Landsat imagery to both measure the intensity of forest disturbances and plot the regrowth of disturbed stands. Illustrating the degree to which this project will draw on the strengths of all collaborators, the change detection algorithms developed by the USDA Forest Service and university researchers will rely on both the mass preprocessing techniques designed by NASA personnel and the plot data and modeling techniques provided by FIA.

Benefits to FIA

This collaboration will greatly increase the spatial precision with which FIA can characterize disturbance across the United States. FIA's sample-based estimates of forest conditions typically are made at the county or State level to assure the consideration of a statistically adequate number of plots. Although the estimation of forest attributes at the county level using FIA plot data is statistically straightforward, it precludes more spatially explicit analyses. This project will produce estimates of forest change at the scale of the Landsat pixel (~ 30 m), permitting fine-scale analyses of disturbances such as harvests, fires, and wind events that are not possible using the sample-based paradigm. Study of the spatial patterns of forest recovery will likewise be possible. This section will describe several potential applications of this project's change products that may be of use to FIA.

Harvest Detection

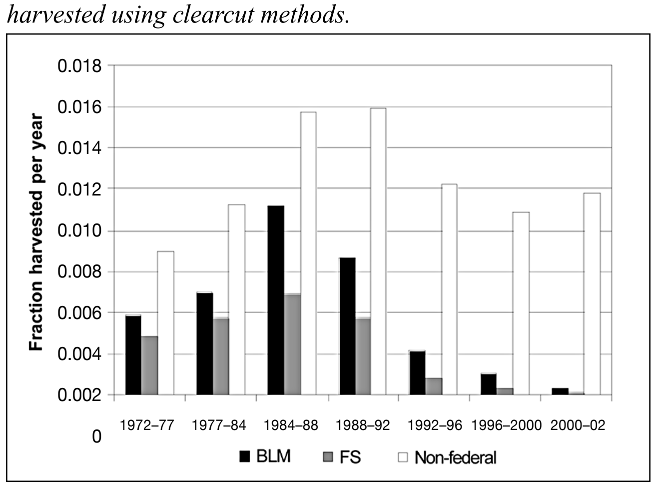
The basic products resulting from this project will be spatially explicit biennial estimates of biomass loss or gain within approximately 25 Landsat scenes. To translate these pixel-scale predictions into maps of disturbance, likely causes of each predicted disturbance will have to be identified. This process will likely focus on spatially contiguous patches of pixels displaying abrupt drops in estimated biomass. Assignment of disturbance type may be automated using rules regarding the size, shape, spatial complexity, or texture of each patch (e.g., Cohen *et al.* 2002). Formulation of these rules will have to be made in consultation with FIA analysts and other local experts. Once the sources of individual disturbances are identified, spatial and temporal trends in harvests and other types of disturbance may be conducted.

Harvest is a significant cause of forest disturbance in many managed landscapes. Harvests that remove most or all of the trees in a stand have been mapped using Landsat imagery with relatively high accuracy (e.g., Cohen *et al.* 2002, Hall *et al.* 1989, Sader and Winne 1992). Several projects have also suggested the potential for the use of historical Landsat imagery to map partial harvests (Collins and Woodcock 1996, Olsson 1994, Sader *et al.* 2003). Landsat's short-wave infrared bands may be particularly useful in modeling the degree of canopy removal involved with a harvest (Healey *et al.* 2006b; Olsson 1994).

The production of spatially and temporally explicit maps of disturbance will enable FIA to augment its current timber output records. It will be possible to summarize harvest trends since 1972 by any combination of geographic variables, including landowner, forest type, topography, or climate. For example, in a study supporting the monitoring component of the Northwest Forest Plan, Healey *et al.* (2006a) reported trends in clearcut harvesting for both Federal and non-Federal landowners in Oregon and Washington from 1972 to 2002 (fig. 1). The study showed that while non-Federal forest owners continued to harvest at relatively high levels during the 1990s (the period coinciding with the Forest Plan), clearcutting of Federal forests virtually stopped.

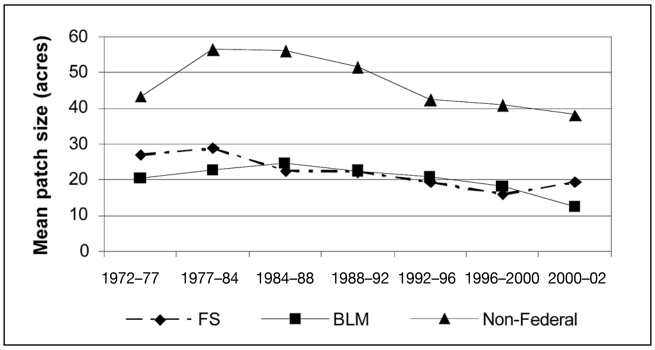
It is technically possible to create similar estimates of harvest by geographic variables using only FIA data because many of these variables are stored as plot characteristics. Satellite-based estimates, however, have at least three advantages. First, while FIA survey protocols and designs may have changed over the past 30 years, the continuity of the Landsat series since 1972 will allow relatively uniform measurement of disturbance in all time periods. Second, the specificity of plot-based estimates of harvest levels is limited by the conditions represented in the sample; harvest levels by a particular type of owner on particular slopes may only be estimated if a sufficient number of plots share those conditions. Lastly, disturbance maps resulting from this project may also be used to support purely spatial analyses for which sample-based methods are poorly suited. Healey *et al.* [2006a] looked at the size of clearcuts across time and owners (fig. 2), showing that Federal forest administrators have consistently used clearcuts that are approximately half the size of non-Federal owners. FIA plot data alone could not support this type of study. Other spatial attributes of harvests that may be of interest to FIA are proximity to streams or population centers, spatial aggregation, and edge ratio. Thus, while FIA currently has the capacity to study harvest levels at the county or State level, the use of plot and Landsat data to create harvest maps will provide significant insight into how harvests are distributed across the landscape.

Figure 1.—*Harvest rates in western Oregon and Washington on USDA Forest Service, BLM, and non-Federal lands, 1972–2002. Shown is the annualized percentage of all forest land harvested using clearcut methods.*



BLM = Bureau of Land Management; FS = Forest Service.
Source: Data from Healey et al. *(2006a).*

Figure 2.—*Mean patch size of clearcut harvest units on USDA Forest Service, BLM, and non-Federal lands in western Oregon and Washington, 1972–2002.*



BLM = Bureau of Land Management; FS = Forest Service.
Source: Data from Healey et al. *2006a.*

Fire Mapping

The USDA Forest Service, through its Remote Sensing Applications Center (RSAC), currently supports two large-scale fire monitoring programs. Burned Area Reflectance Classification maps are produced at RSAC for many forest fires using pre- and post-fire Landsat images. These maps categorize reflectance differences associated with fires, and these differences are then considered along with ancillary data to produce categorical maps of fire severity. These maps are not created for all fires, however, and do not produce an explicit estimate of forest lost. RSAC's other fire-monitoring program is the MODIS Active Fire Mapping Program, a collaboration with NASA Goddard, the University of Maryland, the National Interagency Fire Center, and the Missoula Fire Sciences Lab. This project identifies likely areas of fire activity using the thermal band from the MODIS instruments on the Terra and Aqua satellites. An effort is under way to further classify these active fire maps into fire severity classes. This classification may then be used in conjunction with data from FIA plots within each severity class to create rapid characterizations of the forest types affected by each level of fire severity.

The current Landsat-based project will complement the MODIS-based efforts in that, although fire loss estimates will not be as immediate, they will have greater spatial resolution and they will be in the form of discrete predictions of biomass reduction at the pixel level. In addition, maps will be available for fires occurring in the pre-MODIS era. The information implicit in these maps regarding the spatial distribution of fire effects may have several applications. LANDFIRE, a collaboration between the USDA Forest Service and several other Federal and private partners (www.landfire.gov), is creating maps of fuel conditions in the West using FIA data to train Landsat imagery. Fire intensity maps from the current project may be used to update LANDFIRE fuel layers. Maps of fires and other types of disturbance may likewise be used to update habitat maps (e.g., Lint 2005). Because fires can create conditions favorable for some forest pathogens (Gara 1988), maps of fire damage may also be of use in guiding forest health monitoring activities.

Storm Damage Assessment

Hurricanes and other storms can cause widespread forest damage. Storm damage, however, may be localized; differential mortality rates may result from topography, stand structure, or other factors (Millward and Kraft 2004). Although FIA currently has the capacity to estimate volume loss at the county or multicounty level, it has no way to monitor local storm effects. Spatially explicit estimates of storm damage may provide insight into storm risk at the stand level, particularly in relation to local topography. Going forward, it may also be possible to use post-storm imagery in a "rapid response" mode. In areas where change detection algorithms have already been trained with plot data and historical Landsat imagery, obtaining forest change estimates would require only the normalization of a post-storm image and the application of the existing algorithm. Although ephemeral storm effects such as standing water may somewhat reduce the accuracy of damage estimates obtained immediately after a storm, such estimates may nevertheless have value in pinpointing areas of highest damage. This information may be used to direct salvage crews or damage assessment surveys. At least 2 of the 25 Landsat scenes to be processed through this project depict major storm-affected areas (1989's Hurricane Hugo in South Carolina and the 1999 Boundary Waters wind event in Minnesota). There is substantial FIA plot data from both before and after each of these storms, allowing assessment of this project's estimates of storm damage.

Post-Disturbance Recovery

Just as this project's estimates of biomass over time may be of use in identifying disturbances, the same estimates may allow measurement of the rate of subsequent biomass accumulation. Successional recovery following disturbance can be a highly variable process, both within and across ecosystems (Yang *et al.* 2005). The consequences of slow recovery after a disturbance may include erosion (Agee 1993) and the delay of timber production. Spatially explicit recovery information, like spatial disturbance information, may be used to complement FIA plot-based estimates. Historical recovery maps may be used to update fuel and habitat maps, and they may be considered with other geographic variables to create context-dependent models of recovery. Such models may be useful to managers considering the need for or likely success of active recovery efforts following large-scale disturbances such as fires or storms. The temporal resolution of the biennial Landsat imagery used in this project may be a particular benefit in the monitoring of post-disturbance stand dynamics. The 5- or 10-year remeasurement intervals used by FIA may be less suited than biennial Landsat imagery to characterizing the potentially rapid changes (Oliver and Larson 1996) occurring after a disturbance. Thus, though FIA plot-based estimates may be used to estimate recovery rates at the county or State level, Landsat-based maps of forest recovery may add detail to our understanding of how recovery is spatially and temporally distributed.

Summary

This collaboration represents an opportunity for FIA to greatly expand the spatial information that it can provide to stakeholders and clients. An approach to forest change detection is being developed specifically to take advantage of the existing FIA database. The intrinsically spatial information resulting from this approach will complement the program's current ability to make area-based estimates of disturbance. Several applications of this spatial information in the monitoring of harvests, fires, storms, and regrowth have been suggested in this paper.

The disturbance histories of 25 sample areas across the country are now being processed using Landsat imagery and FIA data. When these initial analyses have been completed, the change detection algorithm, the critical image processing tools developed by the LEDAPS program, and the maps of disturbance and regrowth will be available to FIA for future studies.

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The Status of Accurately Locating Forest Inventory and Analysis Plots Using the Global Positioning System

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Abstract.—Historically, field crews used Global Positioning System (GPS) coordinates to establish and relocate plots, as well as document their general location. During the past 5 years, the increase in Geographic Information System (GIS) capabilities and in customer requests to use the spatial relationships between Forest Inventory and Analysis (FIA) plot data and other GIS layers has increased the value of and requirements on measurements of plot locations. To meet current FIA business requirements, it is essential that GPS locations be accurate. The Northeast FIA program (NE-FIA) used Rockwell Precision Lightweight GPS Receivers (PLGRs) in the late 1990s. This moderately priced unit enables accurate navigation and reasonably accurate locations under a canopy without the requirement of differential correction. NE-FIA tested the PLGR on 12 surveyed points (2 nonforested and 10 forested) and determined the average deviation of GPS coordinates from the known point to be 8.0 m with a standard deviation of 2.0 m. On a set of Maine plots measured in 1999 and again in 2004 using the PLGRs, 85 percent of the paired GPS positions were within 12.5 m of each other. Six percent of the paired plots were separated by more than 20 m. These indications of location accuracy are reasonable; however, 15 percent of the plots still have questionable locations. This inaccuracy is a concern for those doing GIS analysis and modeling. In a few cases, gross errors were encountered due to GPS unit malfunction or user error. Furthermore, significant problems with reprojections of plot locations from different datums were identified by additional tests with two different GPS brands on a survey course. Solutions to these problems and proposed FIA GPS protocol recommendations are discussed.

Introduction

During the 1990s, the U.S. Department of Agriculture Forest Service Forest Inventory and Analysis (FIA) program began collecting Global Positioning System (GPS) coordinates for its field plots. Before the use of GPS, plot locations were recorded in the field by pin-pricking an aerial photograph at the image of the center of the plot position. The pinprick on the photo was then transferred to a U.S. Geological Survey map to determine the geographic coordinates. Plot position coordinates provided by GPS should be more accurate and much more efficient to collect and record.

The GPS receiver most used by the FIA program was the Rockwell Precision Lightweight GPS Receiver (PLGR). Its selection as the primary unit by FIA was justified for field work under forest tree canopies. It is relatively lightweight and inexpensive. It uses standard inexpensive batteries. It has five channels, can average multiple position calculations, has a flexible setup menu for customizing position collection and presentation, and provides reasonable accuracies most of the time for both plot location and field navigation under a forest tree canopy. When it was purchased, it had one other advantage over all other GPS units available. Because it was built for the military to be used in battle, the PLGR did not have any position degradation due to *Selective Availability* (SA). SA is an artificial signal degradation that causes location errors of 100 meters or more. Except for the PLGR, GPS equipment required post processing of the field-recorded data, or the errors would routinely exceed 100 meters. Post processing of the many

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GPS positions collected over very large areas required more expensive hardware and software, plus time-consuming efforts to acquire the differential correction files needed to reduce errors. The Federal Government disabled SA on May 1, 2000.

The obvious disadvantage of the PLGR GPS unit is that the positions could not be differentially corrected for errors from atmospheric and ionospheric effects or clock errors. Furthermore, the plot positions had to be manually entered into a data logger (or written on paper), which makes them vulnerable to transcription errors.

FIA plots in some States and public lands were located using GPS equipment that provided differentially corrected results. Differential correction was the exception. The PLGR units now are being replaced by new equipment. Nearly all plots have at least one location provided by GPS. All newly acquired plots will use GPS positioning. Hundreds of FIA data users are relying on accurate locations. How accurate are these locations? Should we collect additional GPS locations on plots that already have a GPS position? What GPS collection methods and GPS equipment purchase decisions might help ensure accurate plot locations?

FIA Plot Accuracy

The Need

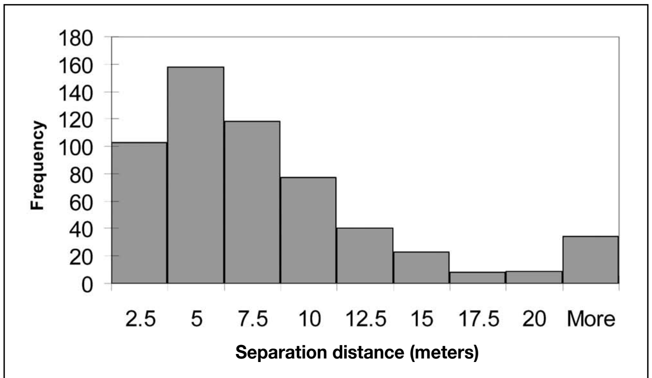
The demand for using FIA plots as a valuable data layer in Geographic Information Systems (GIS) and remote sensing analyses and mapping has increased dramatically since the program started using GPS for more accurate locations. The increase in GIS capabilities and in customer requests to use the spatial relationships between FIA plot data and other GIS layers has increased the value of and requirements on measurements of plot location accuracy. To meet current FIA business requirements, it is essential that GPS locations be accurate. For example, FIA sample stratification requires that plots be as close as possible to true locations to accurately exploit the imagery-plot link. In Connecticut, one-third of the forested plots are within 60 m of the forest edge. An evaluation of the effect of FIA plot and satellite pixel location error indicated that when the combined errors reached 50 m, the resulting forest/nonforest map classification error ranged from 4 to 10 percent (McRoberts and Holden 2006). Recent direction from the national FIA management has charged us with increasing our geospatial product output, a process that also requires the best possible GPS data. The FIA program created a Spatial Data Services Center so customers outside of the FIA program can use the data spatially without compromising plot confidentiality. More than 145 requests for service were received in 2005. As GIS data and imagery (e.g., large scale imagery; State forest land, protected areas and other boundary files) become more accurate, it is absolutely critical that our spatial reference information be as accurate as possible. With accurate spatial locations, not only can we exploit these advances, but also confidently stand behind the data we supply to customers who will be using them.

PLGR Accuracy

FIA plot location accuracy is expected to be as good as that provided by typical resource mapping grade GPS units used by the National Forest System. In general, the PLGR often does not provide the same level of accuracy as the differentially corrected positions of the GPS units used by the rest of the USDA Forest Service. Historically, FIA plot GPS coordinates were intended to assist field crews in establishing and relocating the plots, as well as to document general location. The current edition of the FIA Field Manual requires that the quality (accuracy) of 99 percent of GPS positions be within 42.7 m. The average error of most GPS receivers, including the PLGR, is much lower than 42.7 m, but positions are not that accurate 99 percent of the time. This FIA measurement quality objective cannot be used to indicate the current quality of GPS positioning and is rarely checked or reported.

In field tests of PLGR accuracy conducted by Richard McCullough of the Northeast FIA program (NE-FIA), surveyed markers scattered under a dense 80-ft-tall deciduous forest canopy were located with an average error of 8 m (standard deviation = 2.0 m). By comparison, a set of Maine FIA plots measured in 1999 and again in 2004 using the PLGR reveals similar distance offsets between the measurements in time 1 and those in time 2, with some notable differences (fig. 1). Half

Figure 1.—*Frequency distribution of the separation distance between pairs of Precision Lightweight GPS Receiver positions of 570 remeasured FIA plots (1999–2004).*



FIA = Forest Inventory and Analysis; GPS = Global Positioning System.

the separation distances were less than 5.5 m. Only 20 percent of the distances exceeded 10 m; however, 4 percent exceeded 20 m and 2 percent of the separation distances were greater than 1 km. Small separation distances do not verify accuracy, but rather suggests precision, from which we can infer accuracy. It is unlikely that two GPS units used 5 years apart would give locations of the same ground plot so close together by chance. The most likely reason for this phenomenon is that the units were close to measuring “true” location. Because all of these plots were forested, the PLGR seems to be remarkably accurate on average. The essential field procedure required to determine which plot locations are accurate is to remeasure. Remeasurement identifies a potential inaccuracy with one or both of the GPS coordinates. Users can flag suspect plots and remove them from GIS and remote sensing analyses.

As indicated above, plot location errors of about 20 m can result in map classification errors of 10 percent when combined with common image pixel position errors. Investigators in the North Central FIA unit found the average separation distance of 1,145 remeasured plots was 13.6 m (standard deviation = 46.2 m).

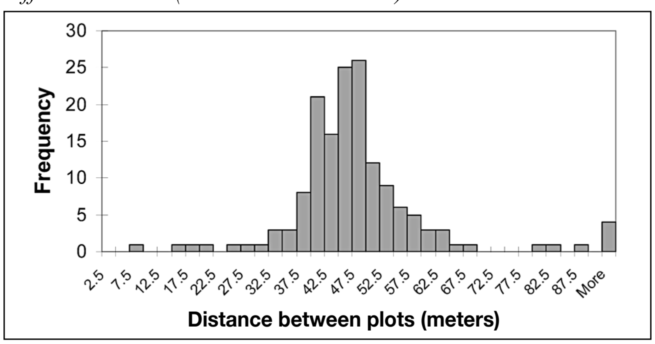
Datum Errors

Another source of error with the PLGR, which we have also found to occur in other types of GPS units used by FIA, is an inaccurate datum conversion formula used to convert coordinates of positions from World Geodetic System 1984 (WGS 84) to North American Datum 1927 (NAD 27). Datums define a set of constants specifying the coordinate system used for geodetic control. GPS software calculates coordinates in the datum WGS 84 and coverts them within the unit to display coordinates for other datums selected by the user. Most FIA plots were collected using NAD 27 because most available maps were based on that datum. The conversion formula used in the PLGR causes location errors of about 12 m in the Northeast and other regions. The solution is to collect data in NAD 83, which is nearly identical to WGS 84 and is currently mandated by the Forest Service Handbook 6609.15, Standards for Data and Data Structures. The standard use of NAD 83 will provide more integrated and accurate data, reduce errors in GPS data, and align FIA with the current Agency and Federal standards.

Starting immediately, all FIA GPS coordinates should be collected using NAD 83, and all of the previous collected GPS coordinates acquired using NAD 27 must be converted to NAD 83. To correctly change a coordinate collected in a non-WGS84 datum (e.g., NAD 27) back to WGS 84, and then subsequently to NAD 83, the operator needs to first use the reverse of the transformation method that the GPS unit applied. For example, the NAD 27 coordinates collected by the PLGR can be converted in ArcGIS using the transformation method called “NAD_1927_TO_WGS_1984_4.” The GPS unit’s documentation or technical support staff can supply the transformation parameters needed. To choose a datum transformation method to apply in ArcGIS, consult http://support.esri.com/index.cfm?fa=knowledgebase.whitepapers.viewPaper&PID=43&MetaID=302. This Internet site lists the transformation method name and the parameters used by ArcGIS to perform the transformation. Conventional wisdom in the GPS community is that it is always appropriate to use North American Datum Conversion (NADCON) to transform any NAD 27 GPS coordinate to NAD 83. This assumption is generally correct, unless your GPS does not use NADCON to convert from WGS 84 to NAD 27. If NADCON is used with PLGR data, the location errors are retained.

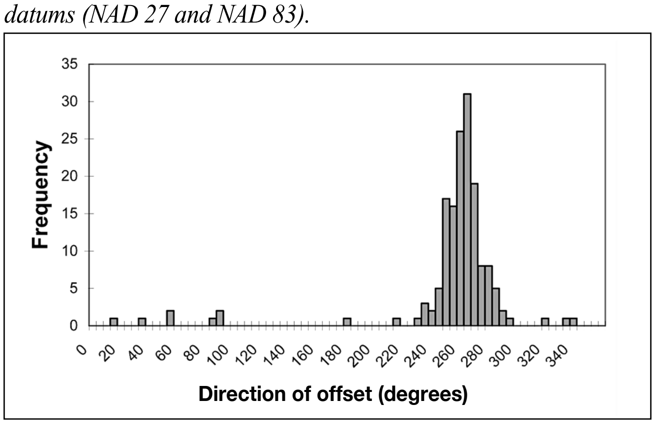
Another datum error common with the PLGR is the unexpected (and unknown to field crews) reversion of the unit to its default datum, WGS 84, without the user selecting it. In several regions in the northeast, all the FIA plot locations were found to have been collected in WGS 84 instead of the "selected" NAD 27. The reason for this uncommanded reversion is unknown, although battery power interruption is suspected. The discovery was made when many of the plots in the region were remeasured. Had this not been the case, there would be no way to tell that the separation distances of the coordinates were averaging 50 or so m in one general direction of 260 degrees. Normally the separation distances would be expected to be less than 10 m and bearing randomly in all directions. If the distance separation between remeasured plot locations are all about the same distance and bearing as a map coordinate varies between NAD 27 and NAD 83, it is likely to be caused by collecting the plots in WGS 84 instead of the assumed NAD 27 datum (figs. 2 and 3). The lesson is clear: collect FIA plots in NAD 83 (coordinates are within 1 m of WGS84) and remeasure all plots until the accuracy is confirmed.

Figure 2.—*Frequency distribution of the separation distance between pairs of Precision Lightweight GPS Receiver positions of 157 remeasured FIA plots (1997–2003) where it is highly likely that all or most of the measured pairs are acquired using different datums (NAD 27 and NAD 83).*



FIA = Forest Inventory and Analysis; GPS = Global Positioning System; NAD = North American Datum.

Figure 3.—*Frequency distribution of the direction between pairs of Precision Lightweight GPS Receiver positions of 157 remeasured FIA plots (1997–2003) where it is highly likely that all or most of the measured pairs are acquired using different datums (NAD 27 and NAD 83).*



FIA = Forest Inventory and Analysis; GPS = Global Positioning System; NAD = North American Datum.

GPS Replacements for the PLGR

During the past few years, FIA has replaced the PLGR with no fewer than six other brands of GPS hardware with various combinations of software and system configurations. This replacement is due mainly to increased hardware problems with the PLGR because of extended field service. Choice of replacement units is still very much influenced by a combination of capability and cost. NE-FIA required 60 replacement units, so cost was a big issue. Several units were tested on a surveyed field course with markers both under a heavy forest canopy and in the open. The GPS unit finally selected has 12 channels, a built in real-time differential correction system called Wide Area Augmentation System (WAAS), and the ability to radio the position to a field datalogger for electronic storage using Bluetooth technology. NE-FIA helped in the design of the software that resides in the field datalogger, which has a detailed setup menu allowing the selection of datum, PDOP limits (PDOP is a measure of accuracy based on the geometry of well-spaced GPS satellites), and the ability to average multiple positions. Multiple field tests of this system over several months show an error of 5.5 m (standard deviation = 3.2 m) under a dense 80 ft deciduous canopy. In the open, the root mean square error (RMSE) was 2.2 m (standard deviation = 0.9 m).

Multiple studies of how well a dozen currently available resource mapping and consumer-grade GPS systems function under forest canopies have been recently published (Bolstad *et al.* 2005, Piedallu and Gegout 2005, Sigrist *et al.* 1999, Tucek and Ligos 2002, Wing *et al.* 2005). These studies indicate that the sophistication of GPS equipment has a significant affect on position accuracy. Furthermore, accuracies are much better in the open than in forested areas. What is surprising is that the average error of all of the units, except one, was less than 7 m under a closed forest canopy. Another useful fact was that differential correction has much less effect on the accuracy of forested plots. Apparently, errors caused by multipath signals due to signal reflections off trees are much greater than the errors that differential corrections can reduce (Piedallu and Gegout 2005). In one study, no significant differences were found between GPS units using WAAS-corrected, differentially corrected, and uncorrected positions (Bolstad *et al.* 2005). WAAS requires the GPS unit to receive a position correcting signal from a satellite. The signal can be blocked by trees and other obstructions. Within a mature forest, the signal may be available less than 50 percent of the time (Bolstad *et al.* 2005). Artificially introduced errors from a SA signal could change the value of differential corrections in the future.

These studies point out the following techniques that could help FIA crews lower errors:

- Raising the antenna height to at least head height or higher increases accuracy (Bolstad *et al.* 2005, Sigrist *et al.* 1999).
- The higher the PDOP, the worse the accuracy. Under a canopy, however, a requirement for a low PDOP may cause very long acquisition times and more error due to multipath signals because the unit is forced to use satellites lower on the horizon that have to send their signal through more trees. PDOP under a forest canopy is 35 percent higher than in the open. Consider using a PDOP limit of eight (the standard is six) under a heavy forest canopy when PDOP stops position collection (Sigrist *et al.* 1999). In general, lower PDOP produce more accurate positions under a forest canopy (Piedallu and Gegout 2005).
- Turn the GPS on in the open and then walk into the forest. It takes five times more signal strength to initially acquire a signal than to keep it (Wilent 2002).
- More expensive GPS units are more accurate under all conditions (Piedallu and Gegout 2005).
- Position errors decrease linearly with the logarithm of the number of position calculations averaged into a final position. Don’t limit the number too much.
- The bigger the nearby trees, the worse the accuracy. Offset plots near big trees (Piedallu and Gegout 2005).

FIA GPS Considerations

- Remeasure all GPS plot locations. A single FIA plot location provided by GPS cannot be determined accurate unless it is compared to a reference. Digital ortho quads could be used to evaluate accuracy, but no proven protocol exists. How many times should a plot be remeasured and what should the threshold for separation distance be for acceptable accuracy? Because the current industry average for GPS accuracy under a forest canopy is about 5 m, a reasonable FIA measurement quality objective (MQO) would be three separately calculated GPS locations all within 10 m of each other. At that time, an average of the three positions will be calculated for the final plot location. Keep all GPS locations in the database for users to evaluate. If the program must have an “official” location for each plot, then use the last one collected. After meeting the MQO, the calculated average shall be the best and final position for the plot unless some other evidence indicates an error.
- Begin recording GPS in NAD83, which is currently an Agency requirement. Convert all plot locations previously collected in NAD27 to NAD83 using the correct procedures as described above. This conversion will require careful attention to maintaining records in the database. Always keep a copy of the original record.
- Build into the data recorder a way to flag a measurement that is more than a specified number of meters (e.g., 20 m) from the position that the field crew is directed by the office staff to locate (indicated in the datalogger by “office_lat /long”). This could be done via a mathematical equation and an if/then statement, which would raise the chances of catching gross errors in the field.
- Standard metadata should be developed for all GPS information. These data should include the equipment serial number, date, datum, number of positions averaged, and other parameters required by the FIA program.
- Require that all field crews, including contract crews, receive adequate training for the field collection of GPS positions.
- Create a FIA GPS steering committee to include data collection staff, analysts, and techniques development

members. Require all GPS equipment that is used to provide official plot locations be approved by the committee after evaluating approved field test results.

The GPS coordinate is one of the most important single measurements taken on the plot. It is in no way analogous to measuring aspect or slope (which is measured with basically foolproof, mechanical devices, and which does not contain many numerical values). Rather, it is prone to hardware, software, operator, and random, unexplainable errors. As we have shown, systematic, gross errors exist in the current GPS data. Every GIS analyst in FIA is intensely concerned with this issue, and it is vital that we address it immediately at both a local and national level.

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Mapping Forest Inventory and Analysis Forest Land Use: Timberland, Reserved Forest Land, and Other Forest Land

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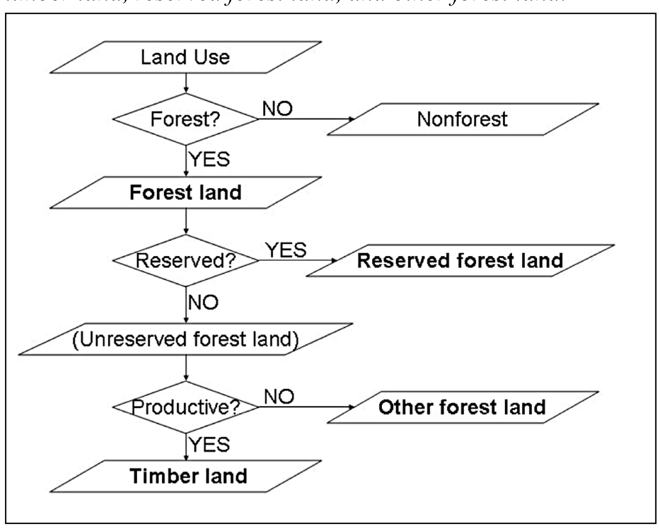
Abstract.—The Forest Inventory and Analysis (FIA) program produces area estimates of forest land use within three subcategories: timberland, reserved forest land, and other forest land. Mapping these subcategories of forest land requires the ability to spatially distinguish productive from unproductive land, and reserved from nonreserved land. FIA field data were spatially interpolated to produce a geospatial data set of forest site productivity. A geospatial data set of lands reserved from wood products utilization was delineated from the Protected Areas Database. The combination of these two geospatial data sets, along with a geospatial data set of forest land cover, provided an initial approach for mapping three subcategories of forest land use. Compared with inventory estimates, the mapping approach led to similar estimates of forest land area, overestimates of timberland and reserved forest land, and an underestimate of other forest land. Additional work is needed to improve geospatial data sets of forest site productivity.

Introduction

Detailed surveys of the Nation's forest land are conducted through the Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture (USDA) Forest Service. Through the FIA program, design-based estimates of forest land area by estimation units (e.g., counties, States, regions) and the Nation are produced. Bechtold and Patterson (2005) provided FIA definitions of forest and nonforest land (appendix A), which include land use constraints and measures of minimum tree stocking, forest land area, and forest land width. Furthermore, using FIA definitions, forest land use can be differentiated into three subcategories: timberland, reserved forest land, and other forest land (appendix A). FIA subcategories of forest land are defined by site productivity and reserved status, (i.e., availability or unavailability of forest land for wood product utilization) (fig. 1).

FIA estimates represent forest land use (e.g., forest land not currently developed for a nonforest use) (appendix A), while satellite-image-based data sets and their derived estimates represent forest land cover. A mapping approach for differentiating land use versus cover would provide a more consistent basis for comparing classified satellite imagery with FIA estimates of forest land area. Nelson *et al*. (2005) explored the efficacy of satellite-image-derived forest land cover maps for portraying forest land use in the United States by comparing estimates obtained from FIA data, the USDA Natural Resources Conservation Service's National Resources Inventory), and

Figure 1.—*Decision rules for classifying forest land into timber land, reserved forest land, and other forest land.*



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four satellite-image-derived data sets: 1991 Forest Cover Types (Zhu and Evans 1994), 1992–93 Land Cover Characteristics (Loveland *et al.* 2000), 2001 Vegetation Continuous Fields (Hansen *et al.* 2002), and the 1992 National Land Cover Data set (NLCD) (Vogelmann *et al.* 2001)). The four satellite-image-derived land cover maps differ in date of image acquisition, classification scheme, and spatial resolution, and show varying degrees of similarity with inventory estimates of forest land use across the conterminous United States (CONUS).

Differentiation of forest land use maps into FIA's three subcategories of forest land would allow for validation and integration of satellite image products with inventory estimates of forest land use. In this paper we address approaches to mapping timberland, reserved forest land, and other forest land.

Data and Methods

Forest Land Cover

The circa 1992 NLCD is a 30-m spatial resolution national land cover data set produced and distributed by the U.S. Geological Survey Center for Earth Resources Observation and Science. Landsat Thematic Mapper imagery from the early 1990s and other sources of geospatial data were used in the classification system, and provided the basis for a consistent hierarchical approach to defining 21 classes of land cover across CONUS (Vogelmann *et al.* 2001). We produced a forest/nonforest cover map by grouping five NLCD classes into a "forest" class: transitional (33)[3], deciduous forest (41), evergreen forest (42), mixed forest (43), and woody wetland (91). The remaining 16 NLCD classes were aggregated into a "nonforest" class. For ease of processing and for integration with other geospatial data sets of coarser spatial resolution, the 30-m forest/nonforest data set was rescaled to a 250-m spatial resolution forest/nonforest data set.

Forest Land Use

Area estimates of forest land use per State were obtained from Forest Resource Assessment 2002 tables on U.S. forest resources, as part of the Forest and Rangeland Renewable Resources Planning Act of 1974 (RPA), P.L. 93-378, 99 Stat. 4765 (USDA 2003). RPA data primarily were derived from FIA data, except for portions of some Western States where National Forest System lands were inventoried independently (Smith *et al.* 2001, USDA Forest Service 2003). RPA 2002 source dates ranged from 1983 to 2000 with an average acquisition year of 1994 (Smith *et al.* 2004). Inventory estimates of forest land area were obtained by multiplying total land area by the mean proportion of forest land from forest inventory plot observations (Scott *et al.* 2005). Although sufficient RPA data exist for Southeast and South Central Alaska, portions of the State's interior have few field plot data. Likewise, Hawaii has few or no field plot data. Therefore, analyses in this study were constrained to CONUS.

Forest Land Productivity

Observations from forest inventory plots were used for spatially modeling forest site productivity. Publicly available geographic location coordinates, land use codes, and productivity attributes were queried from the RPA 2002 database. The resulting records totaled 167,920 forested condition observations on 155,149 RPA plots, and some plots had multiple forested conditions. Nonforest conditions were excluded from the query. Site Class Code (SITECLCD) is the inventory attribute that describes site productivity of each condition observation (Miles *et al.* 2001) (table 1). Area-weighted site productivity (SITEPLT) was calculated for each plot as

$$SITEPLT = \frac{\sum_{i=1}^{N}\left(c_i s_i\right)}{C} \qquad (1)$$

where c_i is the condition proportion (CONDPROP) of the i[th] of N forested conditions on a plot, s_i is the approximate midpoint of the range of site productivity values associated with each SITECLCD for the i[th] condition (table 1), and C is the sum of condition proportions (sum of c_i s) across all N forested conditions on a plot. For some plots, condition proportions summed to < 1.0 when plots contained both

[3] The correct numerical designation for the transitional class is 33; its designation as 31 in Vogelmann et al. (2001) is attributed to a manuscript error (Vogelmann, EROS Data Center, U.S. Geological Survey, personal communication, 10 October 2001).

Table 1.—*Site Productivity Class (SITECLCD), approximate midpoint productivity value (SITECLMID), and resulting forest land use category for nonreserved forest land.*

SITECLCD	Cubic feet/ acre/year	SITECLMID	Forest land use
1	225+	225.0	Timber land
2	165–224	195.0	Timber land
3	120–164	142.5	Timber land
4	85–119	102.5	Timber land
5	50–84	67.5	Timber land
6	20–49	35.0	Timber land
7	0–19	10.0	Other forest land

forested and nonforested conditions, or when forested conditions did not contain trees of suitable size from which to determine site productivity, and this resulted in a no data value for SITECLCD. Excluded from analyses were condition records having SITECLCD values of -1 or 0 (not recorded or no data, respectively), or CONDPROP values of 0. Plot location accuracy was determined by spatially joining plot locations to a geospatial data set of county boundaries (ESRI Data & Maps 2002) and comparing county Federal Information Processing Standards codes between plots and county boundaries, and a subset of plots with erroneous location coordinates were excluded from analyses.

Spatial interpolation of site productivity was performed using the ArcGIS Geostatistical Analyst software package and the Inverse Distance Weighted (IDW) interpolator, with 75 percent of plot observations used for training data and 25 percent for test data. Analyses using IDW interpolations with power levels 1 (IDW), 2 (IDW^2), and 3 (IDW^3) resulted in mean prediction error and root mean square error values, respectively, of 0.3422 and 31.07 for IDW; 0.2665 and 32.15 for IDW^2; and 0.2198 and 33.76 for IDW^3. Subsequent analyses included only the IDW interpolation, which was converted to an ArcInfo GRID with 250-m spatial resolution and was masked to exclude areas outside of CONUS. Pixels with interpolated site productivity values greater than 20 ft^3/ac were considered to meet the criteria for the definition of timberland, given that such land is forested and is not reserved.

Forest Land Reserved Status

A suite of land ownership and protection categories is included in Gap Analysis Program (GAP) State maps. The Conservation Biology Institute aggregated the State GAP map products and other sources of geospatial data into a comprehensive North American data set known as the Protected Areas Database (PAD) (DellaSala *et al.* 2001). Version 3 of the PAD (PAD 2005) was used in this study for differentiating reserved from nonreserved lands. The PAD includes two designations of land protection status: (1) GAP codes and (2) Categories for Conservation Management as defined by the International Union for the Conservation of Nature (IUCN) (appendix B). Based on local knowledge and preliminary assessments, IUCN categories I–V (appendix B) were defined as representing reserved lands, and selecting them resulted in a subset of 37,844 reserved land polygons from the 345,861 PAD polygons within CONUS. Areas within CONUS not designated as reserved according to the PAD data were defined as nonreserved lands. Polygons representing reserved and nonreserved lands were rasterized to a 250-m resolution data set for ease of integration with other data layers.

Geospatial Analysis

ArcGIS software was used to combine the geospatial data sets of NLCD forest/nonforest classes, interpolated site productivity values, and PAD reserved land into a single raster layer. Using these three geospatial data sets and the criteria defined in figure 1, a new data set was attributed with categories of timberland, reserved forest land, other forest land, and nonforest land. Per-State pixel counts and resulting area estimates of each land use category were summarized by intersecting a geospatial data set of detailed State boundaries.

Statewide RPA estimates of forest land, timber land, reserved forest land, and other forest land were compared with modeled geospatial estimates to produce area weighted root mean square deviations (RMSD) using methods derived by Häme *et al.* (2001):

$$RMSD_{rs} = \sqrt{\sum_i \frac{a_i}{A}\left(\hat{p}_{ir} - \hat{p}_{is}\right)^2} \quad (2)$$

where a_i is the area of the i[th] state, A is the total area across CONUS (sum of a_i s for all states), and $\hat{p}_{ir}$ and $\hat{p}_{is}$ denote the estimated proportion of forest land, timber land, reserved forest land, or other forest land area in the i[th] state obtained from the RPA (*r*) and modeled (*s*) estimates.

Results

The map of CONUS timber land, reserved forest land, other forest land, and nonforest land (fig. 2) revealed local spatial distributions of forest land subcategories. Although areas of reserved forest land are evident across CONUS, the largest blocks are most prevalent in the Western United States, where national parks and wilderness areas are more abundant. In nonreserved areas, most forest land is portrayed as timberland, except for arid portions of Southwestern United States, where site productivity values are lower. Compared with RPA estimates of CONUS forest land use, map based area estimates were 1 percent lower for forest land, 8 percent higher for timberland, 12 percent higher for reserved forest land, and 58 percent lower for other forest land (fig. 3). The comparison between map and RPA statewide estimates resulted in largest area-weighted RMSDs for forest land and other forest land; reserved forest land had the smallest RMSD (fig. 4).

Figure 2.—*Conterminous United States map of nonforest (white) and forest land subcategories: timber land (light gray), reserved forest land (medium gray), and other forest land (black).*

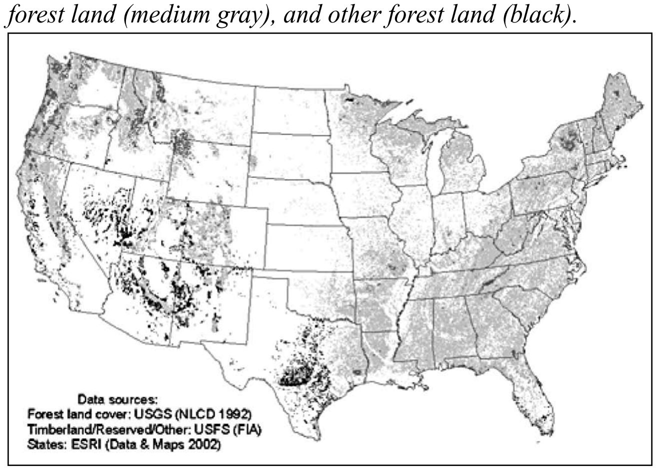
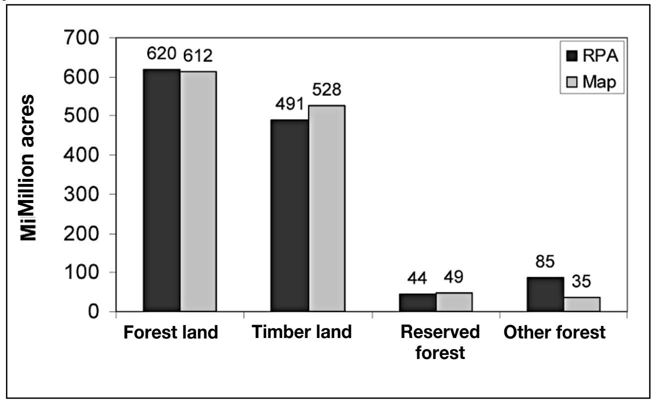
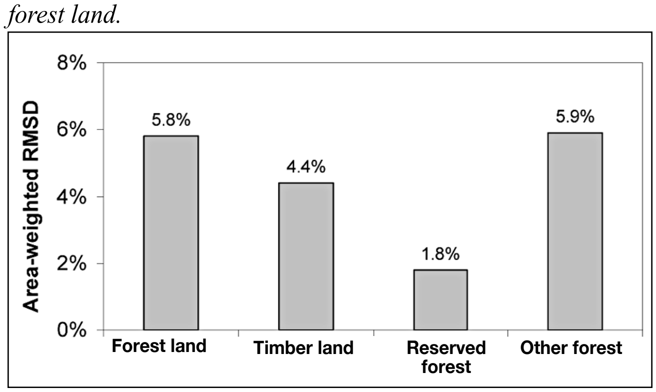


Figure 3.—*Comparison of RPA-based and map-based area estimates of conterminous United States forest land and three subcategories: timber land, reserved forest land, and other forest land.*



RPA = Forest and Rangeland Renewable Resources Planning Act of 1974.

Figure 4.—*Area-weighted root mean square deviations between RPA-based and map-based statewide area estimates of conterminous United States forest land and three subcategories: timber land, reserved forest land, and other forest land.*



RPA = Forest and Rangeland Renewable Resources Planning Act of 1974; RSMD = root mean square deviations.

Discussion

The NLCD-based estimate of CONUS forest land area was about 1 percent less than the RPA inventory estimate, but per-State estimates differed by wider margins, and had an RMSD of 5.8 percent. Inclusion of the NLCD “transitional” class may have offset some of the expected differences between forest land use (e.g., RPA) and forest land cover (e.g., NLCD), because the “transitional” class includes forest clearcuts and other areas of forest regeneration not typically recognized by satellite imagery as forest cover. Differences between modeled estimates and RPA estimates of CONUS timberland and reserved forest land were moderately larger than for forest land, but RMSDs were smaller (fig. 3, fig. 4). The modeled estimate of other forest land was 59 percent smaller than the RPA estimate, and the RMSD for other forest land was the largest of any forest category at 5.9 percent. Reserved forest land, however, appears to be represented adequately using PAD 2001 IUCN Categories I–V when combined with the NLCD forest/nonforest data set.

Interpolation of forest site productivity, using RPA plot data with public coordinates and IDW, lead to overestimation of productive forest land (site productivity classes 1–6) and underestimation of unproductive forest land (class 7). At least two factors could have contributed to this bias. First, the NLCD data set used for representing forest land appears to under-represent RPA estimates of forest land on unproductive sites. In six arid Southwestern States, more than 10 percent of all forest land is considered other forest land. The RPA estimates of other forest land were Arizona (20 percent), California (16 percent), Colorado (11 percent), Nevada (13 percent), New Mexico (14 percent), and Utah (19 percent). NLCD-based estimates of total forest land in these six States were 12–38 percent lower than RPA estimates (Nelson *et al*. 2005). In contrast, NLCD-based estimates of total forest land were 10–61 percent greater than RPA estimates in States where other forest land comprised less than 5 percent (often less than 1 percent) of all forest land. Second, the use of RPA productivity class midpoints may not be representative of the distribution of productivity within each class range. One or both of the midpoints from the two least productive classes may be too large. For example, a hypothetical interpolation of plots equally distributed among only these two classes—midpoint 10 for the 10 to19 class, and midpoint 35 for the 20 to 49 class—would produce mean a site productivity value of about 22.5 ft^3/ac, which is greater than the timberland threshold of minimum productivity (20 ft^3/ac).

Conclusions

Currently available land cover and land use data provide a basis for mapping FIA attributes, but additional assessment of forest cover mapping is recommended, especially in areas of lower site productivity. Specifically, work is needed to improve geospatial data sets of forest site productivity. Future approaches may include optimizing class midpoints and incorporating other geospatial data sets, such as ecological units or topographic information. Work is ongoing to improve mapping of land use versus land cover and forest cover versus tree cover.

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Appendixes

Appendix A.—*Forest Inventory and Analysis definitions of forest land use; from glossary of Bechtold and Patterson (2005).*

forest (forest land). Land that is at least 10 percent stocked by forest trees of any size, or land formerly having such tree cover, and not currently developed for a nonforest use. The minimum area for classification as forest land is 1 ac. Roadside, streamside, and shelterbelt strips of timber must be at least 120-ft wide to qualify as forest land. Unimproved roads and trails, streams and other bodies of water, or natural clearings in forested areas are classified as forest, if less than 120 ft in width or 1 ac in size. Grazed woodlands, reverting fields, and pastures that are not actively maintained are included if the above qualifications are satisfied. Forest land includes three subcategories: timberland, reserved forest land, and other forest land.

nonforest. Areas defined as nonforest land, census water, or noncensus water.

other forest land. Forest land other than timberland and reserved forest land. It includes available and reserved low-productivity forest land, which is incapable of producing 20 cubic ft of growing stock per acre annually under natural conditions because of adverse site conditions such as sterile soil, dry climate, poor drainage, high elevation, steepness, or rockiness.

reserved forest land. Land permanently reserved from wood products utilization through statute or administrative designation.

timber land. Forest land that is producing or capable of producing in excess of 20 cubic ft per acre per year of wood at culmination of mean annual increment. Timber land excludes reserved forest lands.

Appendix B.—*Categories for Conservation Management, International Union for the Conservation of Nature.*

I. Strict nature reserve/Wilderness area.
II. National Park.
III. Natural Monument.
IV. Habitat/Species Management Area.
V. Protected Landscape/Seascape.
VI. Managed Resource Protected Area: protected area managed mainly for the sustainable use of natural ecosystems.

Use of LIDAR for Forest Inventory and Forest Management Application

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Abstract.—A significant impediment to forest managers has been the difficulty in obtaining large-area forest structure and fuel characteristics at useful resolutions and accuracies. This paper demonstrates how LIDAR data were used to predict canopy bulk density (CBD) and canopy base height (CBH) for an area in the Sierra National Forest. The LIDAR data were used to generate maps of canopy fuels for input into a fire behavior model (FARSITE). The results indicate that LIDAR metrics are significant predictors of both CBD (r^2 = 0.71) and CBH (r^2 = 0.59). In summary, LIDAR is no longer an experimental technique and has become accepted as a source of accurate and dependable data that are suitable for forest inventory and assessment.

Introduction

In this article we present an overview of the use of LIDAR for forest inventory and canopy structure mapping and explore the efficacy of a large-footprint, waveform-digitizing LIDAR for the estimation of canopy fuels for utilization in fire behavior simulation models. Because of its ability to measure the vertical structure of forest canopies, LIDAR is uniquely suited among remote sensing instruments to observe canopy structure characteristics, including those relevant to fuels characterization, and may help address the relative lack of spatially explicit fuels data. Two canopy structure characteristics have been identified that help quantify these fuel loads: canopy bulk density (CBD) and canopy base height (CBH). These have been adopted for fire behavior modeling (Sando and Wick 1972, Scott and Reinhardt 2001). CBD is defined as the mass of available canopy fuel per unit canopy volume and CBH is the lowest height in the canopy where there is sufficient fuel to propagate fire vertically into the canopy (Scott and Reinhardt 2001).

This article provides a brief, simple description of the different types of LIDAR systems and how they work and summarizes previous research utilizing LIDAR for landsurface characterization. It also examines the use of large-footprint, waveform-digitizing LIDAR data to predict and create maps of CBD and CBH as well as the use of LIDAR-derived products to run a fire behavior model. LIDAR metrics are compared to field-based estimates of CBD and CBH and, based on the regression models resulting from these comparisons, maps of CBD and CBH are generated that are then tested as inputs into a fire behavior model.

LIDAR

LIDAR (frequently used synonymously with the term *laser altimetry*) provides a direct and elegant means to measure the structure of vegetation canopies (Dubayah and Drake 2000). LIDAR is an active remote sensing technique in which a pulse of light is sent to the Earth's surface from an airborne or spaceborne laser. The pulse reflects off of canopy materials such as leaves and branches. The returned energy is collected back at the instrument by a telescope. The time taken for the pulse

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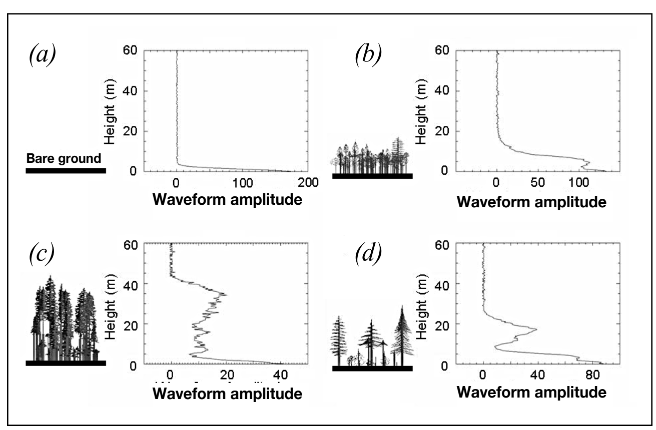
to travel from the instrument, reflect off of the surface, and be collected at the telescope is recorded. From this ranging information various structure metrics can be calculated, inferred, or modeled (Dubayah and Drake 2000). A variety of LIDAR systems have been used to measure vegetation characteristics. Most of these are small-footprint, high pulse rate, first- or last-return-only airborne systems that fly at low altitudes. Other, experimental LIDAR systems are large footprint and full waveform digitizing and provide greater vertical detail about the vegetation canopy. Dubayah *et al*. (2000) and Lefsky *et al*. (2002) provide thorough overviews of use of LIDAR for landsurface characterization and forest studies.

Canopy height, basal area, timber volume and biomass have all been successfully derived from LIDAR data (Drake *et al.* 2002a, Drake *et al.* 2002b, Hyde *et al.* 2005, Lefsky *et al.* 1999, Maclean and Krabill 1986, Magnussen and Boudewyn 1998, Means *et al.* 1999, Naesset 1997, Nelson *et al.* 1984, Nelson *et al.* 1988, Nelson 1997, Nilsson 1996, Peterson 2000). Many of these studies rely on small-footprint systems. Small-footprint LIDARs have the advantage of providing very detailed measurements of the canopy top topography. Most small-footprint (5-cm to 1-m diameters) systems are low flying and have a high sampling frequency (1,000 to 10,000 Hz). Although small-footprint systems typically do not digitize the return waveforms, the high frequency sampling produces a dense coverage of the overflown area. This can provide a very detailed view of the vegetation canopy topography; however, the internal structure of the canopy is difficult to reconstruct because data from the canopy interior are sparse (Dubayah *et al.* 2000).

Recently, LIDARs have been developed that are optimized for the measurement of vegetation (Blair *et al.* 1994, Blair *et al.* 1999). These systems have larger footprints (5- to 25-m diameters) and are fully waveform digitizing, meaning that the complete reflected laser pulse return is collected by the system. LIDAR remote sensing using waveform digitization records the vertical distribution of surface areas between the canopy top and the ground. For any particular height in the canopy, the waveform denotes the amount of energy (i.e., the amplitude of the waveform) returned for that layer (Dubayah *et al.* 2000). The amplitude is related to the volume and density of canopy material located at that height (fig. 1).

Subcanopy topography, canopy height, basal area, canopy cover, and biomass have all been successfully derived from large-footprint LIDAR waveform data in a variety of forest types (Drake *et al.* 2002a, Dubayah and Drake 2000, Hofton *et al.* 2002, Hyde *et al.* 2005, Lefsky *et al.* 1999, Means *et al.* 1999, Peterson 2000). For example, results from Hofton *et al.* (2002) show that large-footprint LIDAR measured subcanopy topography in a dense, wet tropical rainforest with an accuracy better than that of the best operational digital elevation models (such as U.S. Geological Survey 30-m DEM products). Means *et al.* (1999) used large-footprint LIDAR to recover mean stand height ($r^2 = 0.95$) for conifer stands of various ages in the Western Cascades of Oregon. Drake *et al.* (2002a) found that metrics from a large-footprint LIDAR system were able to model plot-level biomass ($r^2 = 0.93$) for a wet tropical rainforest. Dubayah *et al.* (2000), Dubayah and Drake (2000), and Lefsky (2002) provide a thorough overview of forest structure derived using large-footprint LIDAR. In sum, LIDAR is a proven method for deriving many characteristics relevant to forest management. LIDAR data have also been used to measure canopy structure relevant to fire behavior modeling

Figure 1.—*Illustrations showing sample waveforms for different cover types in the Sierra Nevada. (a) Waveform return from bare ground—no canopy return. (b) Waveform return for a short, dense forest stand. The canopy return blends in with the ground return. (c) Waveform return for a tall, dense forest stand. The waveform shows layering in the canopy and the ground return is clearly defined. (d) Waveform return for a tall, sparse forest stand. The waveform shows a distinct upper canopy layer and a layer of low-lying vegetation that mixes in with the ground return. The stand diagrams were created with the Stand Visualization System based on field measurements.*

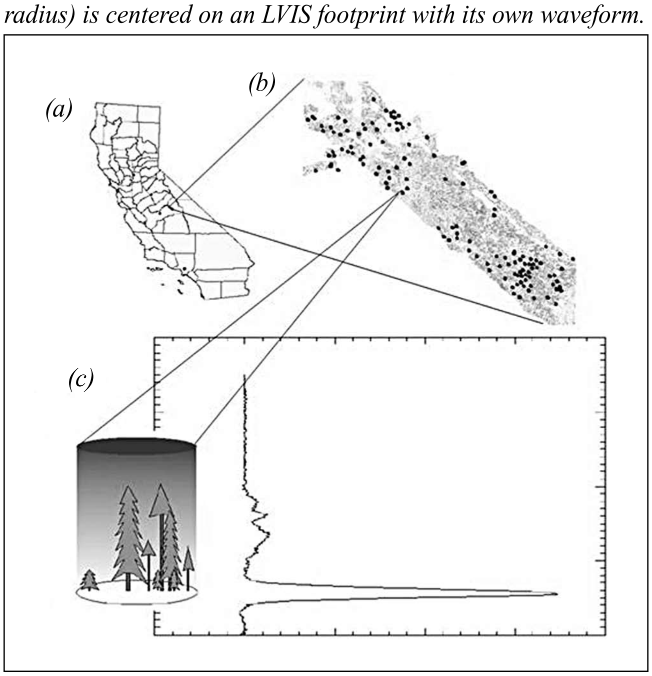


(Andersen *et al.* 2005, Morsdorf *et al.* 2004, Riaño *et al.* 2003, Riaño *et al.* 2004, Seielstad and Queen 2003) and this specific application is explored in the remainder of this paper.

Study Site and Data Collection

The study area is located in the Sierra National Forest in the Sierra Nevada mountains of California near Fresno (fig. 2) and covers a wide range of vegetation types (e.g., fir, pine, mixed conifer, mixed hardwood/conifer, meadow), canopy cover, and elevation. Common species of the region include red fir (*Abies magnifica* A. Murr.), white fir (*Abies concolor* (God. & Glend.) Hildebr.), ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.), Jeffrey pine (*Pinus jeffreyi* Grev. & Balf.), and incense cedar (*Libocedrus decurrens* Torr.), among others. Canopy cover can range from completely open in meadows or ridge tops to very dense, especially in fir stands. The study area extends over nearly 18,000 ha of U.S. Department of Agriculture Forest Service and privately owned lands. The topography varies considerably with some areas characterized by very steep slopes and an elevation range between approximately 850 and 2,700 m.

Figure 2.— *Schematic showing the location of the study site, plot distribution, and footprint-centered plot design. (a) Locator map of the study area in the Sierra Nevada, northeast of Fresno. (b) The study area was delimited by swaths of LVIS data covering the region. The combined area of the swaths is approximately 25 by 6 km. (c) The individual plots were colocated with the LVIS footprints. Each circular plot (15-m radius) is centered on an LVIS footprint with its own waveform.*



LVIS = Laser Vegetation Imaging Sensor.

The LIDAR data used in this study were collected by the Laser Vegetation Imaging Sensor (LVIS) (Blair *et al.* 1999). LVIS is a large-footprint LIDAR system optimized to measure canopy structure characteristics. LVIS mapped a 25- by 6-km area of the Sierra National Forest in October of 1999 in a series of flight tracks (fig. 2). Flying onboard a NASA C-130 at 8 km above ground level and operating at 320 Hz, LVIS produced thousands of 25-m diameter footprints at the surface.

Field data were collected in the summers of 2000–02 in the Sierra National Forest. Circular plots were centered on LIDAR footprints and measured 15 m in radius. The 15-m radius was chosen to ensure complete overlap with the LVIS footprint and to account for trees located beyond the 12.5-m radius of the footprint with crowns overhanging the footprint. Within these plots all trees over 10-cm diameter at breast height (d.b.h.) (diameter at breast height) were sampled. Measurements included tree height, height to partial crown, partial crown wedge angle, height to full crown, four crown radius measurements, and distance and azimuth relative to the plot center. Tree crown shape and species were also recorded.

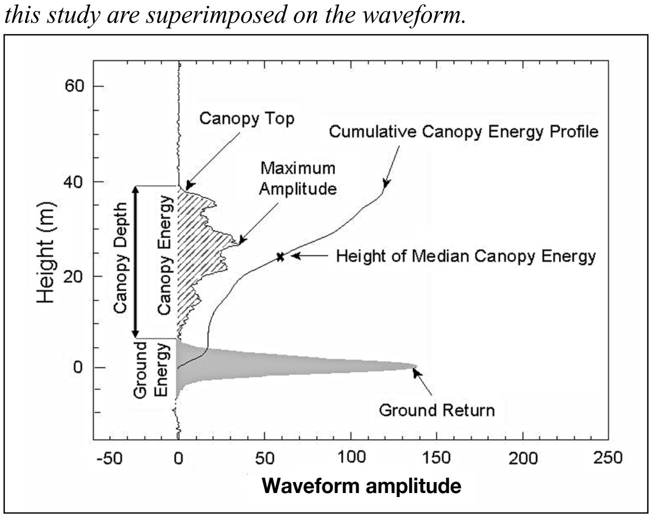
Derivation of CBD and CBH

The data from the 135 plots were used to calculate field-based CBD according to an inventory-based method. The original methodology was presented in Sando and Wick (1972) and relied on conventional field-sampled data (e.g., height, d.b.h., stem count density) to derive quantitative observations of canopy fuels. This method was subsequently modified for inclusion in Fire and Fuels Extension to the Forest Vegetation Simulator (Beukema *et al.* 1997). As described by Scott and Reinhardt (2001) a vertical profile of bulk density is derived by first calculating the foliage and fine branch biomass for each tree in the plot, then dividing that fuel equally into 1-foot (0.3048-m) horizontal layers from the base of the tree's crown through to the maximum tree height and finally summing the fuel loads contributed by each tree in the plot for all 1-foot segments. CBD is estimated by finding the maximum of a 4.5-m deep running average for the horizontal layers of CBD. CBH is typically defined as the height in the profile at which the CBD reaches a predetermined threshold value. In this study, CBH is defined as the height in the profile at which the bulk density equals or exceeds 0.011 kg/m^3 (Scott and Reinhardt 2001).

CBD and CBH were derived from LIDAR data for waveforms that were coincident with the study's field plots. This process involved several steps. First, LIDAR metrics were identified as potential predictors based on previous work deriving other biophysical characteristics from waveform data such as canopy cover, basal area, and biomass. The LIDAR metrics selected were canopy height (HT), canopy height squared (HT^2), canopy energy (CE), canopy energy/ground energy ratio (CE/GE), lowest canopy return (L), canopy depth (D), peak amplitude (MAX), and the height of median cumulative canopy energy (HMCE) (fig. 3).

Second, individual waveforms were normalized by dividing the energy present in each waveform bin (representing the energy returned for each vertical resolution unit, in this

Figure 3.—*Schematic of an individual LIDAR waveform showing LIDAR metrics. A pulse of laser energy reflects off canopy (e.g., leaves and branches) and the ground beneath, resulting in a waveform. The amplitudes of individual peaks in the waveform are a function of the number of reflecting surfaces at that height. The different LIDAR metrics used in this study are superimposed on the waveform.*



case approximately 30-cm deep) by the total energy in the waveform. The normalization process accounts for flight-to-flight as well as footprint-to-footprint variations in energy in the waveform, caused, for example, by flying at day versus night or by the incident angle of the laser beam. Normalization allows for easier comparison of waveform-derived metrics.

Third, the waveform metrics listed above were calculated for each of the normalized waveforms. HT was determined by subtracting the range to the ground (defined as the midpoint of the last peak) from that of the first detectable canopy return above noise. HT^2 is the squared value of HT. CE and GE are derived by separating the waveform into a canopy portion and a ground portion and then summing the bin values for those portions of the waveform. L is the height of the bottom of the canopy portion of the waveform. D is the vertical extent of the canopy portion of the waveform. MAX is the peak amplitude value in the canopy portion of the waveform. HMCE is the height at which the cumulative energy in the canopy portion of the waveform reaches the 50th percentile. Several additional metrics were derived to predict CBH from the cumulative canopy energy profile. The additional LIDAR-derived CBH metrics include the 0.5th-, 1st-, 5th-, and 10th-percentile heights of the cumulative canopy energy.

A transformation was also applied to the LVIS waveforms. Some previous studies (Lefsky *et al.* 1999, Means *et al.* 1999) have maintained that LIDAR waveform data need to be adjusted to correct for shading of lower foliage and branches by higher foliage and branches. This adjustment consists of applying an exponential transform to the waveform (modified MacArthur-Horn [1969] method) and is described in detail in Lefsky *et al.* (1999). The transform has the effect of increasing the amplitude of the waveform return from the lower part of the canopy.

Once the LIDAR metrics were calculated, they were used as explanatory variables in multiple linear regression analyses to determine which set of metrics best predicted CBD and CBH. Separate regression equations were derived for different vegetation types. The vegetation type categories used in this study were red fir, white fir, ponderosa pine, miscellaneous pine (comprised of Jeffrey pine, sugar pine, and lodgepole pine), Sierra mixed conifer, mixed hardwood conifer/mixed hardwood, and meadow/bare ground. Because the number of plots in two of the vegetation classes (white fir and ponderosa pine) was small, some explanatory variables were dropped out of the regression equations for these classes. Stepwise regression techniques were used to determine which variables should be dropped because they had relatively low explanatory power. The same suite of LIDAR metrics were recalculated from the waveforms once the modified MacArthur-Horn transformation was applied. The metrics derived from the transformed waveforms were then used as variables in the same series of regression analyses for the different vegetation types as described above.

The LIDAR-predicted and field-derived CBD compared rather well. The r^2 value of 0.71 ($p < 0.0001$, root square error (RSE) = 0.036) is based on the correlation between the collective observed and predicted estimates of CBD. The regression analyses were then repeated using the transformed LIDAR data. This dropped the r^2 value to 0.67. The comparison between the LIDAR-based and field-based estimates of CBH is also rather good. For CBH, the regression model was improved when using the LIDAR metrics derived from the transformed waveform. The r^2 using the transformed data was 0.59 ($p < 0.0001$, RSE = 0.573) as compared to an r^2 of 0.48 using the metrics from the original waveform. Again, the reported r^2 for the CBH derivation is based on the correlation between the collective observed and predicted estimates.

The differences between the various vegetation-type specific regression models most likely reflect structural differences among the various forest stands included in the study. For most of the vegetation types the relationship between the LIDAR-metrics and field-derived CBD is fairly strong (i.e., $r^2 > 0.6$), the exception being the mixed conifer class ($r^2 = 0.3811$), where, in the higher range of values, the predicted CBD was lower than the observed CBD. The greatest error in predicting CBD occurred in stands characterized by a dense canopy layer of mid and understory trees with a few dominant tree crowns interspersed. The equations used to calculate CBD from the field data could be overestimating the canopy loads of the codominant and subdominant trees. The trees in denser stands have crowns that are often irregular in shape, meaning that actual fuel load for these trees is likely much lower than predicted when a regular shape is assumed in an algorithm. In addition, there is considerable variation in crown shape among species. White fir, for example, tends to be rather cone shaped while sugar or ponderosa pine crowns are more parabolic. Furthermore, the field-based estimates of CBD only consider the fraction of fuels made up of fine (e.g., foliar) material rather than the total biomass in the plot, which is recorded by the LIDAR waveform.

We believe that at least part of the error in the CBH derivation can be attributed to the fact that trees less than 10 cm d.b.h. were not sampled in the field. For certain plots (especially mixed conifer) this excludes a significant number of smaller stems and could lead to an erroneously high derivation of CBH from the field data. The omission of smaller trees could cause the amount of material assigned to the lower part of the density profile to be less than it should be.

Other factors such as slope and varying footprint size (due to changes in surface elevation) were explored to determine if they might be a source of error for both the CBD and CBH LIDAR derivations. No relationship between the residuals of the regression and these factors could be discerned, however.

Interestingly, the results of the CBH regression analyses show that LVIS metrics that were derived from waveforms transformed using the modified MacArthur-Horn method were better able to predict CBH ($r^2 = 0.59$) than the untransformed metrics ($r^2 = 0.48$). The transform increases the amplitude of the return in the lower portion of the waveform and therefore it has a greater impact on the metrics derived from that part of the waveform. The overall effect of the transform was to lower the height of several metrics. This caused the correlation between predicted and observed CBH at the shorter end of the range (0–2 m) to improve, thereby also improving the overall r^2. The poorest results were again for the mixed conifer class.

FARSITE Simulations

The fire behavior model used in this study is the Fire Area Simulator (FARSITE, Finney 1998). FARSITE is a Geographic Information System-based fire behavior model in common use with agencies throughout the Unites States. In all, FARSITE has eight input layers (Finney 1998). The first five (elevation, slope, aspect, fuel model, and canopy cover) are all that are needed to simulate surface fires. The last three (canopy height, CBD, and CBH) are needed to model crown fire behavior.

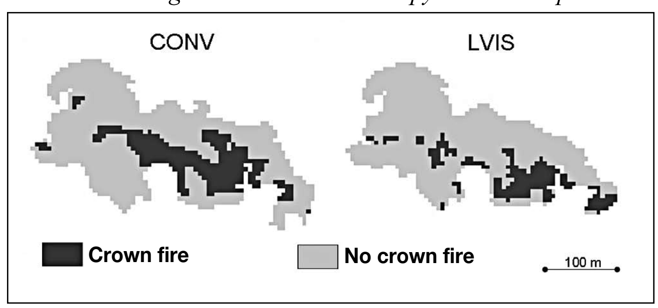
Once the regression models for CBD and CBH were developed they were used to derive CBD and CBH from all of the LVIS waveforms in the study area. First, the required LIDAR metrics were calculated from the waveforms. Then the LVIS data were classified by land cover type and the vegetation-type specific regression models were applied. This created point data of CBD and CBH for the entire study area. These point data were then gridded into 25-m raster layers using ArcInfo. These grids are hereafter referred to as LVIS grids. An inverse difference weighting (IDW) technique was used for gridding and to compensate for gaps in the data caused by irregularities in the flight lines. To complete the set of canopy structure data needed to run FARSITE, an LVIS-derived canopy height grid was also created. Hyde *et al.* (2005) validated the LVIS canopy height measurement for the Sierra Nevada study site. For this study, the height data were also gridded to 25 m using the IDW technique.

Once the LVIS grids were created they were first compared to canopy height, CBD, and CBH data layers that were generated using conventional methods, referred to hereafter as CONV grids. The CONV grids were only available for a smaller part of the study area—at the far southeastern end of the flight lines. Therefore, the LVIS grids were clipped to match the extent of the CONV grids. There are obvious differences between the two sets of data. Of particular note is the increased spatial heterogeneity contained in the LVIS grids relative to the CONV grids.

FARSITE was then run twice: once using the LVIS canopy structure grids and once using the CONV input grids. All other spatial inputs were kept constant as was the point of ignition. The wind and weather input data used for the two model runs were representative of a dry, warm day and the simulated duration was set to 40 hours.

Figure 4 shows the output (crown fire/no crown fire status) for the two model runs. The extent of the fire spread is very similar for both of the model runs. Though occurring in similar locations, the occurrence of crown fire as discrete clusters in the LVIS output is very different from the larger, continuous areas of crown fire shown in the CONV output grid. In the LVIS output grid the crown fire clusters appear to be associated with the presence of higher CBD values and lower CBH values, which are assumed to promote the spread of fire to the canopy. Future research will explore not only the effect of increasing or decreasing the canopy structure values on model outputs but also the effect of increased spatial heterogeneity in the input layers.

Figure 4.—*FARSITE crown-fire/no-crown-fire outputs for two model runs using LVIS and CONV canopy structure inputs.*



CONV = conventional; LVIS = Laser Vegetation Imaging Sensor.

Conclusions

LIDAR systems of different types have had success in recovering forest structure characteristics for a variety of vegetation types in a comparatively simple and direct manner. In recent years LIDAR has become recognized as a valuable remote sensing tool for forest inventory and structure mapping and is gaining in use for informing forest management decisionmaking. Because of its ability to measure canopy structure both horizontally and vertically, LIDAR has potential for providing the type of forest structure required for fuels estimation and fire behavior modeling. The results of this paper demonstrate that waveform data from a large-footprint system may provide the spatially explicit forest structure needed for fire behavior modeling. We will continue to explore and improve on methods for deriving CBD and CBH from LIDAR. One option to be considered is to incorporate various remote sensing data from other sensor types into a fusion-based approach for deriving the canopy structure variables. These results also have implications for remote-sensing-based inventory at larger scales. ICESAT and other near-future space-based LIDAR systems are or will likely be large footprint and waveform digitizing. Though these are not imaging systems, the global samples of three-dimensional structure that they will provide can be incorporated into forest inventory.

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Area-Independent Sampling for Basal Area

James W. Flewelling[1]

Abstract.—An unbiased direct estimator of total basal area for a stand (Flewelling and Iles 2004) is reviewed. Stand area need not be known. The estimator's primary application is in conjunction with a randomly positioned grid of sample points. The points may be centers for horizontal point samples or fixed-area plots. The sample space extends beyond a stand's boundary, though only trees within the boundary are tallied. Measured distances from sample trees to stand boundaries are not required.

Introduction

Most methods of estimating basal area for a stand are area dependent in that they are the product of an estimated basal area per hectare and a known or estimated area. A major concern in applying these methods is the avoidance of edge bias. Such bias can arise when the distance from a tree to the stand's edge affects its sampling probability and the estimator is not able to fully account for the varying probabilities. Unbiased estimators do exist, but are difficult or impossible to apply with complex stand boundaries. Methods which adjust for edge bias are reviewed by Schreuder *et al*. (1993). The "walkthrough" solution (Ducey *et al*. 2004) offers an operationally simpler alternative to the mirage method of Schmid-Haas (1969, 1982). The foregoing methods confine sample points to being within the stand boundaries. Schmid-Haas (1982: 264) also suggested a substantively different approach to the edge bias problem: "One possibility is obvious; sample plots whose centre lies outside the area under investigation are also included in the sample, care being taken to ensure that the probability density for such plot centers is the same as for those within the (stand) area." That concept is embodied in the toss-back method by Iles (2001) and in the area-independent method reviewed here.

Sample Protocol and Estimators

The sampling protocol addressed here is that of a regular grid of sample points. The orientation of the grid is predetermined. A starting point is randomly located within an area corresponding to a grid cell, and the sample points extend indefinitely to areas inside and outside the stand. Other protocols are addressed by Flewelling and Iles (2004). Each sample point may be the center of a fixed-area plot or a horizontal point sample. No distinction is made between sample points that fall inside the stand, and those that fall outside the stand. At each point, only the sample trees within the stand are considered.

For fixed-area plots, the estimator of total basal area is

$$\hat{G} = A_g \times \Sigma\, g_i \qquad (1)$$

where A_g is the area per grid point as established by the grid spacing, g_i is the basal area per hectare on the i^{th} sample plot, and the summation is over all sample plots. For horizontal point samples, the estimator is

$$\hat{G} = T \times F \times A_g \qquad (2)$$

where F is the basal area factor and T is the total tree count, summed over all sample points. Modified versions of horizontal point sample may use several different basal area factors depending on tree size, and may invoke fixed-area plots for certain ranges of tree sizes. The generalized estimator for these modified samples is

$$\hat{G} = A_g \times \sum_{\text{points}} \sum_{\text{trees}} F_v \qquad (3)$$

where F_v is a variable basal area factor, the first summation is over all sample points, and the second summation is over all the trees at a particular sample point. For tree sizes being sampled with an angle gauge, F_v is the basal area factor of the gauge. For

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tree sizes being sampled with fixed area plots, F_v is the ratio of the tree's basal area to the plot area.

Discussion

The most likely application of the area-independent estimator is for stands where the area is unknown. An example is in the determination of the basal area of that portion of a stand which excludes riparian corridors whose extent and area are unknown.

The appeal of the area-independent estimator is not limited to stands with unknown areas. This estimator and the toss-back method both are unbiased for any stand geometry and are relatively easy to use. The exact delineation of the stand boundary in the vicinity of the sample points is not required. Independent random errors in the location of sample points would seem not to introduce bias. This lack of sensitivity to location error is not shared by methods that limit sample points to a stand's interior; this feature could be used to advantage by using hand-held Geographic Positioning System units to navigate to sample points. An operational difficulty of the method is that some of the sample points outside of the stand may be inaccessible; for those sample points, the selection of sample trees will be much more difficult than making a prism sweep.

The Forest Inventory and Analysis (FIA) program is generally not concerned with individual stands. Instead, forest attributes are sought within populations such as States or counties, and by various condition classes such as forest cover type. The FIA's grid of ground plots have a constant sampling density and could be analyzed with the area-independent estimator to make unbiased estimates of basal area by cover type. The FIA sampling program, however, is multiphase; the first phase measures or estimates forest area (Reams *et al*. 2005), and could potentially subdivide the forested area into condition classes. Hence, area-dependent estimators for basal area and other attributes are being used; these should be presumed to have lower variance than would the area-independent estimators.

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On Estimation in *k*-tree Sampling

Christoph Kleinn and František Vilčko[1]

Abstract.—The plot design known as *k*-tree sampling involves taking the *k* nearest trees from a selected sample point as sample trees. While this plot design is very practical and easily applied in the field for moderate values of *k*, unbiased estimation remains a problem. In this article, we give a brief introduction to the history of distance-based techniques in forest inventory sampling, present a new and simple approximation technique for estimation, and describe how to eventually develop a design-unbiased estimator. This article draws on two manuscripts that were recently published (Kleinn and Vilčko 2006a, Kleinn and Vilčko 2006b), in which more details are elaborated.

Introduction

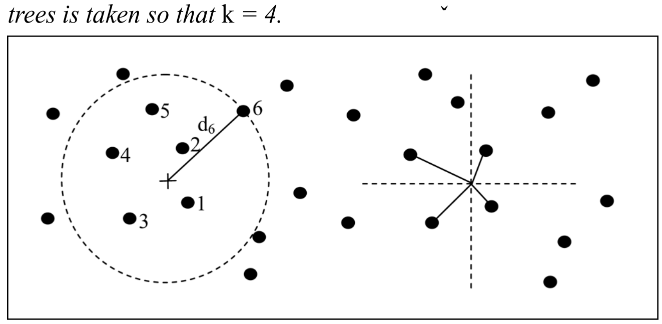
The plot design known as *k*-tree sampling, in which from a sample point the *k* nearest trees are taken as sample trees, is a practical response design if *k* is not too big. We call this approach here "classical *k*-tree sampling" to distinguish it from variations such as the point-centered quarter method (fig. 1) or T-square sampling. (e.g., Krebs 1999).

Estimation for *k*-tree sampling is frequently done in a design-based manner with expansion factors that "expand" the per-plot observation to per-hectare values. One of the frequently used estimation approaches for classical *k*-tree sampling is to use the distance to the *k* nearest tree as radius of a virtual circle plot and calculate a per-plot expansion factor. Another approach is to take the mean distance to the *k* tree from all *n* sample points to calculate an overall expansion factor to be applied to all *n* sample points.

It had long been known, however, that *k*-tree sampling is not an unbiased estimator, but leads on average to a systematic overestimation of the population parameters. From simulation studies on different populations, Payandeh and Ek (1986) suggest that the relatively rare application of *k*-tree sampling in forest inventory has to do with the lack of an unbiased estimator. While some authors see minor problems regarding application of *k*-tree sampling because it is practical and because the bias in the commonly used estimators was found to be modest in many cases (Krebs 1999), others tend to advise against it when unbiased estimation is an issue because it violates basic principles of statistical sampling (e.g., Mandallaz 1995, Schreuder 2004).

Empirical approaches for estimation have been investigated and various techniques are available. One may distinguish two major groups of estimators: (1) design-based estimators that attempt to find from the *k*-tree sample a suitable plot size that allows good extrapolation, and (2) approaches under model assumptions in which estimation depends on the spatial pattern that needs to be captured and described from the sample. Picard *et al.* (2005) give a comprehensive overview of many of these approaches.

Figure 1.—*Two strategies of* k*-tree sampling. Left: the "classical"* k*-tree plot, in which the* k *trees nearest to a sample point (+) are taken as sample trees. Right: the point-centered quarter method, in which the space around the sample point is subdivided into four quadrants; in each of those the nearest trees is taken so that* k *= 4.*



Source: Kleinn and Vilčko (2006a).

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In this article, we give a brief overview of the history of *k*-tree sampling and present a new and simple empirical approximation technique for the classical *k*-tree plot that is elaborated in Kleinn and Vilčko (2006a). The way toward designing unbiased estimation is shown in the last section. More details about that approach are in Kleinn and Vilcko (2006b).

On the History of *k*-tree Sampling

Loetsch *et al.* (1973) state that the first use of distance techniques in forestry applications was mentioned in the book "Forstmathematik" (forest mathematics) by König (1835). König (1835), in fact, had recognized and elaborated with empirical results that stand attributes such as number of stems and basal area depended on inter-tree distances. He developed a model (presented as a table) with which he determined basal area per hectare as a function of mean stand diameter and average distance between trees. This model obviously was not a point-to-tree distance technique, however, but a tree-to-tree distance technique. These tree-to-tree distance techniques were further developed for forest inventory in the 1940s and 1950s (among others, Bauersachs 1942, Köhler 1952, Weck 1953). Essed (1957) analyzed these tree-to-tree distance techniques and explicitly pointed to the problem of systematic overestimation.

According to a literature review, Stoffels (1955) was among the first to elaborate point-to-tree distance sampling in forest inventory. His target attribute was number of stems per hectare (density). He investigated three-tree sampling and recommended to count tree number three only half (meaning that in the three-tree sample there were actually only two and a half trees counted), which was a simple empirical way to attempt compensating for the then unexplainable systematic overestimation. In Germany, with the studies of Prodan (1968) and Schöpfer (1969a, 1969b), *k*-tree sampling was broadly introduced into practical application of forest management inventories. Those authors recommended $k = 6$ because they found it to be a practical number for application and good in terms of statistical performance. Prodan (1968) knew about the systematic overestimation with the simple expansion factor approach that became clear in simulation studies in test stands. To correct for that bias he recommended taking the attributes of the sixth tree only half because that tree was only half contained in the sample plot. While this ad-hoc approach is difficult to justify in theoretical terms, various simulation studies have shown that it works reasonably well under many conditions (Lessard *et al.* 1994, Payandeh and Ek 1986).

In general, *k*-tree sampling has not been as readily used for forest inventory as fixed area plots and relascope sampling. A number of recent applications have been found, however, many of them under difficult conditions in tropical forested landscapes: Hall (1991, Afromontane catchment forests); Lynch and Rusdyi (1999, Indonesian teak plantations); Sheil *et al.* (2003, East Kalimantan natural forests); and Picard *et al.* (2005, Mali savannah). The test data used for simulations in this present study come from the Miombo woodlands in Northern Zambia.

A New and Simple Technique for Estimation in Classical *k*-tree Sampling

The systematic overestimation of the expansion factor-based estimator for the classical *k*-tree plot has been described and illustrated early by Essed (1957). By taking the distance to the *k* tree as a radius of a virtual sample plot, one defines systematically the smallest possible circular sample plot for the contained *k* trees and, therefore, the largest possible expansion factor—which leads immediately to the observed systematic overestimation. Using the distance to the (k+1) tree as plot radius for a *k*-tree plot, the expansion factor (and therefore the estimations) would be smaller and thus lead to systematic underestimation.

If using the distance to the *k* tree as plot radius produces a systematic overestimation and the distance to the (k+1) tree causes a systematic underestimation, we may conclude that the "true" (i.e., adequate for estimation) circular plot radius must be in between.

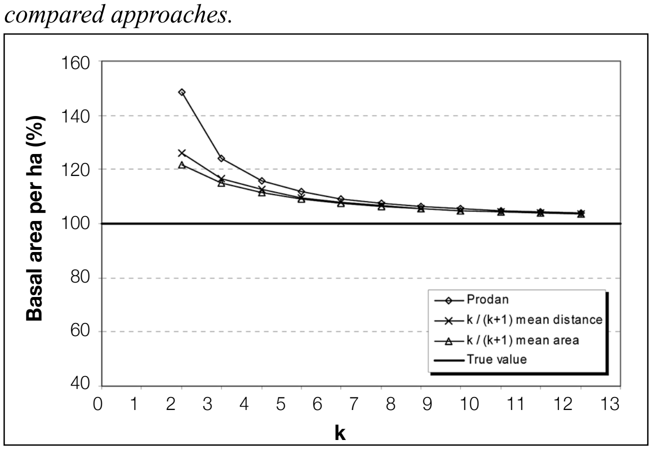
Our idea is simply to use an average plot size from the two distances to the k and k+1 tree, in which we tested two approaches of calculating the plot radius:

(1) The radius is calculated as arithmetic mean of the distances d_k to the k and d_{k+1} to the k+1 tree.

(2) The radius is calculated as geometric mean of the circular plot areas from $r = d_k$ and $r = d_{k+1}$. This may be geometrically interpreted as the arithmetic mean of the circle plots with radii d_k and d_{k+1}.

The bias of the these two approaches in comparison to Prodan's (1968) approach is given in figure 2, in which results of a simulation study using a tree map are shown. With all three estimators, a clear positive bias exists, which is, however, smaller for our two approaches, particularly for small values of k. For about k = 5 onward, the bias for the three approaches is about the same. We should mention here that Prodan (1968) presented his approach only for k = 6. We applied it here in a manner analogous to k =2..12. Approach (1), in which the plot radius is calculated from the arithmetic mean of d_k and d_{k+1}, produces consistently a smaller bias than approach (2), although the differences are small.

Figure 2.—*Bias of estimating basal area from* k*-tree plots with* k *= 2..12 with different estimators. The two approaches introduced here are contrasted to Prodan's (1968) approach in which the* k *tree is counted half so that the* k*-tree sample actually becomes a (*k*-0.5)-tree sample. While Prodan (1968) proposed that approach for* k *= 6 only, we applied it here to* k *= 2..12. The results are from simulations on a tree map from the Miombo woodlands in Northern Zambia. Our new approaches exhibit smaller bias, in particular for small values of* k*. For about* k *> 6, the bias is about the same for all three compared approaches.*



Source: Kleinn and Vilčko (2006a).

Of course, a simulation study on but one tree map is not an evidence of general superiority, but it may be an indication of promising performance. Kleinn and Vilčko (2006a) present additional simulations with other maps with different spatial patterns with similar results.

Seeing it from a practical point of view and in comparison to Prodan's (1968) approach, for the new approaches one must make one more measurement: the distance to the k+1 tree. This measurement adds some additional effort, because the k+1 tree must be determined. For relatively small values of k, however, this additional effort is expected to be small.

Toward a Design Unbiased Estimator

In Kleinn and Vilčko (2006b), the authors develop a design unbiased estimator for the classical k-tree plot. The approach draws on the inclusion zone concept, in which a polygon is drawn around each sample tree with the area of the polygon a measure for the inclusion probability of this particular tree. Once the inclusion probability of all sample trees is known, the Horwitz-Thompson estimator can be used to obtain an unbiased estimator.

The inclusion zone approach is closely linked to the infinite population approach (Eriksson 1995, Mandallaz 1991), also referred to as continuous population approach (Williams 2001). In these approaches, a forest area is considered an infinite population of sample points of which a subset is selected as a sample. That means that the dimensionless points are the sampling elements, and not trees or plot areas. The value that is being assigned to a dimensionless point comes from the surrounding trees. It is the plot design that defines how these trees around the sample point are to be selected. For fixed-area circle plots, for example, all trees up to a defined distance from the sample point are included. In relascope sampling, this distance is not constant but depends on tree diameter and basal area factor. In k-tree sampling it is the first, second, etc. k nearest tree to the sample point that are included and that determine the value assigned to this particular sample point.

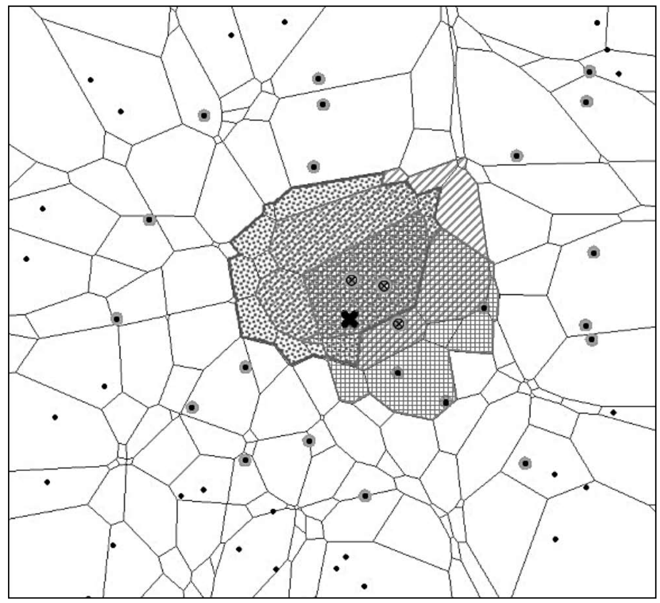
It is more instructive here, however, not to follow that described sample-point-centered approach, but to use a tree-centered approach (Husch *et al.* 1993), which leads immediately to the definition of inclusion zones. Around each tree we build an inclusion zone such that this particular tree is selected by a sample point if it falls into that inclusion zone. It is then obvious, by application of basic principles of geometric probabilities, that the area of this inclusion zone (divided by the total area of the inventory region) defines the probability of selection of that particular tree from which the inclusion probability also can be derived for probabilistic sampling approaches.

Size and shape of the inclusion zone is exclusively defined by the plot design that is being used. For fixed-area circular sample plots, the inclusion zones are circles centered around the trees and with the same size as the sample plot. In relascope sampling, inclusion zones are also circular but size is proportional to the tree's basal area.

To build an unbiased estimator for any plot design, it is sufficient to search for the individual inclusion zones of all sampled trees. Eventually, for *k*-tree sampling, that means that we must find, around an individual sampled "target" tree, the area in which a sample point that falls there has the target tree as nearest, second-nearest, etc. *k* nearest neighbor. For $k = 1$ the solution is simple; the searched inclusion zone polygon are the commonly known Voronoi diagrams or Dirichlet polygons, which have been used in different contexts in forestry (e.g., Lowell 1997, Moore *et al.* 1973, Overton and Stehman 1996).

In Kleinn and Vilčko (2006b), the authors elaborate on inclusion zones for $k > 1$. These inclusion zones contain the set of all points around the target tree for which this particular tree is either the first, second, etc. *k* neighbour. Those polygons are called higher order Voronoi diagrams. Okabe *et al.* (1999) describe approaches for their construction. To do so, the tree positions of neighboring trees must be known; i.e., mapped up to a certain distance. Figure 3 illustrates the approach for $k = 3$, depicting the inclusion zone for all three sample trees. In this case, the coordinates of 15 trees need to be mapped to determine this inclusion zone.

Figure 3.—*Inclusion zones for three trees in a* k*-tree plot for* k *= 3. The sample point is marked by x. The three circled small x's are the three nearest trees. The three differently hatched polygons are the inclusion zones for these trees. Tree positions are marked as dots. To determine the inclusion zones for the* k *= 3 trees, the positions of all trees marked with bold gray dots need to be known.*



Source: Kleinn and Vilčko (2006b).

Shape and size of the inclusion zone depends exclusively on tree positions and not on any attribute value of the target tree. That means that a considerable quantity of additional measurements needs to be done to be able to build the inclusion zones. The proper distance around the sample trees that these position measurements need to be done still has not been determined.

When the inclusion zones of all *k* sample trees are known, then also the inclusion *probabilities* are known, and the Horwitz-Thompson estimator is immediately an unbiased estimator. While application of the Horwitz-Thompson estimator is cumbersome for calculation, Valentine *et al.* (2001) suggest an easier way: one imagines that the tree-specific value of the target attribute is distributed evenly over the inclusion zone, thus forming a density that is constant over the entire inclusion zone. At a selected sample point, one observes the density values of all those inclusion zones that contain the sample point. The sum of these density values is the observation that is used at that point. Another simple approach for calculation would be the one that is commonly used in relascope sampling building on the tree-specific expansion factors.

Conclusions

The inclusion zone approach allows building a design-unbiased estimator (elaborated in detail in Kleinn and Vilčko 2006b). The inclusion zones in *k*-tree sampling are built as higher order Voronoi polygons. Their size and shape vary and depend exclusively on the position of the surrounding trees, a significant difference from inclusion zones of other plot designs. With respect to the expected precision, it is important to note that the size of the inclusion zone—and therefore the inclusion probability as well—is not proportional to any tree attribute. Therefore, it is expected that overall performance of *k*-tree sampling is inferior to other plot designs. This hypothesis, however, is currently being researched by simulation studies. With an unbiased estimator available, it is now possible for the first time to compare *k*-tree sampling to other plot designs, in which also for *k*-tree sampling an unbiased estimator can be used (e.g., Lessard *et al.* 2002, Payandeh and Ek 1986).

Whether our approach will be of relevance for practical field application depends on whether it will be possible to do the required tree mapping around the sample trees with a reasonable amount of effort. Such research is currently ongoing in the research group of the authors; from a selected sample point, polar coordinates of neighboring trees are determined by electronic compass and laser distance meter. The measurement devices are linked to a computer that calculates immediately the Voronoi polygons and indicates whether these polygons change when more and farther trees are included into the mapping; if the polygons do not change any more then tree mapping can be stopped.

It is likely, however, that approximations to estimation will continue to be of great practical relevance. Therefore, a simple approximation approach has been presented in the first half of this paper (elaborated in more detail in Kleinn and Vilčko [2006a]). In addition, it is a subject of research whether simple methods could approximately determine the size of the inclusion zones; for example, by simple regression modeling with the distance to the *k* trees being the independent input variables.

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Grid-Based Sampling Designs and Area Estimation

Joseph M. McCollum[1]

Abstract.—The author discusses some area and variance estimation methods that have been used by personnel of the U.S. Department of Agriculture Forest Service Southern Research Station and its predecessors. The author also presents the methods of Horvitz and Thompson (1952), especially as they have been popularized by Stevens (1997), and shows how they could be used to produce estimates of variance on the fly from plots with static expansion factors. The author also extends the ideas of Horvitz and Thompson to the Forest Health Monitoring ozone grid.

Introduction

Bayesian analysts speak of "prior" and "posterior" distributions. The prior distribution is the initial estimate, and the posterior distribution is the corrected estimate. In the Forest Inventory and Analysis (FIA), the prior estimate is called phase 1, and is based solely on the dot count (if photointerpreters are estimating land cover) or pixel count (if remote sensing data is used). The posterior estimate is called phase 2, and is based on phase 1 but corrected for field calls.

An example that demonstrates area estimation procedures is given in the supplement (FIA documentation 2005) to Bechtold and Patterson (2005).

The phase 1 data is shown in table 1.

Thus, the phase 1 estimate is an H x 1 vector **n**', where H is the number of strata, and its proportions in the H x 1 vector **w**. The field sites that are visited are held in an entirely different H x 1 vector **n**; in the context of this example, it is left to the field crew to decide how much of a plot is out of the population. The expansion factor— how much area a plot represents—is determined by A_T (114,000 acres for this hypothetical county), times n'_h divided by $(n'n_h)$, where h is the appropriate subscript of each vector.

The phase 2 data is shown in table 2.

Thus, the plot count is held in **N**, while the row-wise proportions are held in **W**. For example, the number of plots that were photointerpreted to be forest and verified to be forest by the field crew is 7.3. Given that the photointerpreter called a dot forest, we find that there was an 83.9 percent chance that the field crew agreed. Given that the photointerpreter called a dot nonforest, we find that there was a 13.2 percent chance that the field crew found it to be forested. Given that the photointerpreter called a dot census water, we find that

Table 1.—*Phase 1 data.*

Phase 1 strata	Photo dots/pixel count	Stratum weight	Plot count, excluding out of population	Phase 1 expansion factor $A_T n'_h / (n'n_h)$
1 (A) Forest land	$n'_1 = 75$	$w_1 = 0.5515$	$n_1 = 8.7$	7226.1663
2 (B) Nonforest land	$n'_2 = 44$	$w_2 = 0.3235$	$n_2 = 6.8$	5423.8754
3 (C) Census water	$n'_3 = 17$	$w_3 = 0.125$	$n_3 = 2$	7125
	$n' = 136$		$n = 17.5$	

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Table 2.—*Confusion matrix.*

	Forest	Nonforest	Census water	Total
Forest	$n_{1,1}$ = 7.3	$n_{1,2}$ = 0.4	$n_{1,3}$ = 1	$n_{1,\bullet}$ = 8.7
	$w_{1,1}$ = 0.839	$w_{1,2}$ = 0.046	$w_{1,3}$ = 0.115	
Photointerpretation nonforest	$n_{2,1}$ = 0.9	$n_{2,2}$ = 5.567	$n_{2,3}$ = 0.333	$n_{2,\bullet}$ = 6.8
	$w_{2,1}$ = 0.132	$w_{2,2}$ = 0.819	$w_{2,3}$ = 0.049	
Call census	$n_{3,1}$ = 0.7	$n_{3,2}$ = 0.5	$n_{3,3}$ = 0.8	$n_{3,\bullet}$ = 2
Water	$w_{3,1}$ = 0.35	$w_{3,2}$ = 0.25	$w_{3,3}$ = 0.4	
Total	$n_{\bullet,1}$ = 8.9	$n_{\bullet,2}$ = 6.467	$n_{\bullet,3}$ = 2.133	$n_{\bullet,\bullet}$ = 17.5

there was a 35 percent chance that the field crew found it to be forested. Thus, the phase 2 estimate is merely $\mathbf{p} = \mathbf{W}^T\mathbf{w}$, where matrix transposition is indicated by a superscript T, and one need only multiply by A_T to get **a**, the land area estimate.

Doing this calculation, we obtain $\mathbf{p}$ = [0.5493 0.3215 0.1292]^T, which in acres for this hypothetical county would be $\mathbf{a}$ = [62,620 36,648 14,732]^T. Now, suppose we check the Census Bureau's gazetteer for this hypothetical county and it tells us that there are 59,569,965 m^2 (14,720 acres) of water in the county, representing 0.1291 of the county's total area. Alas, a contradiction is raised: the estimate is ever so slightly different from its known value.

The Statistics Band's proposed resolution to this contradiction may be found in the statement, "If census water is known (i.e., subtracted from A_T), condition classes in census water would be treated as out of the population, the same as plots that straddle national boundaries" (FIA documentation 2005). This statement seems to imply that merely dropping the census water column from **N** or **W** is enough, without any adjustment necessary to w_3.

If we drop the census water column from **N** and then recompute **W**, we get $\mathbf{a}$ = [63,615 35,665 14,720]^T, almost a 1,000-acre increase in forest and nearly the same decrease in nonforest. Census water, however, should be filtered out of the **w** vector as well, although w_3 should not be reduced all the way to zero.

Thus, it is appropriate to ask, "What other prior distribution **v**, most consistent with the existing prior distribution **w**, when multiplied into the confusion matrix ($\mathbf{W}^T$), gives a posterior with the known amount of census water?"

First, the total weight (sum of the vector's components) should be 1. Second, the weighted sum of census water should equal the amount of census water in the gazetteer. Third, the weights for the unknown components should be proportional to their phase 1 estimates. The following are the formal equations:

$$v_1 + v_2 + v_3 = 1 \tag{1}$$

$$w_{1,3}\, v_1 + w_{2,3}\, v_2 + w_{3,3}\, v_3 = p_3 = 0.1291 \tag{2}$$

$$v_1 - \frac{w_1}{w_2} v_2 = 0 \tag{3}$$

where:

$w_{i,j}$ = the weights from the confusion matrix **W**, and

w_i = the weights from the phase 1 estimate **w**.

Solve this system and get $\mathbf{v}$ = [0.55169 0.32366 0.12465]^T, and now $\mathbf{p} = \mathbf{W}^T\mathbf{v}$ = [0.5494 0.3215 0.1291]^T, while $\mathbf{a}$ = [62,629 36,651 14,720]^T. If **w** differs greatly from **v**, there are at least three possibilities. First, field crews may have misidentified census water as noncensus water, or vice versa. Second, there might be bias in the phase 1 estimate. For instance, digital photography may not cover the population. Producers of digital orthophotos may have deliberately excluded vast areas of territorial sea. Third, the estimate could be biased if the centers of the phase 1 cells are different from the remainder of the phase 1 cells.

Expansion Factors

Once **a** is estimated, these acres must be apportioned to plots by expansion factors. In work done by personnel of predecessors to the Southern Research Station, plots were not stratified according to photointerpretation. If anything, they were stratified by ownership, but ownership was determined by the field crews. Typically, expansion factors were calculated by dividing the estimate of forested acres by the number of forested plots. Return to the original solution, where **a** = $[62{,}620\ 36{,}648\ 14{,}732]^T$. Now divide 62,620 by the number of forested plots (as determined by the field crew), 8.9, to get an expansion factor of 7,036 acres per plot. A plot such as #14 in Supplement 5, or any such plot, that is 60 percent forested would have an expansion factor of 7,036 x 0.60 = 4,221 acres for this particular condition.

Meanwhile, there are 36,648 acres of nonforested land, divided by 6.467 nonforested plots (as determined by the field crew), and this yields an expansion factor of 5,667 acres per plot. A plot such as #14 in Supplement 5 that is 40 percent forested, or any such plot, would have an expansion factor of 5,667 x 0.40 = 2,267 acres.

With the two conditions taken together, plot #14 is apparently 4,221 acres / (4,221 acres + 2,267 acres) = 65 percent forested. This percentage is called the *adjusted condition proportion*.

Horvitz-Thompson

Horvitz and Thompson (1952) produced a fairly elegant method that does not require use of an adjusted condition proportion. Their method of estimating area is equivalent to that of the Statistics Band. Plot #14 in Supplement 5 was photointerpreted as forest. The field crew found the plot to be 60 percent forested. Thus, the expansion factor for that condition is 60 percent times the phase 1 acres (7,226, shown in table 1), or 4,336 acres. The expansion factor for the nonforested condition is 40 percent, or 2,890 acres.

Meanwhile, plot #3 was photointerpreted to be nonforest. The field crew found it to be 90 percent forested and 10 percent nonforested land, so the condition expansion factors are 4,882 and 542 acres, respectively. Again, there is no need for an adjusted condition proportion. The price for this simplicity is that plots in different strata now carry a different number of acres.

The total number of forested acres is the same in both methods, but the number of acres assigned to any particular plot is likely to differ from method to method. Thus, the estimate of area will be unaffected, but because acreage expansion factors are allotted differently, the estimates of volume, biomass, and total basal area, for instance, will be different.

Estimated Standard Errors

If there are only two strata of unknown proportions, the following equation for the variance of forested area, $s^2(p_1)$, may be used. In McCollum (2003), it was derived from Goodman (1960, 1962), although this equation was used before then. It may also be derived from Schumacher and Chapman (1954).

$$s^2(p_1) \approx \frac{w_1 w_2}{n_{\bullet,\bullet}}(w_{1,1} - w_{1,2})^2 + \frac{w_1^2 w_{1,1} w_{2,1}}{n_{1,\bullet}} + \frac{w_2^2 w_{1,2} w_{2,2}}{n_{2,\bullet}} \qquad (4)$$

The Statistics Band offers two different formulae for variance estimation. One is for use with stratified random sampling:

$$v(\hat{A}_d) = \frac{A_T^2}{n}\left[\sum_h^H W_h n_h v(\bar{P}_{hd}) + \sum_h^H (1 - W_h)\frac{n_h}{n} v(\bar{P}_{hd})\right] \qquad (5)$$

where:

A_T = the total area of the area of interest (e.g., a county).
n = the total number of plots.
h = an index variable indicating the stratum.
H = the total number of strata.
W_h = the weight of stratum h (defined in this paper as w_h).
n_h = the number of plots in stratum h.
$\bar{P}_{hd}$ = the mean of the plot proportions in the domain of interest d assigned to stratum h.

The other formula was for use with double sampling for stratification:

$$v(\hat{A}_d) = A_T^2 \left\{ \sum_h^H \left(\frac{n'_h - 1}{n' - 1} \right) \frac{n'_h}{n'} v(\bar{P}_{hd}) + \frac{1}{n'-1} \sum_h^H \frac{n'_h}{n} (\bar{P}_{hd} - \bar{P}_d)^2 \right\} \tag{6}$$

where:

n' = the total number of pixels.

n'_h = the number of pixels in stratum h.

$\bar{P}_d$ = the estimated proportion of the population in the domain of interest d.

All other symbols are as defined in equation (5).

The Statistics Band points out that these formulas are difficult, if not impossible, to implement with static expansion factors and arbitrary subsets of plots.

Inclusion Probabilities

Horvitz and Thompson (1952) as well as Yates and Grundy (1953) have developed a couple of estimators that could handle the problem of calculating standard errors on a subset of plots with static expansion factors. It would be necessary to attach the inclusion probability and the joint inclusion probability for a plot of each stratum to the plot record.

The Horvitz-Thompson estimator for variance is:

$$v(\hat{Y}_{HT}) = \sum_{i=1}^{n} \frac{(1-\pi_i)}{\pi_i^2} y_i^2 + 2\sum_{i=1}^{n} \sum_{j>i}^{n} \frac{(\pi_{ij} - \pi_i \pi_j)}{\pi_i \pi_j \pi_{ij}} y_i y_j \tag{7}$$

The Yates-Grundy estimator is:

$$v(\hat{Y}_{YG}) = \sum_{i=1}^{n} \sum_{j>i}^{n} \frac{(\pi_i \pi_j - \pi_{ij})}{\pi_{ij}} \left(\frac{y_i}{\pi_i} - \frac{y_j}{\pi_j} \right)^2 \tag{8}$$

where:

π_I = the inclusion probability for plot I.

$\pi_{i,j}$ = the joint inclusion probability for plots i and j.

y_i = the measured value on plot k (expanded acres, volume, biomass, etc.).

Cochran (1977) observes that:

$$\sum_{i=1}^{n'} \pi_i = n \tag{9}$$

and

$$\sum_{j \neq i}^{n'} \pi_{ij} = (n-1)\pi_i \tag{10}$$

The fact that the inclusion probabilities and the joint inclusion probabilities do not sum to 1 is difficult to grasp at first, but in the example, if there are n' pixels or neighborhoods of dots in the population, and n of them are sampled, the inclusion probability will on average be equal to n / n'.

To estimate inclusion and joint inclusion probabilities, some assumptions have to be made. It is simplest to treat the plot list as a random selection from the list of pixels. Thus, a plot is understood to be no larger than a pixel, and pixels are assumed to be independent. In reality, adjacent Landsat Thematic Mapper pixels are not independent; a subplot is about one-fifth the size of such a pixel.

Under these assumptions, inclusion probability for plot i in stratum h is:

$$\pi_i = \frac{q_{h(i)}}{n'_{h(i)}} \tag{11}$$

where $h(i)$ is a function assigning plot i to stratum h.

Joint inclusion probability for plot i in stratum h and plot j in a different stratum, k, is:

$$\pi_{i,j} = \frac{q_{h(i)}}{n'_{h(i)}} \cdot \frac{(q_{h(j)} - r)}{(n'_{h(j)} - t)} \tag{12}$$

For i and j in different strata, r will typically equal 0 (because no plot has been removed from the second stratum), and for i and j in the same stratum, r will typically equal 1. The simplest assumption for a model without replacement is that t = 0 for plots i and j in different strata, and t = 1 for plots i and j in the same stratum. This assumption produces the largest estimate of variance for Horvitz-Thompson and Yates-Grundy. This estimate can be improved on, however. There are 27 phase 1 dots per phase 2 cell, and it is known to which strata the dots belong. Thus, *t* can equal the number of phase 1 dots belonging to the same stratum as plot *j*.

Ozone Grid

Another use of the Horvitz-Thompson estimator would involve analysis of the current ozone data. The Horvitz-Thompson estimator is:

$$\hat{Y}_{HT} = \sum_{i=1}^{n} \frac{y_i}{\pi_i} \qquad (13)$$

For the 2002 field season, ozone symptoms were collected on an entirely different grid (Smith *et al.* 2001). The four strata were as follows:

Stratum 0: 1 ozone plot per 5,862,400 acres (one plot per 256/7 historic phase 3 cells).

Stratum 1: 1 ozone plot per 1,465,600 acres (one plot per 64/7 historic P3 cells).

Stratum 2: 1 ozone plot per 1,139,911 acres (one plot per 64/9 historic P3 cells).

Stratum 3: 1 ozone plot per 641,200 acres (one plot per 4 historic P3 cells).

Expansions and contractions of the grid are easy to do if the factors are of the form $T = h^2 + hk + k^2$; frequently used factors are T = 3 (h = 1, k = 1), 4 (h = 2, k = 0), and 7 (h = 2, k = 1).

There are 27 phase 2 plots per historic P3 cell. The current ratio is 16.0:1 in some States and 16.2:1 in others. (McCollum and Cochran 2005).

Stratum 0 included all areas that were < 7.5 percent forest, plus all areas that were > 90 percent pinyon-juniper, a species not sensitive to ozone. Stratum 1 included all areas of low-ozone risk. Stratum 2 included areas of moderate ozone risk. Stratum 3 included all areas of high-ozone risk.

With such a sample design, it is inappropriate to report results based on a raw plot count. A weighted average is far more appropriate. Stevens (1997) called a sample design similar to this one a multidensity, randomized-tesselation, stratified design. Inclusion probabilities could be calculated by dividing the number of ozone plots in each risk stratum by the number of phase 1 photointerpretation dots that fall in that stratum. If tabulating the number of phase 1 dots in each ozone risk stratum is impractical, then an alternative could be tabulating the number of phase 2 plots in each ozone risk stratum. If there is no difference between strata in terms of actual ozone risk and it is proper to use raw plot count for the ozone grid, then the sample design does not capture areas of ozone risk.

Conclusions

First, a retrieval system ought to be able to incorporate Horvitz-Thompson or Yates-Grundy variance estimators easily, although it is not clear that an ordinary user could construct either estimator. Other variance estimators may also be constructed on the fly.

Second, the author recommends against abandoning expansion factors, and in favor of keeping static expansion factors. Separate expansion factors will be required for inventory and remeasurement, and the old inventory plus the remeasurement will not equal the new inventory. Expansion factors should be based on the entire cycle. To get an unbiased estimate from one panel or one subcycle of data, the author points out that remeasurement data should be available, and it could be noted what plots have been dropped since the last cycle.

Third, the author recommends that census water be enumerated in the manner set forth in this paper.

Last, the author recommends that the ozone data be analyzed by stratum.

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New Methods for Sampling Sparse Populations

Anna Ringvall[1]

Abstract.—To improve surveys of sparse objects, methods that use auxiliary information have been suggested. Guided transect sampling uses prior information, e.g., from aerial photographs, for the layout of survey strips. Instead of being laid out straight, the strips will wind between potentially more interesting areas. 3P sampling (probability proportional to prediction) uses information not available prior to the survey (e.g., the quality of downed logs), for selection of substrates for species inventories. Then, the surveyor's judgments of the substrates' suitability for the species of interest are used as the base for selection. Initial studies have shown that these methods have a potential to improve the efficiency of surveys of sparse populations.

Introduction

Biodiversity-oriented surveys often need to survey objects that from, a sampling perspective, are sparse or rare, which is problematic because precision of estimates generally will be low unless large areas are covered. In traditional forest surveys, oriented towards variables of interest for timber production, systematically distributed plots have turned out to be a cost-efficient method. When sampling sparse objects, however, the walking time is a proportionally large part of the cost for the survey. In that case, plot-based methods tend to be inefficient because only a small area is covered by the sample and a relatively long time is spent traveling between plots. With a transect-based method such as a strip survey, a larger area is covered for the same walking distance, which should be more cost-efficient (Ståhl and Lämås 1998).

Due to the problems of sampling sparse objects, probability sampling methods are sometimes abandoned for purposive sampling. In these cases, satellite images, aerial photos, or different types of maps together with knowledge about species' preferences are used to select areas to survey. In the surveyed areas, surveyors use their knowledge of species' habitat and substrate preferences to search for the species of interest. Such use of auxiliary information is also useful in probability sampling, both in the design and in the estimation phase, to improve the precision of estimates (e.g., Thompson 1992).

This article presents an approach for sampling sparse objects in which the same type of information and knowledge that is used in purposive surveys is utilized but in a probability sampling context. The approach has two steps, which can be used together or independent of each other. In the first step, information from satellite images or aerial photos is used to improve the design of a strip survey. In the second step, the surveyor's knowledge of species' substrate preferences is used for a more efficient subsampling of substrates for species inventories. Step one is a new method called guided transect sampling (Ståhl *et al.* 2000) and step two is an existing method, 3P sampling (probability proportional to prediction), but with a new application (Ringvall and Kruys 2005). The idea behind the approach is to use probability sampling methods to replicate a skilled surveyor purposively seeking for the species of interest.

Guided Transect Sampling

In the first step, information that can be obtained prior to the survey is used. For example information obtained from satellite images or aerial photos can be available and used at different scales. For example, if information is available at a stand scale it can be used to stratify stands and sample the

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more interesting strata more frequently. If the information is available at a pixel level, it can be used in a plot-based design (at least theoretically) for stratification of pixels. For sparse objects, however, it is probably most efficient to use all time in the forest to actually survey, which means using a transect-based method. Guided transect sampling (GTS) is one way of using auxiliary information with a high spatial resolution in the design of transect-based surveys.

An overview of the method is given in figure 1. Before the survey, the whole area is divided into a grid cell system with cells of some certain size. For each cell, a covariate value is obtained with help of remote sensing. The covariate is some variable that is related to the object of interest. In the first stage, wide strips are selected in the area to be surveyed, for example, with simple random sampling. Inside each selected wide strip a transect is selected across the strip by successively selecting one grid cell in each column. The selection of this survey line can be made in different ways, but the general idea is that it is in some way based on the covariate values in each grid cell. Some straightforward alternatives will later be described. A strip survey is then conducted along the selected line. It should be a continuous survey but it is so far approximated by a survey of the entire grid cells selected. Instead of being laid out straight, the strip will wind between the potentially more interesting areas.

The total of the quantity of interest in each selected first stage strip can be estimated with a Horvitz-Thompson estimator as

$$\hat{Y}_i = \sum_{j=1}^{n_i} \frac{y_{ij}}{\pi_{ij}}$$

Where:

n_i = the number of sampled grid cells in first stage strip i.

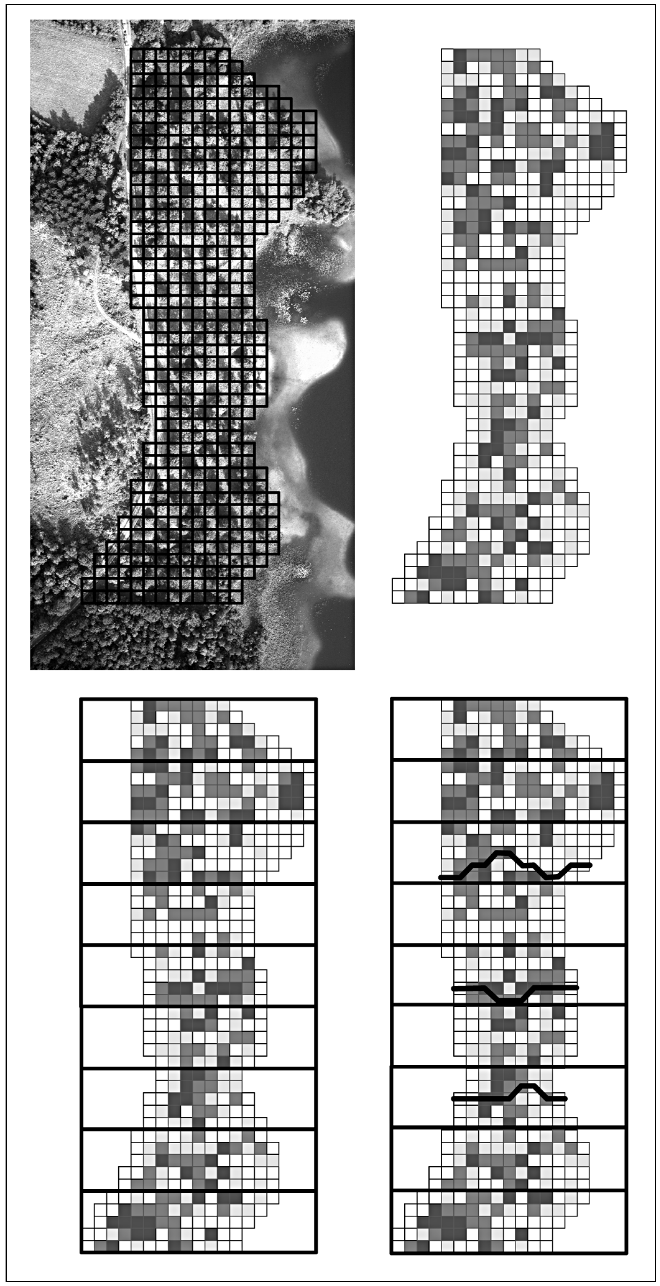
y_{ij} = the value of the variable of interest in grid cell j, first stage strip i.

π_{ij} = the inclusion probability of this grid cell.

The inclusion probabilities depend on how the second stage selection of the survey strip is carried out. The covariate information can be further used for estimation purposes by using a generalized ratio estimator

$$\hat{Y}_{iR} = X_i \frac{\hat{Y}_i}{\hat{X}_i}$$

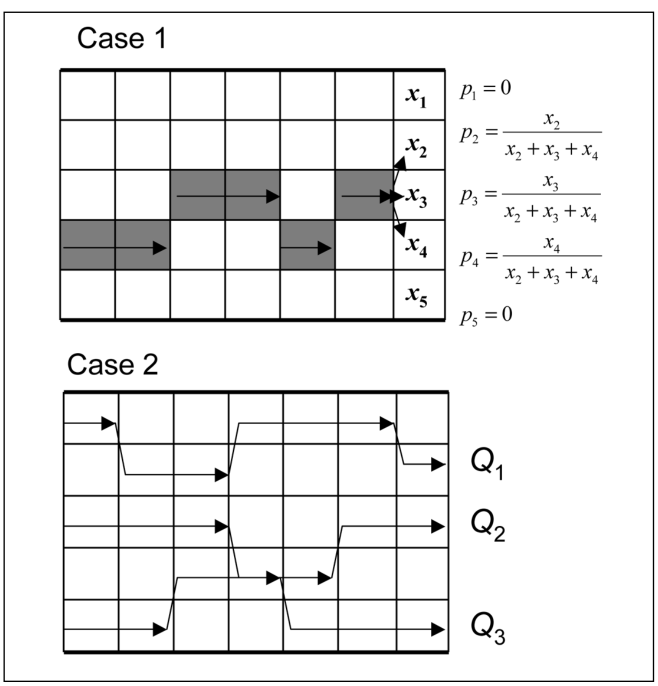
Figure 1.—*An overview of guided transect sampling. Prior to the survey, the area of interest is partitioned into a grid cell system (top left). For each grid cell a covariate value is assessed (top right). In the first stage, wide strips are randomly selected (bottom right), and in the second stage, survey strips are selected within the selected first stage trips by successively selecting one grid cell in each column based on the covariate data.*



where X_i is the total of covariate values in first stage strip i and $\hat{Y}_i$ and $\hat{X}_i$ are the Horvitz-Thompson estimator of the total of the variable of interest and of the covariate variable, respectively. How estimates are made for the whole area of study depends on how first stage strips are selected. For more details about estimation, variances, and derivation of inclusion probabilities see Ståhl *et al.* (2000).

Selecting the transect within the selected first stage strips can be done in different ways. This selection is referred to as the strategy for guidance since it can be seen as it is guided by the covariate information. Two straightforward alternatives for the strategy of guidance are shown in figure 2. With case 1, transitions are made to one of the neighboring cells in the next grid cell column. The selection of the grid cell to enter is made with probability proportional to the covariate values in the neighboring cells in the next column. The inclusion probability for a particular grid cell will depend both on the covariate value in the grid cell and its neighboring cells in the same column but also on the inclusion probabilities in the neighboring grid cells in the previous column so when calculating inclusion probabilities, recursive calculation will be needed. This strategy for guidance is rather short-sighted because at each step only the covariate information in the next column is used. Instead case 2 might be a better use of the covariate information. In this case, many transects are first simulated with transitions between grid cells made as in case 1; i.e., with probability proportional to the covariate values in the neighboring cells. For each simulated transect the covariate values in all grid cells passed are summed giving a sum Q for each transect. One whole transect is then selected with probability proportional to the sum of covariate, the Q-value. The inclusion probability for a particular grid cell will then be the sum of the Q-values for all transects that pass that particular grid cell divided by the sum of the Q-values for all transects simulated. With this strategy, transects that passes many interesting cells will have a higher probability of being selected. Case 1 in this article is equal to case 1 in Ståhl *et al.* (2000). Case 2 in this article is similar to case 3 in Ståhl *et al.* (2000), but with the difference that the probability of transition to a neighboring grid cell is proportional to the covariate value in the grid cell. Case 3 in Ståhl *et al.* (2000) is an equal probability of transition to all neighboring cells in the next column.

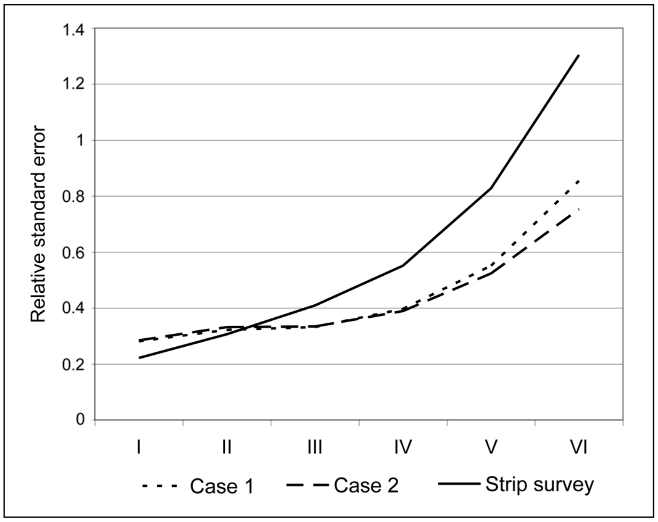
Figure 2.—*Two alternatives for the selection of survey strips in the second stage. With case 1, transitions between grid cells are made with probability proportional to the covariate values in the neighboring cells in the next grid-cells column. With case 2, one whole transect is selected with probability proportional to its Q-value, the sum of covariate values in all cells passed by the transect.*



Evaluation

The two described cases for the strategy of guidance were evaluated in simulated forest types. Although simulated they were created to resemble a real sampling situation. The forest types were created to resemble conifer forest with spots of deciduous trees and the object of interest considered to be some red-listed species connected to deciduous trees. GTS was compared with a standard strip survey with an equal area sampled with both methods. Comparisons were made in terms of standard errors of estimates. For details about the simulated forests and how comparisons were made, see Ståhl *et al.* 2000. The results of the comparison are shown in figure 3 for the case in which ratio estimators were applied, both in GTS and in the strip survey. The width of the first stage strips in GTS was five grid cells. When the object of interest is rather common, the methods perform equally well, but with a decreasing abundance

Figure 3.—*Comparison of the performance of two cases of guided transect sampling and a strip survey in six forest types. Ratio estimators were used both in guided transect sampling and in the strip survey. Forest types are ordered with a decreasing abundance to the right.*



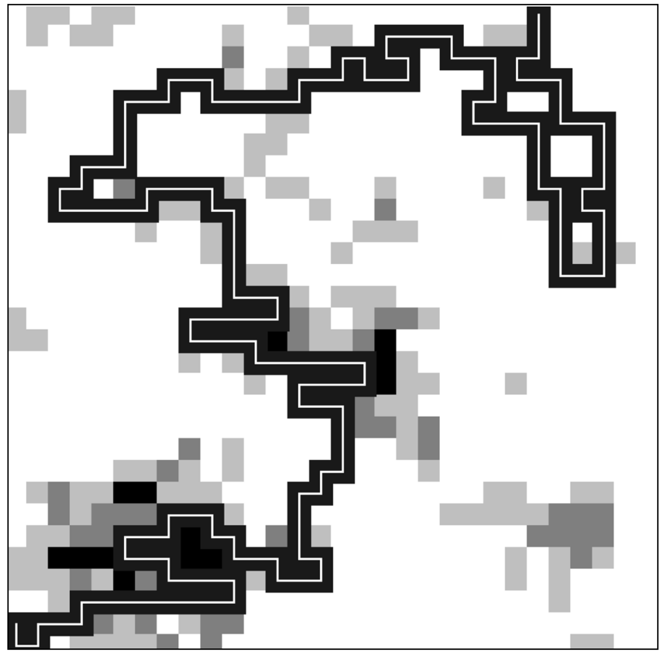
of the object of interest GTS is an improvement over a standard strip survey. The two cases considered were equivalent, so case 2 did not imply a better use of the available information as had been suggested.

Unrestricted GTS

With the strategies for the second stage guidance presented above, only one cell in each column is selected, which can be a restriction because interesting areas can only partly be covered. As an alternative, unrestricted GTS has newly been suggested (Ringvall *et al.* [in press]). With this variant of GTS, the first stage strips are skipped and transects are selected directly through the whole area (fig. 4).

With unrestricted GTS, a large amount of transects are first simulated according to certain restrictions, such as how many cells that must be passed and how transitions between cells are made. Besides giving a higher probability to cells with a higher covariate value, a higher probability can be given to continue in the same direction to avoid too many changes of direction. For each simulated transect, the values of covariate in cells passed

Figure 4.—*Example of a selected survey strip with unrestricted guided transect sampling, with which the first stage strips are skipped and transects are simulated directly through the whole area of interest.*



are summed, the *Q*-value, and finally one transect is selected with probability proportional to this *Q*-value (case 2). Hence, there is a higher probability of selecting a transect that passes a lot of interesting areas.

In the first evaluation of the performance of unrestricted GTS in simulated forest types, however, unrestricted GTS was only a rather limited improvement in comparison with the earlier suggested two-stage design (Ringvall and Ståhl 2007).

3P Subsampling

In the second step of the suggested approach, information that can only be obtained when at the sampling location (e.g., information about the quality of downed logs) is utilized. Whether a plot or strip survey, a species survey on all included substrates can be time consuming. Some sort of subsampling procedure might then be needed. In a purposive survey of specific species, the surveyors use their knowledge of species and substrate preferences to search for the species where they are likely to be found. In a probability sampling framework, 3P sampling has been suggested as a way to use this knowledge for a more efficient subsampling of substrates (Ringvall and Kruys 2005). In the original setup, the selection of sample trees is based on a quick measurement of the volume (e.g., Husch *et al.* 2003). In this context, the selection for sample trees is based on the surveyor's judgment of the probability for finding the species of interest on a given substrate on a scale 0–1. The probability that a substrate is selected for species survey is then proportional to this judge. The judge could also be for the substrates quality for a group of species surveyed on a scale 0–1. The result is that more time will be spent on the potentially more interesting substrates although all substrates have a probability of being selected.

Evaluation

The potential of using 3P sampling in this context was tested in a survey of needle lichens growing on the bark of old and coarse oak trees (Ringvall and Kruys 2005). To see the difference between different judges, three surveyors participated in the study. During the survey the probability of finding the species *Cyphelium inquinans* (Sm.) Trevis was judged by the surveyors. 3P subsampling was compared with a simple random subsampling in terms of standard errors of estimates. Comparisons were made both for estimates of the number of occurrences of the species *Cyphelium inquinans* (one occurrence was one tree with presence of the species) and for the number of occurrences of a group of nine species surveyed. The later case was a test for the ability of the judgment of the probability of finding a specific species to serve as a judgment for the substrate's suitability for a group of species. In one area, 3P sampling was a large improvement, while the improvement was more modest in the other (table 1). In the first area, a clear difference existed between the "good" and the "bad" trees. In the other area, it was more difficult to distinguish the good substrates. For details about the study and further results see Ringvall and Kruys (2005).

Conclusions

In this article, an approach for improving the efficiency of surveys of sparse objects by using the same type of information and knowledge used in purposive surveys has been presented. The evaluations of the methods in the approach have shown that they are promising. The evaluations made so far, however, are rather limited and mainly based on simulated forest types. Before the methods can be recommended and used in real applications, further evaluations are needed. Further, although the methods imply a considerable improvement there is still a risk that, with a reasonable sampling effort, the precision of estimate will be too poor.

Both practical and theoretical problems still need to be solved or considered. A theoretical problem is, for example, variance estimation in unrestricted GTS. Another problem is the availability of auxiliary information. For GTS to be useful, the auxiliary information much be easily available and at a low cost. *k*-Nearest Neighbor estimates providing for larger areas are a good example of such information. Also in these cases, however, the precision of estimates of sparse objects tends to be very low. For example, standard errors of estimates of volume of deciduous trees can sometimes be as high as more than 100 percent (e.g., Mäklelä and Pekkarinen 2001). The suggested methods are based on so called unequal probability sampling,

Table 1.—*The standard errors of a 3P subsampling with a ratio estimator given in percent of the standard errors of a simple random subsampling*[a]*, on an average for three surveyors, and, within parentheses, the range of their results.*

Variable	Area 1 (%)	Area 2 (%)
No. of occurrences of *Cyphelium inquinans*	46 (38–50)	84 (66–99)
No. of occurrences of nine surveyed lichens	58 (56–63)	88 (79–96)

[a] *(SE of 3P sampling/SE of simple random sampling)*100; values below 100 indicates that 3P sampling performed better than simple random sampling. Results are for a subsampling fraction of 0.5.*

and the risk of using such methods is well-known in sampling theory (e.g., Thompson 1992). If units have been assigned very low probability of inclusion while they actually have a high value of the variable of interest, the precision of estimates will be very poor. One way of preventing this is to not allow units to have too low probability of inclusion.

In contrast to these problems, the fast development in the Geographic Information System and field computer area and emerging techniques and improvements in the remote sensing area are promising for a possible implementation of these methods. The approach was described as it resembles the way a skilled surveyor walks through the forest, which might appeal to people who otherwise would prefer purposive methods.

Acknowledgments

The author thanks the co-authors of the paper on which this article is based: Professor Göran Ståhl, Associate Professor Tomas Lämås, and Dr. Nicholas Kruys. The work in these articles was financed by the Swedish Research Council for Environment, Agricultural Sciences and Spatial Planning and Hildur and Sven Wingqvist's Foundation for Forest Research. Participation in the symposium was financed by Bröderna Edlunds Donationsfond and Karl-Erik Önnesjös stiftelse för vetenskaplig utveckling och forskning.

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Location Uncertainty and the Tri-Areal Design

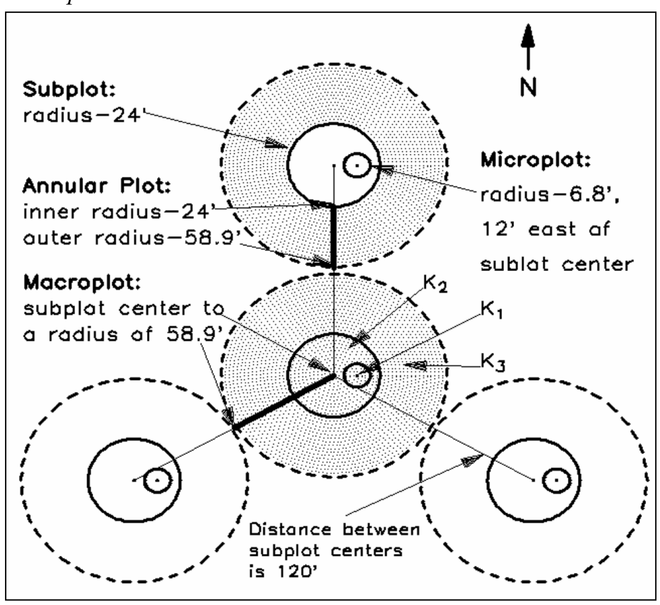
Francis A. Roesch[1]

Abstract.—The U.S. Department of Agriculture Forest Service Forest Inventory and Analysis Program (FIA) uses a field plot design that incorporates multiple sample selection mechanisms. Not all of the five FIA units currently use the entire suite of available sample selection mechanisms. These sampling selection mechanisms could be described in a number of ways with respect to the optional mechanism known as the annular plot. The annular plot is an auxiliary sampling mechanism intended for sampling rare attributes of interest. One explanation is that the subplot, which samples all trees greater than or equal to 5 in diameter at breast height (d.b.h.), is surrounded by an annular plot, concentric with the subplot for the estimation of rare but regionally important events. To date this selection mechanism has only been used to increase the sample of larger trees above a predefined d.b.h., known as a breakpoint diameter. Alternatively, the selection mechanisms could be viewed as disjoint concentric circles. The subplot in this latter view would sample all trees that are greater than or equal to 5 in and less than the breakpoint diameter. The larger circle can be referred to as a macroplot and it serves as the sole sampling mechanism for trees greater than or equal to the breakpoint diameter. This article focuses on the importance of clarity between these two descriptions and the estimation bias that can result from a misunderstanding of the distinctions between them, especially with respect to change estimates.

Introduction

The U.S. Department of Agriculture Forest Service Forest Inventory and Analysis (FIA) program uses a field plot design that is fairly represented by figure 1. The sampling selection mechanisms represented by the plot design could be described in a number of ways with respect to the annular plot portion of the design. The annular plot is an auxiliary sampling mechanism for rare attributes of interest. One explanation is that the subplot samples all tree greater than or equal to 5 in diameter at breast height (d.b.h.) and is enclosed by a circle of radius 24 ft. The annular plot is concentric with the subplot, beginning at a distance of 24 ft from subplot center and ending at 58.9 ft from subplot center, forming an annulus around the subplot. FIA allows this selection mechanism for rare, but regionally important, events. Until now, the annular plot has only been used to increase the sample of larger trees with a

Figure 1.—*The Forest Inventory and Analysis plot design, showing the annular plot view, in which the sample areas are disjoint, and the macroplot view, which is analogous to discrete horizontal point sampling. In the later view, the sample areas overlap.*



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predefined d.b.h., known as a breakpoint diameter. The annular plot view treats the microplot and subplot as the primary sample and the annular plot, consisting of an annulus around the subplot, as an auxiliary sample.

Alternatively, the selection mechanisms could be viewed as disjoint overlapping circles. The subplot in this case would sample all trees that are greater than or equal to 5 in and less than the breakpoint diameter. The larger circle can be referred to as a macroplot, and it constitutes the entire sample of trees greater than or equal to the breakpoint diameter. For simplicity we'll call the former description the annular plot view and the latter the macroplot view. This article focuses on the importance of clarity between these two descriptions and the estimation bias that can result from a misunderstanding of the distinctions between them.

Bechtold and Patterson (2005) define both the bi-areal and the tri-areal plot designs. In relation to the development found there, the annular plot view would hold that the bi-areal design is common throughout the United States and that some regions may choose to include an auxiliary sample collected on annuli surrounding each of the subplots. The macroplot view differs in that each region applies either a bi-areal or a tri-areal design, which coincide exactly only by the definition of the sample selected from the microplot. That is, the subplot samples a different population partition in the tri-areal design than in the bi-areal design, with the macroplot existing in only the tri-areal design. The estimators for a single point in time given in Bechtold and Patterson (2005) can be derived through either view. A practical advantage of the annular plot view is that if the auxiliary sample is not conducted in some regions, then the entire population is still sampled by an identical primary sample.

Enter the Temporal Dimension

An important class of variables exists for which a partitioning of the macroplot into the inner macroplot (equal to the area of the subplot) and the outer macroplot (equal to the area of the annular plot) is necessary. That class of variables consists of those whose ranges are to be partitioned by the various selection mechanisms, and whose measures can change over time. D.b.h. is possibly the most important member of this class of variables.

It is easy to show that from an instantaneous point of view, the macroplot view and the annular plot view both define a probability sample. FIA, however, measures a temporally continuous rather than an instantaneous population. From this perspective, as stated previously, we see that when the macroplot is used to sample large trees (say those with d.b.h. ≥ 25 in), it constitutes three distinct samples of that population. These three samples are (1) a sample (K_1) of trees that have been measured since they attained the 1-in class, selected with probability k_1 (proportional to the area of the microplot); (2) a sample (K_2) of trees that have been measured since they attained the 5-in class, selected with probability k_2 (proportional to the area of the subplot minus the area of the microplot); and (3) a sample (K_3) of trees that have been measured since they attained the breakpoint diameter, selected with probability k_3 (proportional to the area of the annular plot). Ignoring or not explicitly acknowledging the distinction between these samples has the potential to bias estimators of survivor value growth by two of the three primary compatible estimation systems published for remeasured horizontal point samples, due to the resulting location uncertainty. I'll follow others and refer to these three systems as Beers-Miller (Beers and Miller 1964), Van Deusen (Van Deusen *et al.* 1986), and Roesch (Roesch 1988, 1990; Roesch *et al.* 1989, 1991, 1993) estimators. The problem arises implicitly rather than explicitly in the first two systems, because, if data are collected and stored under the macroplot view, and there is a non-zero quality-control tolerance for horizontal distance from plot center, there would be no way of determining for certain whether a large tree recorded as physically located near the edge of the subplot and previously unrecorded was previously missed, previously smaller than 5 in d.b.h., or actually on the annular plot. This knowledge is necessary for strict application of the Beers-Miller and Van Deusen survivor growth estimators because they both require use of time 1 inclusion probabilities. The Roesch survivor growth estimator relies on time 2 inclusion probabilities and therefore would sidestep the problem.

The survivor sample ("s") consists of sample trees measured and above a merchantability limit on consecutive occasions, while the new sample ("n") consists of trees that were above the merchantability limit on both occasions, but eligible to be sampled for the first time on the second occasion. For clarity we'll define the estimators:

Beers-Miller: $\hat{S}_B = s_2' - s_1$

Van Deusen: $\hat{S}_V = s_2 - s_1 + n_2$

Roesch: $\hat{S}_R = s_2 - s_1' + n_2 - n_1'$

where:

S_1 = estimate of time 1 value of the "s" sample using time 1 inclusion probabilities.

S_1' = estimate of time 1 value of the "s" sample using time 2 inclusion probabilities.

S_2 = estimate of time 2 value of the "s" sample using time 2 inclusion probabilities.

S_2' = estimate of time 2 value of the "s" sample using time 1 inclusion probabilities.

n_2 = estimate of time 2 value of the "n" sample using time 2 inclusion probabilities.

n_1' = model estimate of time 1 value of the "n" sample with time 2 inclusion probabilities.

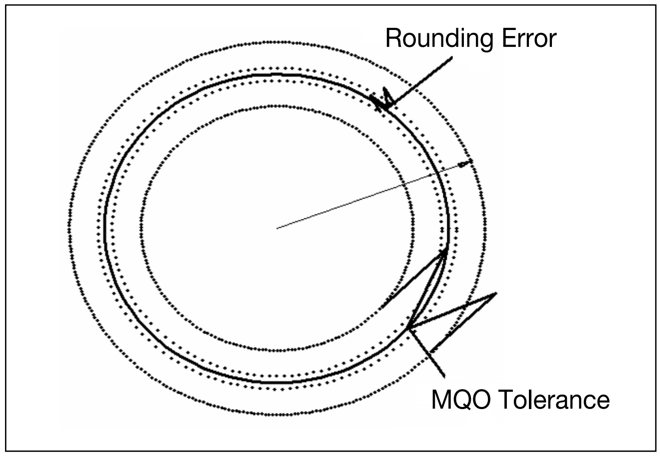
As a point-sampling estimator of survivor growth, $\hat{S}_R$ was shown in the citations above through simulations to dominate the other estimators in terms of squared error loss. It does, however, require predictions of time 1 values that are not required of the other two estimators in the absence of location error. In the absence of location error, all three estimators are unbiased estimators for survivor growth (Beers and Miller 1964, Van Deusen *et al.* 1986, Roesch 1988). We will show below that location error contributes to a bias in the Beers-Miller estimator and the Van Deusen estimator (but not in the Roesch estimator) through two mechanisms:

(1) Rounding error.

(2) Measurement error allowed by the measurement quality objective (MQO).

These errors are depicted in figure 2. Rounding error contributes positive bias to the inclusion probability, while measurement error allowed by the MQO contributes bias and variance. The bias from measurement error is due simply to a symmetric linear error being applied to a point on the radius of a circle.

Figure 2.—*Two potential errors associated with measurement along a radius: rounding to a discrete result and the tolerance allowed by the MQOs.*



MQO = measurement quality objective.

No Measurement Error

Assume that the field crew is not required to determine of the location of trees with respect to K_1, K_2, and K_3, leaving sample assignment to be inferred from the distance from subplot or microplot center, which is rounded and recorded to the nearest $1/t$ foot, where t is a positive integer. This use of rounded distances will result in sample trees that appear to be in the "s" sample that are actually in the "n" sample, thus creating "apparently missed" trees.

For now, also assume that our concern is with merchantable value growth of above-threshold trees. In this case we can ignore the microplot and concentrate on the effects of the tolerance definitions at the border between the subplot and the annular plot. Distance measures are continuous variables that are recorded in discrete units. A recording of distance d would result from rounding of the true distance D in the interval $\left(d - \frac{1}{2t}\right) < D \le \left(d + \frac{1}{2t}\right)$ feet. The difference between D and d is known as rounding error. Assume trees are randomly distributed over the land area. Then D is randomly distributed within the annulus bounded on the inside by $\left(d-\frac{1}{2t}\right)$ and on the outside by $\left(d+\frac{1}{2t}\right)$. This annulus ($A$) has an area of:

$$\pi\left[\left(d+\frac{1}{2t}\right)^2-\left(d-\frac{1}{2t}\right)^2\right]=\frac{2\pi d}{t}. \qquad (1)$$

D is distributed within the annulus as:
$p(D) \sim 1/(2\pi D)$.

Example

Set d = 24 ft. and t = 10, then the annulus has an area of $\frac{2\pi d}{t}=\frac{2\pi 24}{10}=4.8\pi \text{ft}^2$.

This would appear small relative to the nominal area of the subplot, which is $\pi r^2=\pi 24^2\approx 1809.56\text{ft.}^2$ The area outside of the subplot boundary that would appear inside of the boundary after rounding lies between 24 and 24.05 ft and is equal to:

$$\pi\left[\left(24+\frac{1}{2t}\right)^2-(24)^2\right]\text{ft}^2=\pi\left[\frac{24}{t}+\frac{1}{4t^2}\right]\text{ft}^2=$$
$$\pi\left[2.4+0.0025\right]\text{ft}^2=2.4025\pi\,\text{ft}^2$$

resulting in an unrecognized selection bias due to rounding error of $b_S^r=\frac{2.4025}{576}\approx 0.417$ percent.

In a strict application of the Beers-Miller estimator ($\hat{S}_B = s'_2 - s_1$) in the presence of rounding error, we might assume the apparently missed trees (truly members of the "n" sample) were actually missed (i.e., apparently members of the "s" sample), and subtract an estimate of time 1 value from their time 2 value, expand that by the inverse of the subplot area, and add it to the estimate of survivor growth, creating a positive bias (b_B^r), because the value growth of these trees should not have been included in the survivor growth estimate. Therefore the expected value of the Beers-Miller estimator in the presence of rounding error is:

$$E\left(\hat{S}_B^r\right)=E\left(\hat{S}_B+b_B^r\right)=E\left(s'_2-s_1\right)+E\left(b_B^r\right)\approx 1.00417\left(s'_2-s_1\right)$$

because the expected value of the bias due to rounding error is $E\left(b_B^r\right)\approx 0.00417\left(s'_2-s_1\right)$.

Conversely, in a strict application of the Van Deusen estimator ($\hat{S}_V=s_2+n_2-s_1$), we would mistakenly subtract an estimate of time 1 value expanded by the inverse of the subplot from the time 2 value estimate expanded by the inverse of the macroplot. The result will often be a relatively large negative number. Because the apparently-missed tree was actually in the "n" sample, no time 1 value should have been subtracted, therefore a negative bias results. The expected value of the Van Deusen estimator in the presence of rounding error in this case is:

$$E\left(\hat{S}_V^r\right)=E\left(\hat{S}_V+b_V^r\right)=E\left(s_2-s_1+n_2\right)+E\left(b_V^r\right)$$
$$=E\left(s_2-s_1+n_2\right)+\left(E\left(b_B^r\right)-0.00417E\left(s'_2\right)\right)$$

because the expected value of the bias is:

$$E\left(b_V^r\right)=\frac{\pi\left(24.05^2-24^2\right)}{\pi\left(58.9^2-24^2\right)}E\left(-n_1\right)$$
$$=\left[\frac{\pi\left(24.05^2-24^2\right)}{\pi\left(58.9^2-24^2\right)}\right]\left[-\frac{\pi\left(58.9^2-24^2\right)}{\pi 24^2}E\left(s_1\right)\right]$$
$$\approx -0.00417\left(s_1\right)$$

To use the Roesch estimator ($\hat{S}_R=s_2-s'_1+n_2-n'_1$), in the presence of rounding error, the apparently missed trees would be treated in the same manner as the trees in the "n" sample even though they appear to belong in the "s" sample. That is, we would predict the time 1 value and subtract it from the time 2 value, and then multiply the result by the inverse of the time 2 inclusion probability, so the selection bias would not affect the survivor growth estimator.

In the Presence of Measurement Error

Suppose that the following quality control standards for horizontal distance are enforced:

Tolerance:
Microplot: ± t_1 ft
Subplot: ± t_2 ft from 0-22.9 feet; ± t_3 foot for > 23 feet
Macroplot: ± t_4 ft

To simplify the discussion, we'll also assume that the tolerance is to be met 100 percent of the time and our concern is with merchantable value growth. Therefore, we can ignore the microplot and concentrate on the effects of the tolerance definitions at the border between the subplot and the annular plot. A recording of distance d could result from a true distance D in the interval $\left(d - t_4 - \frac{1}{2t}\right) < D \le \left(d + t_4 + \frac{1}{2t}\right)$ feet. Assume trees are randomly distributed over the land area.

This annulus (A) has an area of:

$$\pi\left[\left(d + t_4 + \frac{1}{2t}\right)^2 - \left(d - t_4 - \frac{1}{2t}\right)^2\right] = 2\pi d\left(2t_4 + \frac{1}{t}\right). \qquad (2)$$

Again D is distributed within the annulus:
$p(D) \sim 1/\left(2\pi D\right)$.

The additional error in (2), above rounding error in (1), is within-tolerance measurement error.

If we assume that the horizontal distance error follows any symmetric distribution, more trees will mistakenly appear to be inside of the division line than outside of the division line. Therefore, to calculate the allowed measurement error selection bias, note that we must first calculate the ratio of annular area external to the division line to the annular area internal to the division line:

$$R\left(d,t,t_4\right) = \frac{\pi\left[\left(d+t_4+\frac{1}{2t}\right)^2 - \left(d+\frac{1}{2t}\right)^2\right]}{\pi\left[\left(d-\frac{1}{2t}\right)^2 - \left(d-t_4-\frac{1}{2t}\right)^2\right]} = \frac{\left(2d + t_4 + \frac{1}{t}\right)}{\left(2d - t_4 - \frac{1}{t}\right)}$$

This ratio R is then applied to the selection area to determine the bias:

$$b\left(d,t,t_4\right) = \frac{\left[\frac{R(d,t,t_4)+1}{2}\right]\pi\left[\left(d-\frac{1}{2t}\right)^2 - \left(d-t_4-\frac{1}{2t}\right)^2\right] + \pi\left[\left(d^2 - \left(d - \frac{1}{2t}\right)^2\right) + \left(d - t_4 - \frac{1}{2t}\right)^2\right]}{\pi d^2}$$

$$= \frac{\left[1-R(d,t,t_4)\right]\left[\frac{t_4^2}{2} + \frac{t_4}{2t} - dt_4\right]}{d^2}$$

Table 1 shows the selection bias (b) at 24 ft and its effect on the expected value of the bias in the Beers-Miller estimator when horizontal distance, rounded to 0.1 ft at five MQO tolerances of t_4 equal to 0.1, .05, 1.0, 3.0, and 6.0 ft, is used to determine tree location.

Table 1.—*The selection bias (*b*) at 24 ft and its effect on the expected value of the bias in the Beers-Miller estimator when horizontal distance is rounded to 0.1 ft at each MQO tolerance (t_4).*

Selection bias effect on the Beers-Miller estimator for FIA		
t_4	$b(d=24,t=10,t_4)$	$E(b_B^{rt})$
0.1	0.00002	$0.00419(s'_2 - s_1)$
0.5	0.00042	$0.00459(s'_2 - s_1)$
1.0	0.00173	$0.00590(s'_2 - s_1)$
3.0	0.01555	$0.01973(s'_2 - s_1)$
6.0	0.06220	$0.06637(s'_2 - s_1)$

MQO = measurement quality objective.

Conclusions

We have noted that even a very accurate horizontal distance measurement will contribute an unnecessary bias of about 0.5 percent, because a distance of 24.05 ft would be recorded as 24 ft. The last two rows of table 1, where t_4 equals 3 and 6 ft, clearly show that horizontal distance tolerances that would be quite reasonable if one merely intended to be able to relocate very large trees would contribute to substantial bias if that same measure were later used to determine sample membership with respect to K_2 and K_3. Conversely, a field determination of “in subplot” or “in annular plot” will have an equal variance to the use of horizontal distance for this purpose, but should not be biased. This observation is of concern because the assignment of the trees to areas (subplot or annulus) might not be recorded under the macroplot view of the sample design but is critical for Beers-Miller and Van Deusen growth estimates. In the former (chosen for use by FIA), growth below the threshold diameter for trees currently above the threshold diameter is measured exclusively on the subplot, making it necessary to distinguish between the area of the subplot and that of the annular plot. The alternative design-based Van Deusen estimator is more efficient because it uses the growth information from the annular plot that is ignored by the Beers-Miller estimator. Under the conditions investigated, it would suffer from an expected bias equal in magnitude to that of the Beers-Miller estimator, but of opposite sign. The model-based Roesch estimator would not incur bias due to location error, given an unbiased time 1 estimator for trees in the "n" sample. These predictions contribute a variance component to the Roesch estimator that is not present in the other estimators. That additional variance component will usually be smaller than the variance reduction achieved by the use of auxiliary information.

Although the subplot-microplot analogy to the annular plot-subplot issue is not trivial in all cases, we haven't discussed it here because it has less effect on value growth estimation because most value equations have a result of 0 below 5 in d.b.h., and those that do not have a very low result.

The Beers-Miller and Van Deusen estimators are inherently unbiased estimators. Therefore, the bias discussed in this paper would be an unnecessary artifact of collecting and storing data under the macroplot view if caution were not taken to prevent the confounding of the K_1, K_2, and K_3 samples.

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The Poor Man's Geographic Information System: Plot Expansion Factors

Paul C. Van Deusen[1]

Abstract.—Plot expansion factors can serve as a crude Geographic Information System for users of Forest Inventory and Analysis (FIA) data. Each FIA plot has an associated expansion factor that is often interpreted as the number of forested acres that the plot represents. The derivation of expansion factors is discussed and it is shown that the mapped plot design requires a different expansion factor than the old periodic plot design.

Introduction

Plot expansion factors are important to most users of U.S. Department of Agriculture Forest Service Forest Inventory and Analysis (FIA) data. Expansion factors are typically viewed as the number of forested acres that a plot represents. In fact, they are constructed to ensure that the sum of all expansion factors for plots in a particular county is equal to FIA's current estimate of the forested acres in the county. Therefore, there is some basis in reality for this view of expansion factors. A potential downside to the standard view is the implication that somehow the plot with the largest expansion factor is most important, i.e., it should be given the most weight in an analysis. This is not generally true because all plots were initially selected with equal probability. Plots may receive different weights due to a poststratification process that is performed in some regions, but this has nothing to do with initial selection probability. The purpose here is to show how expansion factors are derived and to point out the implications of using them in several common analyses.

Expansion Factor Computation

The rule of thumb that leads to the formula for plot expansion factors is that expansion factors within a county must sum to the forest area in the county. This leads immediately to

$$w_i = A_c(i) / n_c(i) \tag{1}$$

where $A_c(i)$ and $n_c(i)$ are the forest area and number of plots in county c, which contains plot i. The same rule applies for poststratification with the additional proviso that the sum of expansion factors in stratum h and county c must sum to the stratum area in the county. Poststratified weights are then computed as

$$w_i = A_{c,h}(i) / n_{c,h}(i) \tag{2}$$

where $A_{c,h}(i)$ and $n_{c,h}(i)$ are the stratum h forest area and number of plots in county c which contains plot i.

Expansion factors computed with equation (1) should not be used in an analysis of the data to give varying weights to the plots. They have no relationship to the plot selection probability and do not indicate the importance of the plot in any way. This is not necessarily true for the poststratified weights (equation 2). Some FIA regions use these weights to compute stratified means and variances (Bechtold and Patterson 2005, Van Deusen 2005).

Computations With Poststratified Weights

Plot expansion factors can provide a clever mechanism for users to compute stratified means and variances using standard formulas for weighted means. The generic formula for the stratified sample mean (Thompson 2002, Cochran 1977) is

$$\bar{y}_{st} = \frac{1}{N} \sum_{h=1}^{L} N_h \bar{y}_h \tag{3a}$$

where:
N = total population size.
N_h = the number of population elements in stratum h.

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$\bar{y}_h$ = the estimated mean for stratum h.

An unbiased estimator of the stratified variance is

$$v(\bar{y}_{st}) = \sum_{h=1}^{L} \left(\frac{N_h}{N}\right)^2 \left(\frac{N_h - n_h}{N_h}\right) \frac{s_h^2}{n_h} \tag{3b}$$

Equations (3a) and (3b) are formulated in terms of total population size (N) for the area of interest, but N is unknown in most forest inventory settings. This equation can be converted to a useful form for FIA data by ignoring the finite population correction factor and replacing Ns with As to get

$$\bar{y}_{st} = \frac{1}{A} \sum_{h=1}^{L} A_h \bar{y}_h, \tag{4a}$$

and

$$v(\bar{y}_{st}) = \sum_{h=1}^{L} \left(\frac{A_h}{A}\right)^2 \frac{s_h^2}{n_h} \tag{4b}$$

where the variance estimate for plots in the same stratum is

$$s_h^2 = \sum_{j \varepsilon h} \left(y_j - \bar{y}_h\right)^2 / \left(n_h - 1\right) \tag{4c}$$

Equations (4a) and (4b) are based on the assumption that the stratum areas are known. In practice, these values might come from counting pixels on a classified raster image that covers the region of interest. For the purposes here, assume that the variance of area estimates is small enough to ignore. A further complication is that equation (4c) must be recomputed for each county and stratum and there may not always be sufficient observations in all county strata.

It is easy to show (Van Deusen 2005) that equations (4a) and (4b) are implemented for unmapped plots with the following weighted mean and variance equations:

$$\bar{y}_{st} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}, \tag{5a}$$

and

$$V(\bar{y}_{st}) = \frac{\sum_{i=1}^{n} w_i^2 \sigma_i^2}{\left(\sum_{i=1}^{n} w_i\right)^2} \tag{5b}$$

where σ_i^2 is estimated from equation (4c). The county and stratum of the plots can be ignored for equation (5a) because this data is incorporated into the expansion factors. The variance (σ_i^2) in equation (5b), however, changes for each county and stratum. This variance could be problematic if sample size in a particular stratum is small. Regardless, expansion factors are a very useful component of the FIA database (FIADB) for the old periodic data.

It can be shown (Van Deusen 2005) that when working with mapped plots the weights must be changed to $w_i = A_{c,h}(i)\, a_i / \sum_{j \varepsilon c,h} a_j$ where a_i is the proportion of plot i that falls into the condition of interest. This means that the weights must be modified for each mapped condition. This eliminates the simplicity of working with poststratified data in the FIADB and only a very committed user should attempt to use the weights to compute stratified estimates with mapped plot data. The weighted estimation formulas (5a) and (5b) also change for mapped plots (Van Deusen 2005).

Conclusions

Plot expansion factors provide users with information on forested area by county. In this sense, they serve the same purpose as a Geographic Information System. Users need to understand, however, that these weights were derived to ensure that the expansion factors for all plots in a county add to the forest area in the county. Trying to extract additional information by using expansion factors as weights in a statistical analysis of the plot data is not justified. Some FIA regions incorporate poststratification information into plot expansion factors that enable one to extract the forest area by strata for a county. This information is difficult to properly use for mapped plot data and most users of the FIADB should probably ignore it.

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Improving Coarse Woody Debris Measurements: A Taper-Based Technique

Christopher W. Woodall[1] **and James A. Westfall**[2]

Abstract.—Coarse woody debris (CWD) are dead and down trees of a certain minimum size that are an important forest ecosystem component (e.g., wildlife habitat, carbon stocks, and fuels). Accurately measuring the dimensions of CWD is important for ensuring the quality of CWD estimates and hence for accurately assessing forest ecosystem attributes. To improve the quality of CWD diameter and length measurements, two quality control methods were used to estimate field-applicable taper thresholds to reduce measurement errors. Results indicated that both the taper outlier and taper model methods may be used to set thresholds for detection of egregious CWD dimension measurement errors. The taper outlier method determines the thresholds using three times the interquartile range of taper and a new metric of relative size. The taper model approach predicts large-end diameter based on small-end diameter and length. Both methods may be broadly applied to CWD pieces, regardless of decay, size, and species. Overall, incorporation of CWD taper attributes into field data recorders may allow "on the fly" assessment of possible measurement errors in the field.

National Inventory of Coarse Woody Debris

As defined by the U.S. Department of Agriculture Forest Service's Forest Inventory and Analysis (FIA) program, coarse woody debris (CWD) are down logs with a transect diameter ≥ 3 in and a length ≥ 3 ft (Woodall and Williams 2005). CWD are sampled during the third phase of FIA's multiscale inventory sampling design (USDA Forest Service 2004, Woodall and Williams 2005). CWD are sampled on transects radiating from each FIA subplot center. Each subplot has three transects 24 ft in length. Information collected for every CWD piece intersected by the transects are transect diameter, length, small-end diameter, large-end diameter, decay class, species, and presence of cavities. Transect diameter is the diameter of a down woody piece at the point of intersection with a sampling transect. Decay class is a subjective determination of the amount of decay present in an individual log. Decay class 1 is the least decayed (freshly fallen log), while decay class 5 is an extremely decayed log (cubicle rot pile). The species of each fallen log is identified through determination of species-specific bark, branching, bud, and wood composition attributes (excluding decay class 5 CWD pieces).

To date, the FIA program provides the only nationwide, pseudosystematic sampling of CWD resources. Forest fire, carbon, and wildlife sciences all depend on quality CWD data to provide information for numerous investigations and assessments (Woodall and Williams 2005). Therefore, ensuring the quality of CWD measurements is critical for ensuring the national credibility of FIA's down woody materials inventory.

CWD Measurement Errors

Accurate measurement of the dimensions of CWD pieces is essential for quality estimates of CWD weight/volume. Because CWD are measured in tandem with other field measurements, field crews sometimes inadvertently confuse the differing measurement precisions required of standing live and down dead trees. The diameters of standing live trees are measured to the nearest tenth of an inch, while the diameters of down dead trees are measured to the nearest inch. Additionally, field crews may record an additional digit for heights (e.g., turning

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18-ft CWD pieces into 180-ft oddities). Although this error is very rare, its occurrence can lead to extreme errors in plot-level estimates of CWD attributes. Using hypothetical data for one subplot (table 1), the differences in uncorrected and corrected CWD piece measurements can result in plot-level estimates nearly 50 times larger than the corrected estimate. Overall, rather obvious measurement errors on a relatively small proportion of FIA inventory plots may be skewing population estimates across the United States when left uncorrected.

Table 1.—*Coarse woody debris uncorrected and corrected data for one hypothetical FIA subplot.*

Type	CWD piece	Small-end diameter (in)	Large-end diameter (in)	Length (ft)
Uncorrected	1	3	40	10
	2	4	6	140
	3	30	70	34
Corrected	1	3	4	10
	2	4	6	14
	3	3	7	34

CWD = coarse woody debris; FIA = Forest Inventory and Analysis.

A Taper Solution?

The most desirable methodology for reducing field measurement errors is to prevent them at the source: field inventory crews. Crews enter data into Portable Data Recorders (PDRs) that often check for ranges in tree diameter at breast height, species, and length, among numerous other variables. If a simple metric of a CWD piece's dimensions could be used to ascertain acceptable CWD measurements, then this metric could be rapidly implemented into field crew PDRs. Taper is one metric of tree spatial dimensions that might be applied to CWD pieces. Taper is defined as change in a tree's diameter over a defined length (inches/foot). For this study, the taper of CWD pieces will be defined as

$$Taper_{cwd}=(D_L-D_S)/L \qquad (1)$$

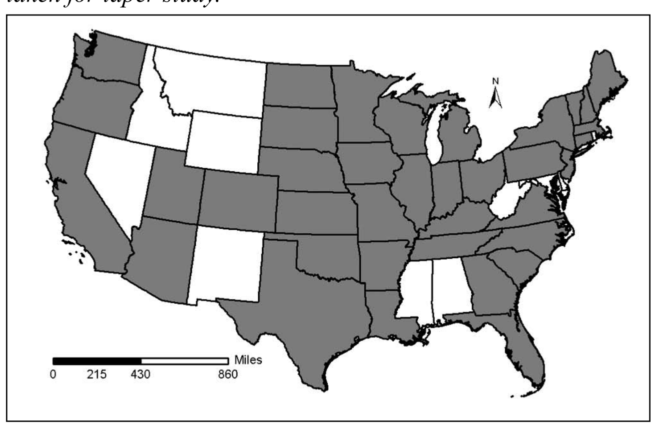
where:
D_L = the large-end diameter (in).
D_S = the small-end diameter (in.).
L = the total length (ft).

Using the taper of an individual CWD piece as one metric of its spatial dimensions is attractive for application for CWD data quality control. First, taper incorporates all three dimensional measurements of CWD pieces, so if even one of the dimension measurements is in error it will be reflected in taper. Second, a well-established base of knowledge on the taper of standing trees may be used to develop new CWD taper equations (Martin 1981). Finally, a single metric of taper may be easily programmed into PDRs, allowing for rapid field application. Therefore, the objectives of this study are (1) to estimate mean taper of CWD pieces by classes of transect diameter, species, and decay class, (2) to determine a methodology for using CWD taper outliers to identify CWD measurement errors, (3) to use a taper model (small diameter = f[large diameter, length]) to identify CWD measurement errors, and (4) to recommend a methodology for reducing CWD measurement errors based on study results.

Data/Analysis

The study data set consisted of individual CWD piece measurements sampled by the FIA program across the Nation from 2001 to 2004 (fig. 1). The information for every CWD piece included transect diameter, small-end diameter, large-end diameter, length, decay class, and species. The study data set had 20,018 observations and 190 individual tree species.

Figure 1.—*States (filled in) in which CWD measurements were taken for taper study.*



CWD = coarse woody debris.

Mean taper and standard errors were determined for CWD pieces by classes of transect diameter, decay class, and species. CWD taper outliers were determined by estimating the Interquartile Range (IQR) of CWD tapers and multiplying the IQR times three. Observations not within ± three times IQR of the median value were considered outliers. To investigate the effect of abnormally long CWD pieces, a metric of Relative Size (RS) was estimated by dividing length by large-end diameter. RS outliers were examined using the same outlier methodology (IQR times three) as with taper. Finally, a taper model was used to examine taper:

$$E\left(D_S\right) = \beta_0 + \beta_1 L + \beta_2 D_1 + \beta_3 DC_1 + \beta_4 DC_2 + \beta_5 DC_3 + \mu \quad (2)$$

$$\varepsilon \sim N\left(0, \delta_1 L \times D_l^{\delta_2}\right) \quad (3)$$

where:
E(.) = the statistical expectation.
D_s = the small-end diameter.
L = the total length.
D_l = the large-end diameter.
DC_i = decay class indicator variables.
β_i = parameters to be estimated.
ε = the random errors term.

Taper Outliers

Mean tapers (in/ft) increased with increasing transect diameter and with increasing states of CWD decay, but varied with no discernible pattern by species group (table 2). When we examine the distribution of taper by transect diameter class, taper appears to be constrained by the small-end diameter of CWD pieces (fig. 2). Most observations had taper below 1 in/ft; however, there were numerous outliers with tapers approaching 12 in/ft. CWD pieces with a small-end diameter of 30 in had an exceedingly large number of taper outliers. Because field crews measure standing trees to the nearest tenth of an inch and CWD pieces to the nearest inch, 3 in is the most common small-end diameter measurement for CWD pieces and is probably accidentally entered as 30 in into field PDRs. Based on interpretation of means, taper appears to be most dependent on the transect diameter of the CWD piece and thus should be an integral variable for taper outlier identification.

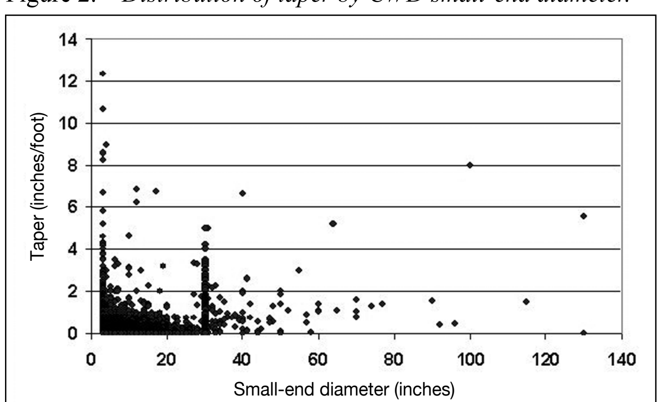
The percentile distribution of CWD tapers was determined and used to define an interval beyond which a taper observation would be considered an outlier +/- three times IQR (table 3). The median taper for all observations was 0.14 in/ft with 99 percent of taper observations below 1.33 in/ft. The IQR was estimated to be 0.155 in/ft, creating an acceptable taper interval of 0.000 to 0.6073. Unfortunately, this interval did not include pieces that taper too little such as a CWD piece with a small-end diameter of 5 in, a large-end diameter of 7 in, and a total

Table 2.—*Mean and associated standard errors for CWD taper by transect diameter class, decay class, and species groups.*

Variables	Classes	Mean taper (in/ft)	Standard error
Transect diameter (inches)	3.0–7.9	0.170	0.002
	8.0–12.9	0.236	0.004
	13.0–17.9	0.311	0.016
	18.0 +	0.760	0.045
Decay class	1	0.197	0.011
	2	0.191	0.004
	3	0.205	0.004
	4	0.224	0.005
Species groups	Spruce/fir/cedar	0.187	0.005
	Pines	0.217	0.005
	Maples	0.211	0.010
	Birches	0.171	0.010
	Hickories	0.242	0.049
	Oaks	0.256	0.010

CWD = coarse woody debris.

Figure 2.—*Distribution of taper by CWD small-end diameter.*



CWD = coarse woody debris.

Table 3.—*Order statistics for CWD taper and relative size.*

Percentiles	Taper	Relative size
100 (Maximum)	12.333	56.000
99	1.333	9.333
95	0.513	6.000
90	0.375	5.000
75 (Quartile 3)	0.238	3.667
50 (Median)	0.143	2.359
25 (Quartile 1)	0.083	1.400
10	0.000	0.833
5	0.000	0.600
1	0.000	0.300
0 (Minimum)	0.000	0.023
IQR (Q3-Q1)	0.155	2.267

CWD = coarse woody debris.

length of 150 ft. Another CWD dimensional metric, RS, may be used to help indicate suspect CWD dimensional measurements. Trees with relatively long lengths should have corresponding increases in large-end diameters. For instance, a length of 80 ft and a large-end diameter of 4 in appear questionable because most trees do not have 80 ft of length between a 4-in large-end diameter and the top of the tree (or end of branch). Thus, large RS values would indicate a suspect relationship between large-end diameters and lengths. The percentile distributions of RS for all study observations were determined, once again using three times IQR to define an outlier interval (table 3). The median RS was 2.359 ft/in with 99 percent of observations below 9.333. The IQR for RS was estimated to be 2.267 ft/in, creating an acceptable RS interval of 0 to 9.159 ft/in. Based on the study dataset, the taper and RS intervals "flagged" 5 percent of observations as being possible outliers.

Model-Based Approach

The taper model (eq. 2) had an r-squared of 0.69 with a root mean squared error of 2.07. The linear model was fitted using CWD decay classes as indicator variables due to differences in taper attributable to the decay of CWD pieces. In an operational sense, the taper model predicts small-end diameter given a set of field measurements (large-end diameter, length, and decay class). Also, the model error variance (eq. 3) is based on large-end diameter and length with the standard error as the square root of the variance. The small-end diameter prediction +/- two times the standard error allows for creation of an interval over which the small-end diameter measurement is likely to be valid. The model parameters for equation (2) were estimated to be β_0 =1.5928, β_1 = -0.05229, β_2 = 0.5323, β_3 = -0.1578, β_4 = -0.1128, and β_5 = -0.0702. Estimates of parameters for equation (3) were δ_1 = 0.000913 and δ_2 = 2.4191. Given these parameter estimates and the defined interval (+/- two times standard error), the taper model would have excluded 7.1 percent of the study data set observations.

Field Recommendations

Currently, range checks are used with numerous field variables (e.g., permissible codes for tree species) to maintain the quality of field measurements. Differences in precision required for standing tree and down, dead tree measurements exacerbate measurement errors in the field. These errors may be reduced by implementing simple data checks programmed into PDRs. The taper outlier and model methods both possess attributes attractive for field implementation. Both approaches can be easily programmed into PDRs. In addition, they both may be used to "flag" a small number of field measurements (between 5 and 7 percent of field measurements as demonstrated in this study). There is a balance between the quality of measurements and the efficiency of the sample protocols used to acquire CWD measurements. The key is to pick a method that increases the quality of measurements while not impacting measurement efficiency or complexity. Given these prerequisites, the outlier method may be deemed superior to the model method given its simplicity and ability to easily adjust the interval (3, 3.5, or 4 times IQR). Despite its complexity, however, the adjustable variable interval of the model method (1.5, 2, or 2.5 times the standard error) might be advantageous in certain field applications. Whether the taper or model method is selected for field implementation, both offer efficient alternatives for increasing the quality of CWD dimensional measurements and both should be tried in field situations.

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Evaluating Ecoregion-Based Height-Diameter Relationships of Five Economically Important Appalachian Hardwood Species in West Virginia

John R. Brooks[1] **and Harry V. Wiant, Jr.**[2]

Abstract.—Five economically important Appalachian hardwood species were selected from five ecoregions in West Virginia. A nonlinear extra sum of squares procedure was employed to test whether the height-diameter relationships, based on measurements from the 2000 inventory from West Virginia, were significantly different at the ecoregion level. For all species examined, the null hypothesis was rejected indicating that at least one of the ecoregion specific parameters was not equal to zero. In addition, 56 percent of the paired ecoregion tests indicated significant height differences. Across all species and ecoregion combinations, average height error ranged from –3.6 to 7.6 ft for the statewide model.

Introduction

Height-diameter relationships are the driving force behind most tree volume, form, and weight relations. In a recent study by Jiang *et al.* (2004), yellow poplar (*Liriodendron tulipifera* L.) tree form and cubic foot volume were found to be statistically different between two major ecological regions in West Virginia. To further investigate whether the underlying height-diameter relationship also varied by ecoregion, the 2000 Forest Inventory and Analysis (FIA) data for West Virginia (Griffith and Widmann 2003) was used for evaluation. Five economically important Appalachian hardwood species were selected for study and included black cherry (*Prunus serotina* Ehrh.) (BC), red oak (*Quercus rubra* L.) (RO), red maple (*Acer rubrum* L.) (RM), sugar maple (*Acer saccharum* Marsh.) (SM), and yellow poplar (YP). Species specific measured total tree heights and diameters were used to fit the well-known Chapman-Richards growth model to determine whether the height-diameter relationship was statistically different by ecoregion. This technique has been employed for both jack pine (*Pinus banksiana* Lamb.) and black spruce (*Picea mariana* (Mill.) in Ontario (Peng *et al.* 2004, Zhang *et al.* 2002). Results from the jack pine study indicated that provincial models resulted in an average bias of 1 to 10 percent when applied to each ecoregion in Ontario (Zhang *et al.* 2002). The objectives of this study are to evaluate whether ecoregion-based diameter-height relations are statistically justified, to test for differences between ecoregions for the five hardwood species selected, and to evaluate the percent bias associated when a statewide model was compared to individual ecoregion models.

Methods

West Virginia was divided into five major ecoregions based on a combination of current subregions for Region III and IV (Bailey *et al.* 1994) and the land-based regions identified by the U.S. Soil Conservation Serivce (USDA Soil Conservation Service 1981).

This allocation was made on a county-by-county basis based on the county designation of the FIA plot location and the major subregion (by area) represented by each county. The following five major subregions employed are depicted in figure 1:

CALG: Central Allegheny Plateau.
CUPM: Cumberland Plateau and Mountains.
EALG: Eastern Allegheny Plateau and Mountains.

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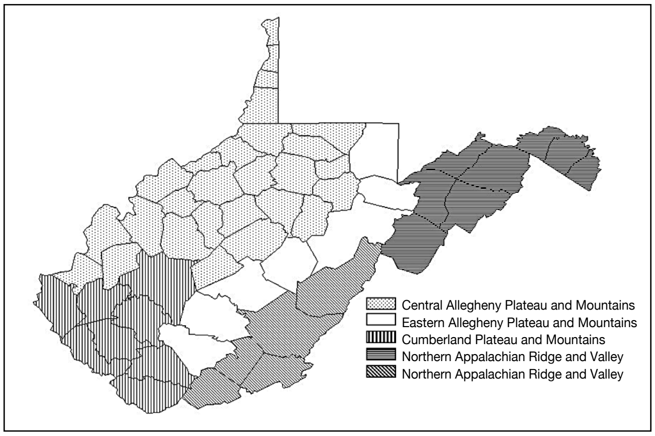
Figure 1.—*Identification of the five ecological regions within West Virginia used to evaluate height-diameter relationships.*



NARV: Northern Appalachian Ridges and Valleys.
SARV: Southern Appalachian Ridges and Valleys.

The 2000 FIA data for West Virginia (Griffith and Widmann 2003) was used as the base data. A subset of the individual tree data was selected based on trees with measured diameters and total heights and the species identified previously. The ecoregion classification was added based on the county designation of the FIA plot location. The resultant dataset included 1,379 BC, 2,083 RO, 5,725 RM, 3,826 SM, and 3,714 YP.

The Chapman-Richards growth function was selected to model the nonlinear relationship between tree diameter and height due to its biologically interpretable coefficients (Pienaar and Turnbull 1973) and its documented flexibility for modeling height-diameter relationships in forest tree species (Fang and Bailey 1998; Huang *et al.* 1992; Pienaar and Shiver 1980, 1984). The Chapman-Richard function is a three parameter model of the form

$$H = 4.5 + \alpha \left(1 - Exp\left\{-\beta * D\right\}^{\gamma}\right) \qquad (1)$$

where:
H = total tree height (ft).
D = diameter at breast height (d.b.h.) (in).
α, β, r = asymptote, scale and shape parameters.

To test for differences between the overall model (state) and each ecoregion, a nonlinear extra sum of squares procedure was employed (Neter *et al.* 1996). This procedure involves the use of dummy variables for the ecoregions in the full model form, while the reduced model form is represented by a three-parameter model representing the height-diameter relationship across all ecoregions (statewide). The full model form uses the following indicator variable (r_i) approach to represent the five ecoregions:

If ecoregion = EALG, r_1 = 1, all other r_i = 0.
If ecoregion = CUPM, r_2 = 1, all other r_i = 0.
If ecoregion = NARV, r_3 = 1, all other r_i = 0.
If ecoregion = SARV, r_4 = 1, all other r_i = 0.
If ecoregion = CALG, all r_i = 0.

The form of the full model for each species tested is

$$H = 4.5 + \left(\alpha + \sum_{i=1}^{4} \alpha_i r_i\right)\left[1 - Exp\left\{-\left(\beta + \sum_{i=1}^{4} \beta_i r_i\right) D\right\}\right]^{\left(\gamma + \sum_{i=1}^{4} \gamma_i r_i\right)} \qquad (2)$$

where:
H = total height for a specific species (ft).
r_i = indicator variable for region r_i, i = 1.4.
D = tree d.b.h. for a specific species (in).
α, β, r = parameters to be estimated from the data.

The full model form has 15 parameters and an error sum of squares (SSE_F) with N-15 degrees of freedom (df_F), where N is the total number of trees for each species-specific test. The form of the reduced model is that of equation (1) and has three parameters and an error sum of squares (SSE_R) with N-3 degrees of freedom (df_R). The full model test has the following null and alternative hypotheses for each of the five species:

$$H_0\text{:}\ \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$$

and
H_a: at least one parameter is not equal to 0.

Rejecting the null hypothesis would indicate that the height-diameter relationship is not the same for all ecoregions. Failure to reject the null hypothesis would indicate that the reduced model form (equation [1]) could be applied to all ecoregions. These tests were conducted independently for each of the five species investigated.

In addition, similar test were conducted for each of the 10 pairwise ecoregion comparisons for each of the five hardwood species investigated. The same indicator variable approach was applied to the specific ecoregion test where the full model was of the form

$$H = 4.5 + \left(\alpha + \alpha_1 r_1\right)\left[1 - Exp\left\{-\left(\beta + \beta_1 r_1\right) D\right\}\right]^{\left(\gamma + \gamma_1 r_1\right)} \quad (3)$$

and the reduced model form is that of equation (1). The full model form has six parameters to be estimated and an error sum of squares (SSE_F) with N-6 degrees of freedom (df_F). The reduced model is the same as previously identified. For each species tested, the full model test has the following null and alternative hypotheses:

$H_0 : \alpha_1 = \beta_1 = \gamma_1 = 0$

and

H_a: at least one parameter is not equal to 0.

Rejecting the null hypothesis would indicate that the height-diameter relationship is not the same for both ecoregions tested. Failure to reject the null hypothesis would indicate that the reduced model form (equation [1]) could be applied to both ecoregions for that species. These tests were conducted independently for each of the five species investigated.

The significance of the full and reduced model comparisons are based on an F-test of the form

$$F = \frac{\dfrac{SSE_R - SSE_F}{df_R - df_F}}{\dfrac{SSE_F}{df_F}}$$

It is possible that significant differences can be identified but these differences may not be of practical significance. To evaluate the magnitude of the differences between using the ecoregion specific and statewide models, the mean height prediction error ($\bar{\varepsilon}$), standard deviation of the prediction error (S_e), and the prediction bias as a percent of mean actual height (Bias %) were calculated and defined as follows:

$$\bar{\varepsilon} = \frac{\sum_{i=1}^{m}\left(\hat{H}_i - H_i\right)}{m} \quad (4)$$

$$S_e = \sqrt{\frac{\sum_{i=1}^{m}\left(\varepsilon_i - \bar{\varepsilon}\right)^2}{m-1}} \quad (5)$$

$$\text{Bias (\%)} = \frac{\bar{\varepsilon}}{\bar{H}} * 100 \quad (6)$$

where:

m = number of trees for each species.

H_i = measured height of tree i.

$\hat{H}_i$ = predicted height of tree i.

$\bar{H}$ = mean of observed tree heights.

Two comparisons were made. One compared the ecoregion specific prediction equation and actual total height and one compared the statewide model and the actual height measurement.

Results

An initial test was conducted to determine whether the height-diameter relationship for each of five economically important Appalachian hardwood species could be modeled with a single three-parameter Chapman-Richards growth model. For all species tested, the null hypothesis was rejected, indicating that at least one of the ecoregion parameters was not equal to zero. P-values for this test ranged from < 0.0001 (SM, RM, and RO) to 0.0054 (BC) (table 1). Results of the initial statewide test led to further comparisons of individual ecoregion models. The same full and reduced model approach was employed to test differences between the 10 combinations of the five ecoregions identified (fig. 1). Of the 10 comparisons, the null hypothesis was rejected in 3 comparisons for BC and 7 comparisons for RO and RM when using a single comparison alpha value of 0.05 (table 2). Rejection of the null hypothesis indicates that the height-diameter relationship between the two ecoregions tested are not the same.

Existence of statistically significant differences between the ecoregions tested does not dictate that these differences are of practical significance. For each of the five species examined, the average error ($\bar{\varepsilon}$), standard deviation of the prediction error (S_e), and percent bias $\left(Bias\%\right)$ between the actual total height and predicted total height based on the statewide based height model was examined (table 3). Across all species and ecoregion combinations, average height error ranged from –3.6 to 7.6 feet

Table 1.—*Results of the full and reduced model comparisons indicating whether a single height-diameter model could be used across all five ecoregions examined.*

Species test	Full model		Reduced model		N	F-value	P-value
	df_F	SSE_F	df_R	SSE_R			
BC	1,364	227,591	1,376	232,308	1,379	2.3558	0.0054
RO	2,068	305,301	2,080	352,005	2,083	26.3630	< 0.0001
RM	5,710	705,396	5,722	714,415	5,725	6.0839	< 0.0001
SM	3,811	500,292	3,823	512,491	3,826	7.7439	< 0.0001
YP	3,699	609,529	3,711	615,036	3,714	2.7850	0.0009

BC = black cherry; RM = red maple; RO = red oak; SM = sugar maple; YP = yellow poplar.

Table 2.—*P-values associated with the full and reduced model tests for height-diameter relations between all combinations for the five ecoregions in West Virginia.*

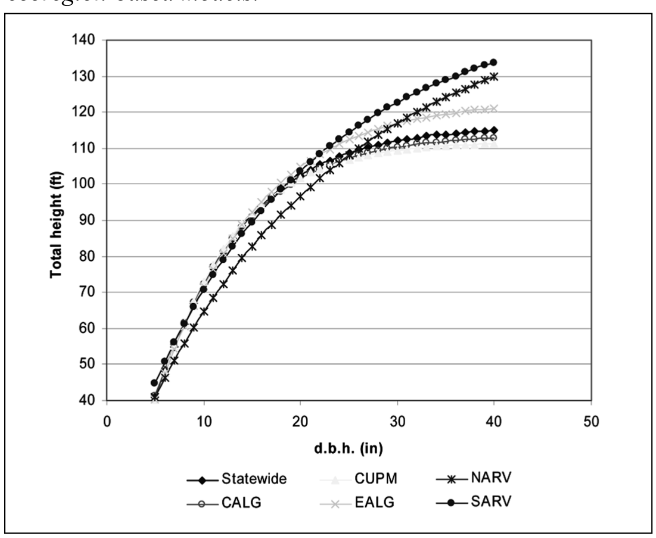
Ecoregion test	Species				
	BC	RO	RM	SM	YP
CUPM vs CALG	0.2158	0.0816	0.0832	0.6316	0.6467
EALG vs CALG	0.0562	0.0991	0.4161	**0.0013**	**0.0455**
NARV vs CALG	0.1460	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0.0025**
SARV vs CALG	0.1031	**< 0.0001**	**< 0.0001**	0.6064	0.2071
EALG vs CUPM	0.2745	0.6139	**0.0093**	0.0668	0.0718
NARV vs CUPM	**0.0136**	**< 0.0001**	0.0553	**< 0.0001**	**0.0007**
SARV vs CUPM	0.1992	**0.0109**	**0.0231**	0.3407	**0.0360**
NARV vs EALG	**0.0129**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0.0018**
SARV vs EALG	0.1477	**0.0003**	**< 0.0001**	0.1108	0.1050
NARV vs SARV	**0.0071**	**< 0.0001**	**0.0002**	**< 0.0001**	**0.0038**

BC = black cherry; CALG = Central Allegheny Plateau; CUPM = Cumberland Plateau and Mountains; EALG = Eastern Allegheny Plateau and Mountains; NARV = Northern Appalachian Ridges and Valleys; RM = red maple; RO = red oak; SARV = Southern Appalachian Ridges and Valleys; SM = sugar maple; YP = yellow poplar.

for the statewide model. The average percent bias ranged from –5.3 to 12.1 percent. Average percent bias for the ecoregion-based models ranged from –0.06 to 0.04 percent.

To visually examine the differences in height curves by ecological region, height curves based on each ecoregion for YP as well as the statewide model are displayed in figure 2. For YP, very little difference can be ascertained from trees less than 20-inches d.b.h. For other species (SM, RO and RM), visual separation can be discerned by the 15-inch class. For BC, this separation occurs by the 10-inch class.

Figure 2.—*YP total height prediction based on statewide and ecoregion-based models.*



CALG = Central Allegheny Plateau; CUPM = Cumberland Plateau and Mountains; EALG = Eastern Allegheny Plateau and Mountains; NARV = Northern Appalachian Ridges and Valleys; SARV = Southern Appalachian Ridges and Valleys; YP = yellow poplar.

Table 3.—*Prediction error and model fit statistics for five species in each of the five ecological regions within West Virginia.*

				Ecoregion specific model			Statewide model			
Ecoregion	**Species**	**N**	$\overline{H}$	$\hat{H}$	**S_e**	**Bias%**	$\hat{H}$	**Mean error**	**S_e**	**Bias%**
CALG	BC	471	57.7558	57.7566	12.58	0.00	58.5705	0.8147	12.62	1.39
CUPM	BC	48	62.1875	62.1860	11.20	0.00	59.7648	– 2.4227	11.87	– 4.05
EALG	BC	450	64.3356	64.2974	13.50	– 0.06	63.2847	– 1.0509	13.58	– 1.66
NARV	BC	138	54.2174	54.2069	12.17	– 0.02	57.4757	3.2583	12.62	5.67
SARV	BC	272	60.7353	60.7195	12.91	– 0.03	59.8830	– 0.8523	13.07	– 1.42
CALG	RM	1,718	57.4499	57.4373	10.97	– 0.02	57.1181	– 0.3319	10.98	– 0.58
CUPM	RM	743	54.5303	54.5242	11.05	– 0.01	55.1978	0.6675	11.09	1.21
EALG	RM	1,853	59.6487	59.6419	11.48	– 0.01	59.2049	– 0.4438	11.53	– 0.75
NARV	RM	525	53.2762	53.2913	10.65	0.03	55.3875	2.1113	10.94	3.81
SARV	RM	886	55.9029	55.9107	10.86	0.01	55.5765	– 0.3264	11.01	– 0.59
CALG	RO	476	71.6555	71.6588	12.12	0.00	68.0394	– 3.6160	12.78	– 5.31
CUPM	RO	280	69.2571	69.2694	12.02	0.02	67.4228	– 1.8343	12.16	– 2.72
EALG	RO	436	73.0803	73.0723	13.12	– 0.01	70.8743	– 2.2060	13.38	– 3.11
NARV	RO	398	55.3719	55.3753	12.46	0.01	62.9613	7.5895	15.53	12.05
SARV	RO	493	64.3753	64.3729	10.93	0.00	64.7406	0.3654	11.00	0.56
CALG	SM	1,498	56.1195	56.1106	11.11	– 0.02	55.9268	– 0.1927	11.12	– 0.34
CUPM	SM	410	58.2659	58.2399	12.22	– 0.04	57.4155	– 0.8504	12.26	– 1.48
EALG	SM	992	59.2218	59.2340	11.67	0.02	58.2318	– 0.9900	11.79	– 1.70
NARV	SM	417	53.7770	53.7723	11.97	– 0.01	57.7511	3.9741	12.80	6.88
SARV	SM	509	57.7819	57.8012	10.85	0.03	57.7023	– 0.0796	10.86	– 0.14
CALG	YP	1,316	74.5266	74.4997	13.10	– 0.04	74.5036	– 0.0230	13.11	– 0.03
CUPM	YP	1,030	71.3990	71.3782	12.41	– 0.03	71.1402	– 0.2588	12.43	– 0.36
EALG	YP	1,027	76.0448	76.0245	13.15	– 0.03	75.8475	– 0.1973	13.20	– 0.26
NARV	YP	93	60.9462	60.9714	11.12	0.04	65.3363	4.3900	12.29	6.72
SARV	YP	248	71.5282	71.5141	12.14	– 0.02	71.7536	0.2254	12.31	0.31

BC = black cherry; CALG = Central Allegheny Plateau; CUPM = Cumberland Plateau and Mountains; EALG = Eastern Allegheny Plateau and Mountains; NARV = Northern Appalachian Ridges and Valleys; RM = red maple; RO = red oak; SARV = Southern Appalachian Ridges and Valleys; SM = sugar maple; YP = yellow poplar.

Discussion

The analysis indicates that statistical differences in the height-diameter relationship exist between the ecoregions identified in the current study. These differences, however, are only in the magnitude of 4 to 8 feet. Whether these differences are of practical significance depends on the practitioner's willingness to accept this magnitude of error. Use of ecoregion-based height models reduces the height prediction error and the data suggest that this difference is significant in at least half of the ecoregion-based tests for the hardwood species investigated. The effect of these height-diameter differences on individual tree volume differences is currently unknown.

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Using Forest Inventory and Analysis Data To Model Plant-Climate Relationships

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Abstract.—Forest Inventory and Analysis (FIA) data from 11 Western conterminous States were used to (1) estimate and map the climatic profiles of tree species and (2) explore how to include climate variables in individual tree growth equations used in the Forest Vegetation Simulator (FVS). On the first front, we found the FIA data to be useful as training data in Breiman's (2001) Random Forests classification and regression tree algorithm to relate climate variables to the presence and absence of species, thereby defining a species' contemporary climate profile. Predicted bioclimatic maps are presented for Douglas fir (*Pseudotsuga menziesii*) and Engelmann spruce (*Picea engelmannii*). On the second front, a preliminary modification of the basal area increment equation used in the FVS is presented that includes climate drivers. The focus of this work is to start the process of building a new growth equation suitable for use in FVS so that climate can be taken into account when predicting forest dynamics. A framework is introduced that integrates the climate-driven increment equation with genetic response functions that represent the adaptiveness of populations to climate change.

Introduction

Climatic factors play a controlling role in shaping tree distributions (Langlet 1936, Pearson and Dawson 2003, Turesson 1922, Woodward 1987), and it follows that these factors are also important in determining growth and mortality (Rehfeldt *et al.* 2003). These facts, coupled with knowledge that our climate is changing (Houghton *et al.* 2001), suggest that tree distributions will change, and that the growth and mortality rates inherent in forest growth and yield models will be questioned.

How much difference could global warming and associated changes in precipitation make in (1) the distribution of trees, and (2) individual tree growth over the next 60 to 90 years? This time span is well within the expected lifetime of many of the trees currently growing in the West and is therefore quite relevant to those preparing forest management plans. The Forest Vegetation Simulator (FVS) (Crookston and Dixon 2005, Stage 1973, Wykoff *et al.* 1982) is a tool used in preparing those plans. Modification of this model to account for climate change is therefore necessary.

In this article, Forest Inventory and Analysis (FIA) data from 11 Western conterminous States are used to (1) develop bioclimatic models for the occurrence of Douglas fir (DF) (*Pseudotsuga menziesii*) and Engelmann spruce (ES) (*Picea engelmannii*) and (2) calibrate a modified version of the diameter growth model for DF to includes climate variables. The bioclimatic models of species occurrence define the species' contemporary climate profile. For contemporary climate, maps of this profile are predictions of the current species distribution.

Adding climate predictors to the growth model in FVS and recalibrating it using FIA observations of growth, provides a prediction equation that is intuitively appealing but conceptually incomplete. FIA measurements of growth capture the growth response to climate for trees growing in contemporary climates, but not for currently living trees growing in future climates.

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Current observations reflect the current states of (1) genetic adaptation and (2) competitive relationships at play at the time of measurement. Therefore, relationships based only on those measurements cannot be used to represent the growth response to climate change. A conceptual framework for further modifying this growth model to represent tree responses to climate change is presented. This conceptual framework recognizes that trees genetically adapt to their climates and that trees from different genotypes will respond differently to climate change.

Methods

Climate Data

The Rehfeldt (2005) climate model consists of thin plate spline surfaces from which a set of climate indicators were predicted. The model is calibrated for all locations within the conterminous Western United States and southwestern Canada, from longitudes between 102 °W and 125 °W and latitudes between 31 °N and 51 °N. The predictions are based on weather observations normalized for 1961 to 1990, the period defined by meteorologists for calculating climatic normals. We believe that these normals suitably overlap the time period of the FIA plot data collected between 1980 and 2004.

Actual plot latitude, longitude, and elevation data were used, rather than the publicly available fuzzed and swapped locations, as input into the climate model. Table 1 lists the variables that were computed for each location; these variables, plus 20 interaction terms, form the list of climate predictors that were used in the analysis.

Table 1.—*Climate variables and their acronyms used as independent variables in regression analyses.*

Name	Definition
mat	mean annual temperature
mtcm	mean temperature in the coldest month
mmin	minimum temperature in the coldest month
mtwm	mean temperature in the warmest month
mmax	maximum temperature in the warmest month
map	mean annual precipitation
gsp	growing season precipitation, April through September
tdiff	summer-winter temperature differential, *mtwm-mtcm*
dd5	degree-days > 5 °C
dd0	degree-days < 0 °C
mindd0	minimum degree-days < 0 °C
sday	Julian date of the last freezing date of spring
fday	Julian date of the first freezing date of autumn
ffp	length of the frost-free period
gsdd5	degree-days > 5 °C accumulating within the frost-free period
d100	Julian date the sum of degree-days > 5 °C reaches 100
ami	annual moisture index, *dd5/map*
smi	summer moisture index, *gsdd5/gsp*
pratio	ratio of summer precipitation to total precipitation, *gsp/map*

Tree Data

Tree data were compiled primarily from three FIA sources. For Idaho, Montana, Wyoming, Nevada, Utah, Colorado, New Mexico, and Arizona, the data were retrieved from the FIA Web site (retrieved March 2005 from http://ncrs2.fs.fed.us/4801/fiadb) and merged into a single database. A key feature of these data is that every FIA plot location is represented in the data, not just those in forested zones. For Washington, Oregon, and California, version 1.4-1 of the Integrated Database (IDB) (Waddell and Hiserote 2004) was combined with newer National Information Management System (NIMS) data provided directly by the Pacific Northwest FIA unit. Combining the data was necessary because the IDB contains plots only from forested zones while the NIMS data has plot records for both forested and non-forested zones. The FIA plot design is generally a cluster of four subplots with a total size of about 0.07 ha for most tree measurements (Bechtold and Patterson 2005). Note that the IDB contains data collected by Federal agencies other than FIA and the sampling designs are not the same. The data in the IDB normalizes the data structure of these disparate inventories, providing a convenient source for analysis.

Presence and Absence Modeling

Breiman's (2001) Random Forests classification and regression tree algorithm was used to model the presence and absence of an individual species. Details of these methods are presented by Rehfeldt *et al*. (2006).

Briefly, Random Forests built a set of 150 to 200 independent classification and regression trees. For each tree, a bootstrap sample of the observations was drawn. Each case was defined by the presence/absence data and the climate variables. The bootstrap sample was used to build the tree and observations left out of the sample were used to compute the classification error. A prediction was made by running a case down each regression tree resulting in one classification for the case. The class that receives the plurality of votes—a vote is a regression tree predicting a specific class—is the predicted class for a case.

Generally, we ran Random Forests twice. In the first run, all the climate variables were included, and in the second run, the 10 or so most important variables (variable importance is scored by Random Forests) from the first run were used to make runs with larger numbers of regression trees. The latter analysis was then used to predict the presence or absence of the species at each 1-km grid cell in the study area.

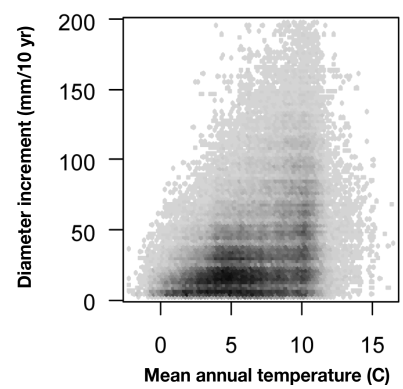
Several versions of Random Forests are available. The one we used is in R (R Development Core Team 2004) and is based on the original program written by Leo Breiman and Adele Cutler (Liaw and Wiener 2005).

Basal Area Increment Modeling

To incorporate climate predictors into FVS, there must be a relationship between increment and climate variables. Figure 1 is a scatter diagram of hexagons in which the intensity of black is proportional to the number of observations in each hexagon. This plot shows (1) the maximum growth for DF occurs at a mean annual temperature (*mat*) of about 10 °C, (2) high growth observations are essentially absent at low temperature sites, (3) that upper range of observations essentially stops at about 13 °C, and (4) that the data contains a huge amount of variability. Similar plots were studied for other climate variables. Studying plots like these suggested that a relationship in the data exists between growth and climate, and that relationship should be modeled in a way that provides for a maximum growth to occur below the maximum value of climate predictors.

Wykoff's (1990) basal area increment model is used in FVS. The dependent variable, delta-diameter-squared (*dds*), is directly proportional to basal area increment. The model was fit to the natural log of *dds* to address the statistical properties

Figure 1.—*Observed Douglas fir diameter increment plotted over mat. The intensity of gray is proportional to the number of observations inside a hexagon. The maximum growth for this species occurs at about 10 °C and there are only incidental observations above 13 °C.*



of errors and because the log transformation linearized the essential relationship between the key variables. In the resulting model, *dds* is a product of tree size, site, and competition. Tree *dbh* is the tree size measure. Competition is measured by crown ratio (*CR*), crown competition factor (*CCF*) (Krajicek *et al*. 1961), and the amount of basal area in trees larger than the subject tree (*BAL*). Variables that measure site include slope, aspect, elevation, geographic location, and habitat type (Daubenmire and Daubenmire 1968).

To incorporate climate predictors, we modified Wykoff's model by replacing habitat type and geographic location with *mat* and mean annual precipitation (*map*). In addition to replacing these two site terms, *CCF* was replaced by total plot basal area (*BA*) as done by Stage and Wykoff (1998) to simplify calculations, and $Elev^2$ was removed because it did not improve the model. A squared term *mat* and *map* would have provided for a maximum growth increment (as the scatter plots indicated would be warranted), but those terms also did not statistically improve the model. The resulting equation is

$$\begin{aligned}\ln(dds) &= b_0 + b_1\ln(dbh) + b_2 dbh^2 + b_3 BAL/\ln(dbh+1) + \\ & b_4 Slope[\cos(Aspect)] + b_5 Slope[\sin(Aspect)] + b_6 Slope + \\ & b_7 Slope^2 + b_8 Elev + b_9 CR + b_{10} BA + b_{11}\ln(mat+10) + \\ & b_{12}\ln(map).\end{aligned} \tag{1}$$

The nonclimate predictors were derived from the FIA data. Plot *BA* and *BAL* were computed at the FIA subplot level. *Slope* and *Aspect* were taken for the *condition* in which the tree was growing. A condition is a mapped subdivision of the plot that describes homogeneous area. *BA* was backdated to the beginning of the growth measurement period by adding recent mortality. No attempt was made to back date plot density for recent growth. Tree *dbh* was backdated by subtracting measured increment. Past 10-year increment data was measured using increment cores and not based on measures based on successive observations of diameter. When more than one measurement for a given location was found in the data, only the first measurement was used.

Note that predictors *BAL*, *BA*, *CR*, and *dbh* are influenced by climate, but for this preliminary analysis we did not address this issue. Nor did we address two additional statistical issues that should be addressed in a final study: (1) the log transformation introduces bias when *dds* is back transformed and (2) the sample trees are clustered on plots and therefore the errors are partially correlated. Neither of these issues influence the main points made below.

Results

Species Distributions

The classification error for DF is 9.4 percent and for ES it is 9.9 percent. At just under 10 percent, the classification error falls into the category of excellent for comparisons of this type (Landis and Koch 1977). The most important variables (table 1) for DF predictions are *ami, map, tdiff·map*. For ES they are *map·mtc, dd5/gsp,* and *ami* (in the order specified). These variables measure major elements of temperature, precipitation, and seasonal interactions. Grid locations of 1 km predicted to be within the climatic profiles of DF and ES (fig. 2) are presented along with Little's (1971) species distribution maps.

Predicting Diameter Increment

Table 2 contains values for parameters of equation (1) for DF. All are highly significant (P<.001, 61,761 observations), and have signs and magnitudes that are generally consistent with previous work (Stage and Wykoff 1998, Wykoff 1990). The model accounts for about 66 percent of the variance in log (*dds*). Attempts to use climate variables other than *mat* and *map* did not materially improve the model. Note that *Elev* is a likely surrogate for climate but attempts to fit the model without it resulted in a poorer model. The modeled response to *mat* and *map* is illustrated in figure 3.

Figure 2.—*The white areas are the predicted distribution FIA-style plots that have one or more Douglas fir trees (left), or Englemann spruce (right), mapped at a 1-km grid on a shaded relief map. The black lines are Little's (1971) mapped distributions. The inset on the left is a small area showing the relative resolution of the predictive model versus Little's map. The inset on the right is Sweetgrass Hills, MT, an area that was omitted from Little's range map but correctly predicted to have Englemann spruce.*

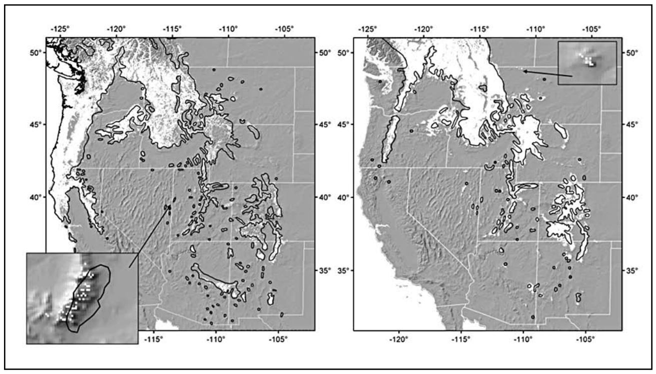
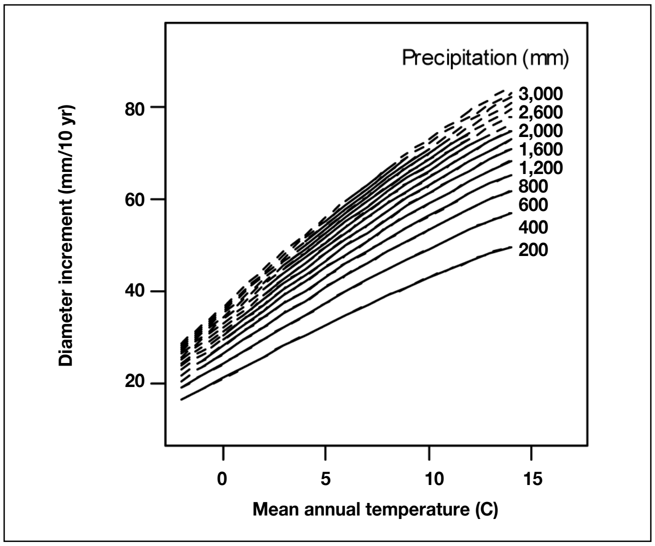


Table 2.—*Regression estimates for equation (1) fit to the Douglas fir data.*

Parameter	Corresponding predictor	Unit	Value
b_0	Intercept	*dds* is in^2	– 4.088
b_1	ln(*dbh*)	*dbh* is in	1.051
b_2	*dbh*^{2}	*dbh* is in	– 0.0003178
b_3	*BAL*/log(*dbh*+1)	*BAL* in ft^2/acre	– 0.008130
b_4	*Slope*[cos(*Aspect*)]	% and radians	0.01973
b_5	*Slope*[sin(*Aspect*)]	% and radians	– 0.07356
b_6	*Slope*	%	– 0.0845
b_7	*Slope*^{2}	%^{2}	– 0.4575
b_8	*Elev*	ft	– 0.00008782
b_9	*CR*	%	0.01468
b_{10}	*BA*	ft^2/acre	0.0003967
b_{11}	ln(*mat*+10)	°C	0.9160
b_{12}	ln(*map*)	mm	0.2260

Figure 3.—*The effects of temperature and precipitation on diameter increment as portrayed by equation (1). The dark lines indicate the approximant range of the temperature and precipitation measurements coincident with observations of Douglas fir growth.*



Discussion

Species Distributions

Rehfeldt *et al*. (2006) explore the results of these analyses in detail. They also present results for seven additional species, provide predictions for the biotic communities of Brown *et al*. (1998), and make predictions on how predicted global warming will cause major shifts in the spatial distribution of contemporary climate profiles.

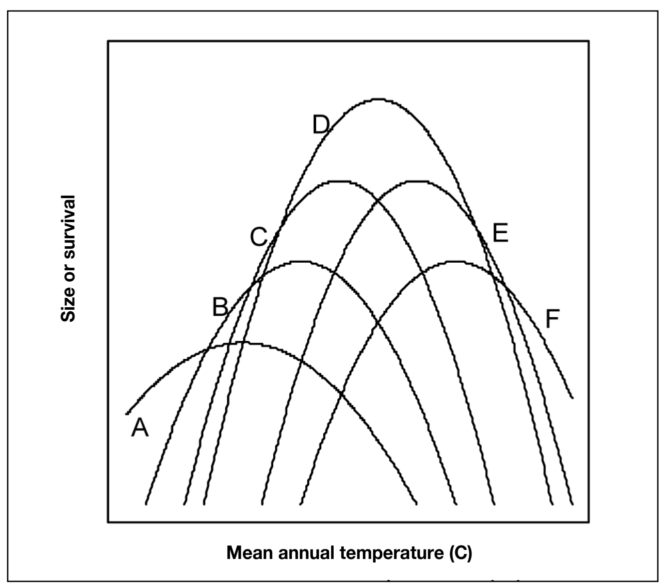
The Random Forests predictions are, in our view, astonishingly good. To the casual observer this raises the question that the procedure is overfitting the data. Note that Breiman (2001) has proven that the method cannot overfit the data, and we found no evidence that the classification error approached zero as parameters were added. To the contrary, as superfluous predictor variables are added, prediction errors increase.

Predicting Diameter Increment

The modified diameter increment model (fig. 3) predicts that an increase or decrease in temperature or precipitation will translate directly into a corresponding increase or decrease in growth. On the surface, therefore, it would appear that we have achieved our goal of modifying the FVS growth equation so that it is sensitive to global warming. The curves, however, illustrate the breadth of physiologic plasticity within the species, not within individual trees. Individual trees are adapted to only a portion of the environmental heterogeneity faced by the species. The equation, therefore, is suitable for predicting a change in growth given a change in climate only to the extent that the individual trees undergoing the climate change are adapted to the new climate. The adaptive response of individual trees, measured by the response for individual genotypes, determines the individual growth response to climate change (Langlet 1936; Rehfeldt *et al*. 1999, 2002, 2003).

Figure 4 illustrates the response of populations of trees to gradients in *mat*. For geneticists, a population is an artificial grouping of trees all of which are adaptively similar and, therefore, grow in similar environments. An implication from

Figure 4.—*Diagrammatic representation of the response of populations to mean annual temperature and competitive pressures from other populations. The realized niches of each population is limited to the locations on the curves that are not overlapped. Population D is growing at its optimum mat, which also happens to be the optimum for the species as a whole, while other populations are growing below their own optimums and their individual optimums are below the population optimum.*



Source: Rehfeldt et al. *1999.*

figure 4 is that if *mat* increases in a forest currently inhabited with trees from population A, a forester will observe an increase in growth up to the optimum for population A and then observe a decrease in growth at *mat* levels that are still much lower than the optimum for the species as a whole. To capture the increase in growth one would expect from a warming climate, the trees from population A must be replaced with members of a more suitable population.

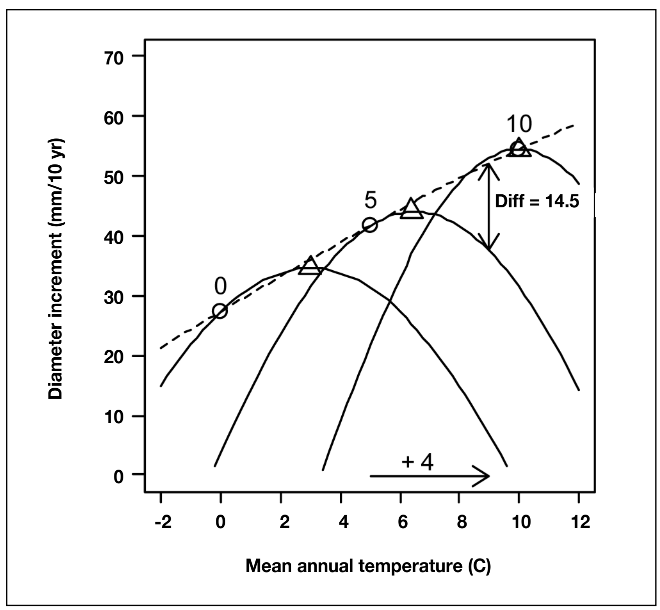
To incorporate climate variables into FVS, two kinds of information must be integrated: (1) thousands of observations from the FIA plots represent observations from the realized niche (figs. 1 and 3) and (2) results from the genetic experiments (as represented by the stylized drawing in figure 4) that represent the fundamental niche.

Our suggestion for integrating these model components is illustrated in figure 5. At the beginning of simulations, and so long as climate change does not occur, the growth for individual trees follows equation (1). Growth under climate change scenarios is a function of the corresponding solid lines. In a simulation, each tree will be represented by a different solid line. The parameters for the shape and location of the solid line are derived from species-specific relationships developed from common garden experiments. For trees growing in the extremes of a population, the mean realized niche (circles) is much further to the left of the corresponding optimum for the population (triangles).

It is reasonable to question why approaches like those of Wensel and Turnblom (1998) and Yeh and Wensel (2000) were not chosen as the basis for our efforts. These researchers related annual deviations from model-based estimates of growth to contemporary weather. The models used did not contain climate variables. Their work is relevant to the job of accounting for short-term deviations around average trends while our approach concentrates on accounting for shifts in the averages. Despite this difference in temporal resolution, the dearth of data available for understanding climate effects on growth justifies further work toward capitalizing on both fronts.

Another question is why we are not proposing using so-called process-based models to account for these effects. For example, why not use the weather-driven model built by Milner *et al.* (2002)? That group adapted Running and Coughlan's (1988) whole stand physiological model (Forest-BGC) to an individual tree, distance independent model for use with FVS. Forest-BGC contains empirical components that drive the disaggregation of net biomass production to individual trees. The net production is nonspecific, assuming that a suitable photosynthetic engine exists on the site. The species present on the site, and the assumptions that they are appropriately adapted, are exactly the same for Forest-BGC as for the Wykoff-style diameter increment model. That is, they too fail to account for the genetic factor.

Figure 5.—*Diagram shows how the proposed combined model should work. The dotted line is the base increment model (equation [1] with 800 mm of precipitation, dbh = 30 cm, 80 percent crown, no basal area in larger trees, flat ground, and other predictors set at their sample means), and the circles correspond to three example locations along the mat gradient. The two arrows illustrate the difference in predicted growth using dotted lines model and the solid lines for an increase in mat from 5 to 9 °C.*



Conclusions

FIA data proved useful in predicting species distributions, and the Random Forests program proved to be a powerful tool for this purpose. In addition, these data, coupled with climate data, provide a strong basis for building models of diameter increment as a function of contemporary climate. These data alone, however, do not provide a way to predict increment in the face of climate change. Measurements are needed from individual trees growing in places where growth has been followed through periods of climate change that are about equal in magnitude to the magnitude of the future expected change, or where members of genetic populations (provenances) have been planted in a range of climatic conditions and then monitored. In either case, the broad-scale measurements of diameter increment supplied by FIA have a place in this work.

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A *k*-Nearest Neighbor Approach for Estimation of Single-Tree Biomass

Lutz Fehrmann[1] **and Christoph Kleinn**[2]

Abstract.—Allometric biomass models are typically site and species specific. They are mostly based on a low number of independent variables such as diameter at breast height and tree height. Because of relatively small datasets, their validity is limited to the set of conditions of the study, such as site conditions and diameter range. One challenge in the context of the current climate change discussion is to develop more general approaches for reliable biomass estimation. One alternative approach to widely used regression modelling are nonparametric techniques.

In this paper we use a *k*-Nearest Neighbor (*k*-NN) approach to estimate biomass for single trees and compare the results with commonly used regression models. The unknown target value of a certain tree is estimated according to its similarity to sample tree data stored in a database.

Introduction

Estimation of forest biomass has gained importance in the context of the legally accepted framework of the United Nations Framework Convention on Climate Change and the Kyoto Protocol. Reliable and general estimation approaches for carbon sequestration in forest ecosystems are needed (Brown 2001, Joosten *et al.* 2003, Rosenbaum *et al.* 2004, Wirth *et al.* 2003). In the past, the standard methodology in single-tree biomass estimation was based on fitting parametric regression models with relatively small datasets. Numerous models have been built from destructive sampling studies, most of which are allometric functions. They allow predicting tree biomass as a function of easily observable variables like such as diameter at breast height (d.b.h.) and tree height. Typically, these models are specific to the tree species and site conditions of the underlying particular study. Extrapolation beyond this set of particular conditions is critical.

Different attempts have been made to derive more general functions by meta-analyses of the published equations (e.g., Jenkins *et al.* 2003, Zianis and Mencuccini 2004, Chave 2005). In many cases such studies have been constrained by the absence of primary data and are focused on the reported regression functions only (Montagu *et al.* 2004). Therefore, one major goal of future research in the field of single-tree biomass estimation can be seen in the generalization of models based on compilation of empirical data from sample trees. Once a suitable single-tree database is given, nonparametric modelling approaches, such as the *k*-Nearest Neighbor (*k*-NN) method, might be suitable alternatives to regression modelling. The basic difference is that nonparametric models do not require concrete queries before they are developed.

Methods

k-NN Technique

The *k*-NN approach is a nonparametric and instance-based machine learning algorithm. It is known as one of the oldest and simplest learning techniques based on pattern recognition and classification of unknown objects. It was described as a nonparametric approach for discriminant analysis (lazy similarity learning algorithm) by Fix and Hodges (1989) or Cover and Hart (1967), for example.

This approach classifies an unknown feature of an object (an instance) based on its "overall" similarity to other known

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objects. Therefore, the instances with known target values are stored in a database (the so-called training data).

To estimate the unknown feature of a query instance, the most similar known instances are identified by means of a set of known variables. The weighted or unweighted mean of the target variable of a number *k* of nearest instances (neighbors) to the unknown instance is then assigned. To identify the most similar training instances, it is necessary to define measures of similarity and quantify their distance or dissimilarity to the query instance (Haendel 2003).

In contrast to parametric models, the result of the *k*-NN estimation is not a "global function" for the entire feature space, but a local approximation of the target value that changes in every point of the feature space depending on the nearest neighbours that can be found for a certain query point (Mitchell 1997).

In forestry, applications of this approach can be found in Haara *et al.* (1997), Korhonen and Kangas (1997), Maltamo and Kangas (1998), Niggemeyer (1999), Tommola *et al.* (1999), and Hessenmöller (2001). In this paper, the methodology is mainly used to estimate stand parameters or as an alternative to parametric growth models. Sironen *et al.* (2003) applied a *k*-NN approach for growth estimations on single-tree data. Applications of different nonparametric approaches including *k*-NN are also in Malinen (2003a, 2003b), Malinen and Maltamo (2003), and Malinen *et al.* (2003).

The *k*-NN technique has long proved applicable and useful in the context of integration of satellite imagery into large-scale forest inventories estimations (Moer and Stange 1995, Tomppo 1991). Satellite images are classified using the similarity of spectral signatures of single-pixel values (Holmström *et al.* 2001, McRoberts *et al.* 2002, Stürmer and Köhl 2005).

For local approximation of a continuous target value, the *k*-NN algorithm assigns the mean of the target values of a certain number of most similar training instances to the query instance as

$$\hat{f}\left(x_q\right) \leftarrow \frac{\sum_{i=1}^{k} f\left(x_i\right)}{k} \tag{1}$$

Where:
$\hat{f}\left(x_q\right)$ is the estimator for the unknown target value of a query instance x_q.
$f\left(x_i\right)$ are the known target values of training instances.
k is the number of nearest neighbours used for estimation.

To quantify the dissimilarity between instances and to identify a number of *k* nearest neighbours, known measures of proximity from multivariate analyses, such as discriminant or cluster analysis, may be used. For practical application the Minkowski metric or L-norm is a suitable and flexible multivariate distance measure (Bortz 1989, Backhaus *et al.* 1996):

$$d_{i,j} = \left[\sum_{r=1}^{n} \left|x_{ir} - x_{jr}\right|^{c}\right]^{\frac{1}{c}} \tag{2}$$

where:
$d_{i,j}$ = the distance between two instances *i* and *j*, x_{ir} and x_{jr} being the values of the r^{th} variable for the respective instance.
n = the number of considered variables.
$c \geq 1$ = the Minkowski constant.

In case of $c = 1$, the result of this metric is the so called Manhattan or taxi driver distance, which is the sum of all variables differences. For $c = 2$, this measure is the Euclidean distance in an *n*-dimensional feature space.

To take the unequal importance of different variables for the development of the target value into account and to avoid the distorting influence of different scaled feature spaces, the variables have to be standardized and weighted according to their influence. Because the single variable distances are explicitly obvious in the given distance metric, the standardization and weighting can be included in the calculation of an overall distance by modifying it to the following:

$$dw_{i,j} = \left[\sum_{r=1}^{n} \left(w_r \frac{\left|x_{ir} - x_{jr}\right|}{\delta_r}\right)^{c}\right]^{\frac{1}{c}} \tag{3}$$

where:
$dw_{i,j}$ = the weighted distance.
w_r = the weighting factor for variable *r*.

δ_r = a standardization factor that can be coupled to the range of the variable.
In our study we set δ_r to $2\sigma_r$ whereas σ is the standard deviation of the respective variable.

Even if both steps are a kind of transformation of the feature spaces of the considered variables, one should distinguish between feature standardization and weighting. While standardization is necessary to ensure the comparability of the single variable distances, the weighting of the different variables in a multidimensional space is an expression of their unequal relevance for the target value (Aha 1998, Wettschereck 1995).

Feature weighting can have a great influence on the identification of the nearest neighbours, making it relevant for the quality of the derived estimation. Suitable weighting factors can be derived from several alternatives. Tomppo *et al.* (1999) proposes deriving feature weights based on the coefficient of correlation between the different variables and the target value. Another possibility is using the relation between the regression coefficients of the included variables from a suitable regression model to derive the weighting factors. Iterative optimization algorithms such as genetic algorithm or simulated annealing can also be used to find an appropriate relation of feature weighting factors (Tomppo and Halme 2004).

If the distances between a query point and all training instances in the database are known and the k nearest neighbours are identified, they can also be used to derive a weighted mean. According to Sironen *et al.* (2003), or similarly Maltamo and Kangas (1998), the weighting of the neighbours according to their distance can thereby be derived as

$$w_k = \frac{\left(\frac{1}{d_{q,i}}\right)^t}{\sum_{i=1}^{k}\left(\frac{1}{d_{q,i}}\right)^t} \tag{4}$$

where:
w_k = the weight of the k^{th} neighbour.
$d_{q,i}$ = the distance between a query point x_q and the neighbour x_i.
t = a weighting parameter that influences the kernel function.

Implementing this distance-weighted mean as estimator formula (1) becomes

$$\hat{f}_w\left(x_q\right) \leftarrow \frac{\sum_{i=1}^{k} w_k f\left(x_i\right)}{\sum_{i=1}^{k} w_k} \tag{5}$$

In this case, the estimator is equivalent to the *Nadaraya-Watson estimator* (Atkeson et al. 1997, Haendel 2003, Nadaraya 1964, Watson 1964). Because of the decreasing influence of training instances with increasing distance, all training instances can be included in the estimation process in this approach, which is also known as Shepard's method (Shepard 1968).

Even if the k-NN algorithm is referred to as a nonparametric method in the context of searching a number of nearest neighbours, this description does not apply for the distance function that is used. In the basic k-NN approach, the weighting factors for the different variables, which are normally defined in a deterministic manner, and the parameters k, n, c, δ and t of the above mentioned distance function (3) and estimator (5) are defined globally.

As a result of an asymmetric neighbourhood at the extremes of the distribution of observations, instance-based methods come with a typical bias-variance dilemma. The number of neighbours considered in the estimation must be determined as a compromise between an increasing bias and the decreasing variance of estimates with an increasing number of neighbours (Katila 2004). To find an approximation for an optimal number for k, we applied the root mean square error (rMSE%) as error criterion. The objective criteria is the minimization of the rMSE% by means of a leave-one-out cross validation with a changing size of the considered neighbourhood and/or the parameter setting in the distance and weighting function. In a cross validation, a query instance is a tree that is excluded from the training instances and for which estimation is derived based on the N-1 remaining trees. Each training instance is in turn used as query instance (Malinen *et al.* 2003). The rMSE% is then calculated as

$$rMSE\% = 100 \times \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{ir} - \hat{x}_{ir}\right)^2}}{\bar{\hat{x}}_r} \tag{6}$$

where:

x_{ir} = the observed value of variable *r* for instance *i*.

$\hat{x}_{ir}$ = the respective estimated value.

n = the number of observations.

$\bar{\hat{x}}_{r}$ = the mean of estimates for the target variable *r*.

Because of the high number of possible parameter combinations, the iterative process was reduced to about 50 different combinations in which the determination of the starting values for the feature weights were based on expertise obtained from the relation of regression coefficients as result of a regression analysis with the respective variables.

Reference Model

As reference to the *k*-NN estimations we derived an allometric regression model based on the same dataset. Independent variables are *dbh* and tree height. To consider for inherent heteroscadicity, an ordinary least square (OLS) regression was built with log transformed variables and aboveground biomass (*agb*) as the dependent variable (Sprugel 1983). The estimated regression coefficients are shown in table 1.

Data

To evaluate the *k*-NN approach in comparison to parametric regression models, we built a single-tree biomass database with training instances from various destructive biomass studies. In this study we used a subset of *N* = 323 Norway spruce trees (*Picea abies* [L.] Karst.) that were compiled from different publications and datasets from central Europe. Parts of the database come from a study of Wirth *et al.* (2003). Additional datasets were taken from literature and project reports.

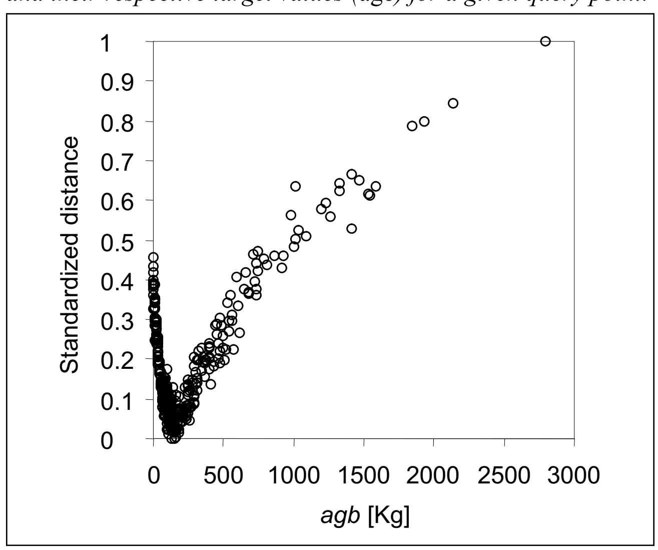
Results

Calculating the distance between a query point and all training data leads to a certain order of instances according to their similarity to the unknown query instance (fig. 1). For the given example, at first only the variables *dbh* and tree height were used in the distance function. Using a nearest neighbour bandwidth, the distance to which neighbours are considered for the estimation is set to the distance of the k^{th} neighbour (Atkeson *et al.* 1997).

The disadvantage of this approach is that a fixed bandwidth selection may increase bias as result of the asymmetric neighbourhood in the extremes of the feature space. Nonparametric approaches such as the *k*-NN method are known to be inappropriate for any kind of extrapolations. In addition, a certain edge effect exists within the feature range of the training data. This fact makes it difficult to compare the *k*-NN based estimations with a given regression model. Figure 2 shows the effect of increasing the neighbourhood, especially on estimations for the biggest trees in this dataset.

The smaller size of the considered neighbourhood leads to a lower bias at the extremes of the feature space. At the same

Figure 1.—*Training data ordered according to their distance and their respective target values (*agb*) for a given query point.*



agb = *aboveground biomass.*

Table 1.—*Estimated coefficients, R^2, and residual standard error for the allometric reference model. Dependent variable is* agb *in kilogram dry mass.*

Model formulation	Linearized form	ln(*a*)	*b*	*c*	R^2	Residual standard error
$agb = a \cdot dbh^{b}\, h^{c}$	$\ln(agb)=\ln(a)+b \cdot \ln(dbh)+c \cdot \ln(h)$	– 2.651	1.888	0.699	0.98	0.1864

agb = *aboveground biomass.*

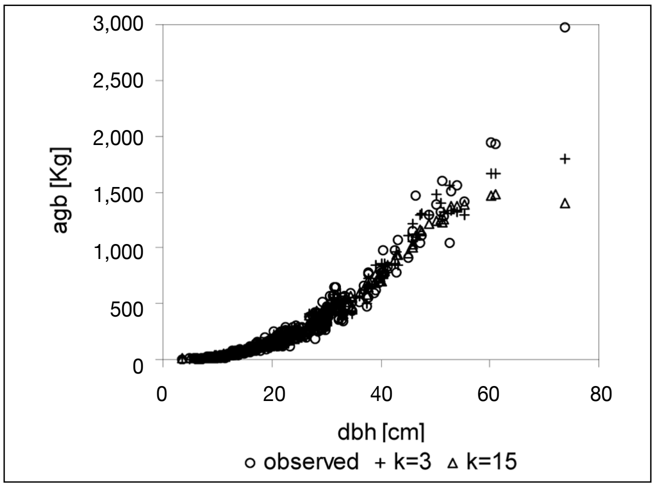
time, however variance is obviously increasing because fewer values of the target values are averaged.

The resulting rMSE% values for different sizes of the neighborhood were calculated by means of a leave-one-out cross validation of the whole dataset for different values of *k*. Figure 3 shows that in case of the underlying data and the used variables, a minimum error can be found for three neighbors. It must be considered that this optimum size of the neighborhood is only valid for the given parameter setting and this certain dataset. The respective rMSE% calculated for the adapted reference model was about 19 percent lower than that of the *k*-NN estimation.

A lower error can be achieved by integrating further single-tree variables, such as tree age or crown length. Figure 4 shows an example where these additional variables were included in the distance calculation. It is obvious that the optimal number of neighbours changes in this case to five. The amount of available training data with information for these search variables decreased to 181 trees.

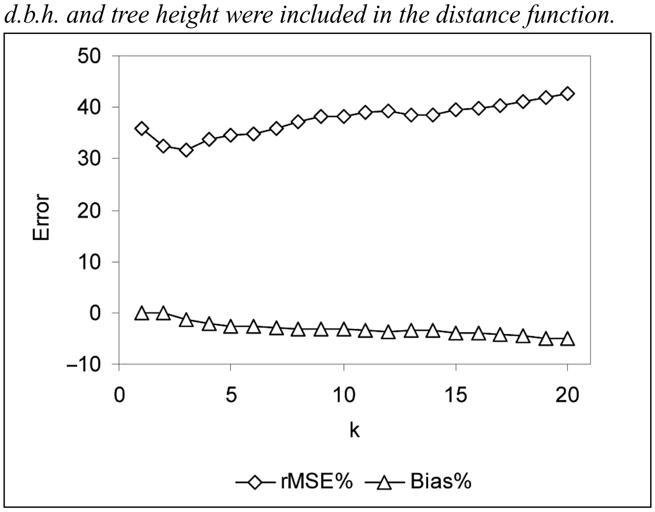
One possibility to lower the influence of the systematic error is to use a kernel function that attenuates the influence of neighbours according to their increasing distance. The distance-weighting function we used in this approach can be modified by changing the parameter *t*. As figure 5 shows, we achieved the lowest errors without any distance weighting in this case. Different simulations with other tree species and different combinations of variables showed that the influence of the parameter *t* on the error is highly dependant on the underlying dataset and the choice of search variables. Similar to the determination of the parameter *c* that influences the type of distance metric as well as the relation of feature-weighting factors, the optimum parameter setting differs highly between different datasets.

Figure 2.—*Observed* agb *and estimations based on* k *= 3 and* k *= 15 neighbors.*



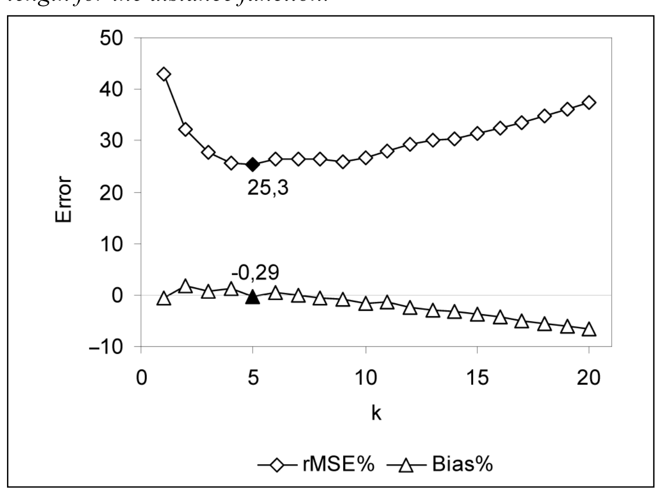
agb = *aboveground biomass.*

Figure 3.—*rMSE % and Bias% of the* k-*NN estimation calculated in a leave-one-out cross validation for different sizes of the considered neighbourhood. In this case only the variables d.b.h. and tree height were included in the distance function.*



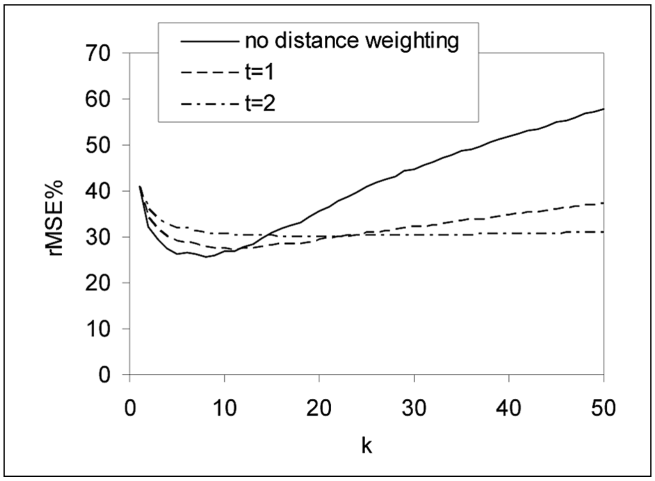
d.b.h. = diameter at breast height.

Figure 4.—*rMSE% and Bias% for a certain parameter setting using the variables d.b.h., tree height, tree age, and crown length for the distance function.*



d.b.h. = diameter at breast height.

Figure 5.—*Influence of the distance-weighting parameter* t *on the development of the rMSE% for different sized neighborhoods.*



Discussion

In the given example, the errors of the *k*-NN estimations were higher than those of an allometric regression model derived from the same dataset and with the same independent variables. One reason for the errors is that we only used one combination of feature weights and/or parameter settings. The goal of this study was primarily to evaluate the general applicability of the *k*-NN method for single-tree biomass estimation. Future work will be focused on optimization of this method for the given purpose.

Another reason for the comparatively bad performance of the approach in comparison to the given regression model is that the number of training data as well as the number of variables included in the distance function was untypically low for a nonparametric method. One advantage of the *k*-NN method is that it is easily possible to include a high number of independent search variables in the distance function. This advantage was not used in this basic and general example. More variables and information components can be included in the estimation process. For examples, the process could include site parameters such as the height above sea level, the site quality, geographic coordinates, or further information on tree species. If enough variables with a certain discriminatory power in the context of dissociating trees of different species are available and are able to bring the training data in a correct order according to their distances, estimations over different species are possible.

For the optimization of the *k*-NN estimations, the high number of parameters for the distance and weighting function we used in this example causes problems. An approximation for an optimal combination or relation of parameters can be found by using iterative processes such as optimization algorithms. The target in this case is the minimization of the error criterion (e.g., the rMSE%) by a stepwise change of the parameter settings. For the given example we only used a low number of iterations, whereas the starting values were predefined based on expertise gained in the regression analysis and the first experience with a software application of the *k*-NN algorithm. It must be assumed that the given intermediate results are far from an optimal solution and that future work can enhance the performance of the *k*-NN method which might then be an alternative to the given approaches, particularly in the context of the generalization of biomass models.

Conclusions

Trees can be interpreted as instances of more or less one basic form, consisting of an individual pattern of principal components such as stem, branches, leaves, and roots. If certain key variables on a single-tree level are known, pattern recognition algorithms such as the *k*-NN method can be used to identify the most similar instances (trees) from a database and use their known target values to derive estimations for unknown instances. Often additional meta-information about forest stands, site characteristics, or species-specific information such as mean wood density are available and can be used in the context of this methodology. Different authors (Hessenmöller 2001, Malinen 2003a, Sironen *et al.* 2003) have proved this nonparametric method applicable and useful as well for single-tree applications, in which its performance is obviously highly dependent on the amount of training data. One of the main future challenges in the field of biomass estimation will be the generalization of estimation approaches and/or models.

To ensure a certain reliability of the generalized models, the compilation of destructive sampled data will be necessary. If it is possible to implement a single-tree database in a central and free accessible place, instance-based methods can also be applied as server-client applications in future.

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A Bayesian Approach To Multisource Forest Area Estimation

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Abstract.—In efforts such as land use change monitoring, carbon budgeting, and forecasting ecological conditions and timber supply, demand is increasing for regional and national data layers depicting forest cover. These data layers must permit small area estimates of forest and, most importantly, provide associated error estimates. This paper presents a model-based approach for coupling mid-resolution satellite imagery with plot-based forest inventory data to produce estimates of probability of forest and associated error at the pixel level. The proposed Bayesian hierarchical model provides access to each pixel's posterior predictive distribution allowing for a highly flexible analysis of pixel and multipixel areas of interest.

Introduction

Most large forest inventory programs use stratified estimation techniques to couple inventory data collected from field plots and ancillary data, such as satellite imagery, to increase the precision of their estimates. Satellite imagery has provided a useful and cost effective source for deriving the data layers required for stratified estimation (McRoberts *et al.* 2002). These stratified estimation techniques can produce satisfactory estimates and precision for medium to large geographic areas, but they typically fail to satisfy precision expectations for small areas. Obtaining forest area estimates for small areas requires more spatially intensive sampling designs, more and different kinds of ancillary data, and/or methods that extract more information from inexpensive sources of ancillary data. The increased costs associated with more intense sampling and a larger suite of ancillary data often precludes these approaches. Therefore, approaches to make better use of common and affordable satellite imagery merit consideration.

This paper presents a model-based approach that can be used to couple field inventory data from the Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture (USDA) Forest Service with mid-resolution satellite imagery to predict pixel-level forest probability with associated error estimates. The Bayesian hierarchical model presented provides access to each pixel's full predictive distribution from which we calculate the desired inferential statistics. Further, when combined with an appropriate area estimator, these individual pixel estimates can provide area and error estimates for arbitrary areas of interest (AOI).

This paper builds a logistic-regression-based Bayesian hierarchical model for incorporating spatial structure then describes methods for parameter estimation of fixed effects and random spatial effects. A procedure for model-based prediction of probability of forest in arbitrary AOIs is described.

Statistical Modeling

Nonspatial Logistic Model

We first outline a basic logistic model that can be used for modeling the forestation. Suppose we have $i = 1,\ldots,n$ subplots. Based on the percent canopy cover and additional forest structure variables, FIA records single condition subplots as either forest or nonforest. We set y_i as the binary variable designating this classification with $y_i = 1$ denoting that subplot i is forested and $y_i = 0$ otherwise. Conditional on the set of independent variables (spectral characteristic for us), say x_i for subplot i ,

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we assume that the y_i s follow an independent and identically distributed (i.i.d.) Bernoulli distribution, $y_i \sim Ber(p(\mathbf{x}_i))$ with $P(y_i = 1 \mid \mathbf{x}_i) = p(\mathbf{x}_i)$. The association between the dependent data vector $\mathbf{y} = (y_1, ..., y_n)$, and the $n \times m$ matrix of m spectral independent variables $X = [\mathbf{x}_1^T, ..., \mathbf{x}_n^T]$, where each $\mathbf{x}_i^T$ is the $1 \times m$ vector of spectral characteristics for the i-th point, is modeled through a logistic link regression

$$p(\mathbf{x}_i) = \frac{\exp(\mathbf{x}_i^T \theta)}{1 + \exp(\mathbf{x}_i^T \theta)}, \qquad (1)$$

where $\theta = (\theta_1, ..., \theta_m)$ is the vector of parameters to be estimated.

Letting $Data$ denote all the available information, say $\mathbf{y}, X$ above, the likelihood function for the data given the above model is

$$L(\theta; \text{Data}) = \prod_{i=1}^{n} p(\mathbf{x}_i)^{y_i} (1 - p(\mathbf{x}_i))^{1-y_i} = \prod_{i=1}^{n} \frac{\exp\left(\mathbf{x}_i^T \theta\right)^{y_i}}{1 + \exp\left(\mathbf{x}_i^T \theta\right)}. \qquad (2)$$

This yields the corresponding log-likelihood function as

$$\ln\left(L(\theta; \text{Data})\right) = \sum_{i=1}^{n} y_i \left(\mathbf{x}_i^T \theta\right) - \sum_{i=1}^{n} ln(1 + \exp(\mathbf{x}_i^T \theta)). \qquad (3)$$

Typically, from equation (3) iterative methods are used to obtain the maximum likelihood estimates of the parameters θ (Amemiya 1985). These methods, however, rely on asymptotic (for large samples) distributional assumptions that are rarely verifiable in practice. Alternatively, we adopt a Bayesian paradigm (Gelman *et al.* 2004) that enables direct probabilistic inference for all the model parameters by first specifying prior distributions for them and subsequently using the likelihood in equation (2) to obtain the posterior distribution. In practice, therefore, if $p(\theta)$ is the prior distribution for θ, the posterior distribution of θ is given by

$$p(\theta \mid Data) \propto p(\theta) L(\theta; \text{Dat}$$

Such inference typically proceeds from drawing samples from the posterior distributions of the parameters. Markov chain Monte Carlo (MCMC) integration methods (Gelman *et al.* 2004) provide samples from the full posterior distribution of θ that can subsequently be used for inference.

Logistic Model with Spatial Random Effects

The unexplained residual uncertainty associated with the mean function in equation (1) does not accommodate spatial correlation among subplot observations. Ignoring the spatial structure can impair the precision of predictions. A two-stage hierarchical model allows us to incorporate spatial structure into the basic model. The first stage of the hierarchical model adds spatial random effects to the mean structure in equation (1). If the subplots are spatially referenced (e.g., Easting-Northing or some other coordinate system) as $S = \{\mathbf{s}_1, ..., \mathbf{s}_n\}$, we can envision the response as $y(\mathbf{s}_i) = 1$ or 0 depending on whether the subplot is forested. Within the augmented model, the probability that $y(\mathbf{s}_i) = 1$ depends on spatially-referenced independent variables, $\mathbf{x}(\mathbf{s}_i)$ for subplot $\mathbf{s}_i$, the parameters θ, and the location specific random effects $w(\mathbf{s}_i)$:

$$p(\mathbf{s}_i) = \frac{\exp\left(\mathbf{x}(\mathbf{s}_i)^T \theta + w(\mathbf{s}_i)\right)}{1 + \exp\left(\mathbf{x}(\mathbf{s}_i)^T \theta + w(\mathbf{s}_i)\right)}. \qquad (4)$$

In the present context, $\mathbf{s} \in D$ and D defines the surface of interest within $\Re^2$.

The second stage of the hierarchical model is to specify the spatial random effects. Specifically, we presume that $w(\mathbf{s}) \sim GP(0, \sigma^2 \rho(\cdot, \phi))$ is drawn from a Gaussian Process with mean zero and $\rho(d, \phi) = \exp(-\phi d)$ is an exponential correlation function (Banerjee *et al.* 2004). This implies $\mathbf{w} \sim N(0, \sigma^2 R(\phi))$ where $\mathbf{w} = (w(\mathbf{s}_1), .., w(\mathbf{s}_n))^T$ is the $n \times 1$ vector of spatial random effects and R is the $n \times n$ correlation matrix with elements $R_{i,j} = \exp(-\phi d_{i,j}$ where $d_{i,j} = \left|\mathbf{s}_i - \mathbf{s}_j\right|$ is the Euclidean distance between locations $\mathbf{s}_i$ and $\mathbf{s}_j$. The spatial process is described by the spatial decay parameter ϕ and the spatial effect variance σ^2. Customarily, we describe the effective range d_0 of the spatial process by solving $\exp(-\phi d_0) = 0.05$ (i.e., $d_0 \approx 3/\phi$.

The Priors and Likelihoods

With the addition of the random effects, we have the parameter set $\Omega = (\theta, \sigma^2, \phi, \mathbf{w}$, with length $m + 2 + n$. A Bayesian analysis requires that we assign appropriate prior distributions $p(\Omega)$ to each parameter. A flat prior can be assigned to θ (i.e., $p(\theta) \propto 1$), a vague Inverse Gamma prior for $\sigma^2 \sim IG(a_\sigma, b_\sigma)$, and Uniform for $\phi \sim U(a_\phi, b_\phi)$. The posterior distribution for Ω becomes

$$P(\Omega | Data) \propto P(\phi) P(\theta) P(\sigma^2) P(\mathbf{w} | \sigma^2, \phi) \times L(\Omega; \text{Data}), \qquad (5)$$

where $\mathbf{y} = (y(\mathbf{s}_1), \ldots, y(\mathbf{s}_n))^T$ is the $n \times 1$ response vector and $L(\mathbf{w}; \mathbf{y}, S)$ is the data likelihood, modified from equation (2) as

$$L(\mathbf{w}; Data) = \prod_{i=1}^{n} P(y(\mathbf{s}_i) = 1 | \mathbf{x}(\mathbf{s}_i), \theta, \mathbf{w}(\mathbf{s}_i))^{y(\mathbf{s}_i)} (1 - P(y(\mathbf{s} = 1 | \mathbf{x}(\mathbf{s}_i), \theta, \mathbf{w}(\mathbf{s}_i)))^{1-y(\mathbf{s}_i)}, \quad (6)$$

with $P(y(\mathbf{s}_i) = 1) = logit^{-1}(\mathbf{x}^T\theta + w(\mathbf{s}_i))$. The Gaussian Process specification implies that the $P(\mathbf{w}|\theta)$ is a multivariate normal $N_n(0, \sigma^2 R(\phi))$. The log-posterior is

$$ln\left(p(\Omega|\mathbf{y})\right) \propto -\left(a_\sigma + 1 + \frac{n}{2}\right)\ln\left(\sigma^2\right) - \frac{b_\sigma}{\sigma^2} - \frac{1}{2\sigma^2}\mathbf{w}^T R^{-1}\mathbf{w} - \frac{1}{2}\ln\left(|R|\right) + \sum_{i=1}^{n} y(\mathbf{s}_i)\left(\mathbf{x}(\mathbf{s}_i)^T\theta + w(\mathbf{s}_i)\right) - \sum_{i=1}^{n}\ln\left(1 + \exp(\mathbf{x}(\mathbf{s}_i)^T\theta + w(\mathbf{s}_i))\right) \quad (7)$$

In the numerical implementation, the prior on ϕ is treated a bit differently. As stated above, its prior is Uniform with the condition

$$p(\phi) = \begin{cases} \frac{1}{b_\phi - a_\phi} \text{ if } \phi \in \left(a_\phi, b_\phi\right) \\ 0 \text{ otherwise.} \end{cases} \quad (8)$$

In principle, this condition is problematic when the posterior is log-transformed (i.e., $ln(0) = -\infty$); however, this is easily treated in the sampling approach described in the following section.

Posterior Sampling

The Metropolis-Hastings algorithm was used to generate the marginal posterior distribution for each parameter in Ω. Initially, candidate values for the parameters were drawn as a single block from a multivariate normal density. In an attempt to maintain a ~23 percent acceptance rate (Gelman *et al.* 1996), we adjusted the diagonal elements (i.e., the tuning values) of the multivariate normal Σ matrix. In our trials, however, it proved extremely difficult to achieve a reliable acceptance rate that would indicate sufficient mixing. In fact the acceptance rate in our initial trials was typically < 1 percent, while a healthy rate should hover around 23 percent (Gelman *et al.* 2004). Therefore we split Ω into its components, and drew candidate values for θ, σ^2, ϕ, and $\mathbf{w}$ separately. This process required four sequential Metropolis-Hastings steps, where θ and $\mathbf{w}$ were still block updated. In this scheme, we monitored four separate acceptance rates, and generally found much better mixing; this was further improved by specifying the covariance structure among the θ (i.e., off diagonal values) as the dispersion of a multivariate normal proposal for θ.

As noted in the previous section, the Uniform prior on ϕ required that it be treated a bit differently than the other parameters. Specifically, each candidate value of ϕ drawn from the normal proposal density was applied to the conditional statement (8). If the candidate ϕ passed (8), it proceeded through the Metropolis-Hastings iteration; otherwise, the candidate was discarded and subsequent candidates were drawn until the condition was satisfied.

Prediction

Once the samples $\{\Omega^{(k)}\}_{k=1}^{N}$ are obtained from the posterior distribution (i.e., the retained post burn-in sample) $P(\Omega|Data)$, the Bayesian prediction framework is especially simple. The posterior *predictive* distribution we seek is

$$P(y(\mathbf{s}_0) = 1 | \mathbf{y}, \mathbf{x}, \mathbf{x}(\mathbf{s}_0)) = \int P(y(\mathbf{s}_0) = 1 | \Omega, \mathbf{y}, \mathbf{x}(\mathbf{s}_0)) P(\Omega | \mathbf{y}, \mathbf{x}) d \quad (9)$$

where $\mathbf{s}_0$ denotes the location for which the vector $\mathbf{x}(\mathbf{s}_0)$ is known and we wish to predict $y(\mathbf{s}_0)$. Samples from equation (9) are obtained by *composition* sampling: for each $\Omega^{(k)}$ from the posterior sample we simply compute $P(y(\mathbf{s}_0) = 1 | \Omega^{(k)}, \mathbf{y}, \mathbf{x}(\mathbf{s}_0))$ for $k = 1, \ldots, N$ for $k = 1, \ldots, N$. Programmatically, we first generate a vector of N samples from $\mathbf{s}_0$'s location effect with each element defined by a draw from a normal distribution with mean

$$\varphi_0^{(k)T} R^{-1}(\phi^{(k)}) \mathbf{w}^{(k)} \quad (10)$$

and variance

$$\sigma^{2(k)}\left[1 - \varphi_0^{(k)T} R^{-1}(\phi^{(k)}) \varphi_0^{(k)}\right] \quad (11)$$

where $\varphi_0^{(k)}$ is the $n \times 1$ vector with i-th element given by $\varphi_{0i}^{(k)} = exp(-\phi^{(k)} \|\mathbf{s}_0 - \mathbf{s}_i\|)$. Then, a vector of probabilities is generated with each element defined by equation (4) replacing $\mathbf{x}(s_i)$ and $w(\mathbf{s}_i)$ with $\mathbf{x}(s_0)$ and $w(\mathbf{s}_0)$. The resulting sample is precisely a sample from the desired predictive distribution in equation (9). A forest probability map can be created using the posterior mean or median (or, for that matter, any other quantile) by simply carrying out the above predictive sampling over a grid of sites. Creating the associated uncertainty map for these predictions is just as simple. For the grid of sites, compute the uncertainty summary (standard deviation or range) from the predictive sample. We point out that the standard deviations computed from MCMC output are biased as these samples are correlated (Gelman *et al.* 2004). This bias becomes negligible, however, as the size of the MCMC sample becomes large. This sample, being in our control (subject to computational limits), is usually taken large enough and this issue is not serious.

Estimating Multiple Pixel AOI

Once complete posterior distributions are obtained for the pixel-level forest probabilities, interest often turns to obtaining forest area for multipixel AOIs. To be precise, suppose we are interested in a region composed of N_A pixels, say $A = \cup_{i=1}^{N_A}\{\mathbf{s}_i\}$ (perhaps after suitable relabeling of the $\mathbf{s}_i$'s). An estimate of the fraction of the forest area in A is given in terms of the corresponding probabilities at the pixel level by

$$F_A = \frac{1}{N_A}\sum_{i=1}^{N_A} P(Y(\mathbf{s}_i) = 1). \tag{12}$$

Hence, samples $\{F_A^{(k)}\}_{k=1}^{N_{MCMC}}$ from the posterior distribution $p(F_A \mid Data)$ are immediately obtained from $\{P^{(k)}(Y(\mathbf{s}_i) \mid Data)\}_{k=1}^{N}$ using equation (12), once the latter are obtained using the methods described in the preceding section. Note that any other functional, such as the total area inside A under forests $\tilde{F}_A = |A| F_A$, where $|A|$ denotes the area of the region A are also immediately accessible to posterior inference.

Summary

This paper described a logistic regression model with hierarchical random spatial effects that can be used to couple field inventory data from the FIA program with mid-resolution satellite imagery to predict pixel-level forest probability with associated error estimates. Once the model's parameters are estimated by the Metropolis-Hastings algorithm, composition sampling is used to delineate each pixel's predictive distribution from which we calculate the desired inferential statistics. These pixel specific predictive distributions of probability forest are then combined to provide forest area and error estimates for multipixel AOIs.

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Compatible Taper Algorithms for California Hardwoods

James W. Flewelling[1]

Abstract.—For 13 species of California hardwoods, cubic volume equations to three merchantability standards had been developed earlier. The equations predict cubic volume from the primary bole, forks, and branches, but do not differentiate between the sources of the wood. The Forest Inventory and Analysis (FIA) program needed taper equations that are compatible with the volume equations. An algorithm (Flewelling 2004) predicts various numbers of solid wood pieces representing the primary bole and branches, each piece having a predicted inside bark and outside bark profile. No actual data on branch size distribution was used.

Introduction

The Forest Inventory and Analysis (FIA) program and other sections of the U.S. Department of Agriculture (USDA) Forest Service have been using a wide variety of volume equations and taper systems, often developed for different standards. It would be beneficial to standardize taper methodologies because they are generally independent of utilization conventions. An unpublished report on available West Coast volume and taper equations (Flewelling *et al*. 2003) does not cite any profile equations for these hardwood species; several options for conditioning taper equations to match specified volume equations are cited. The special difficulties with merchantable wood in multiple stems or branches, however, are not commonly a consideration in compatibility between taper and volume equations. Furthermore, the National Volume Equation Library (NVEL), a standardized software package maintained by the USDA Forest Service Forest Management Service Center, does not include protocols for handling prediction equations that specifically deal with multiple stems. Hence, no road map dictates exactly how to proceed.

The NVEL framework generally requires that a taper equation be integratable to volume, and should be able to give diameter inside bark at any height. When volume is from multiple stems or branches, a taper function can not be used for both of those purposes. A true solution for a multistemmed tree would require that each pathway from the ground to a merchantable diameter limit be estimated in terms of height, total length, diameter, and perhaps straightness. A model of that complexity would be extraordinarily difficult to construct under the best of circumstances. As there are no real data available, the realism of any attempt to describe piece-size distribution is necessarily limited.

Pillsbury and Kirkley (1984) sampled 13 species of hardwoods throughout their native range in California, all of which had a diameter at breast height (d.b.h.) of 5 inches or greater. The species, along with the FIA species codes, are listed in table 1. Decadent trees and trees with major defects were avoided. Exacting measurements were made with the Spiegel Relaskop, with an objective of accurately determining shape and volume for all trees, even the most deliquescent. In addition, bark thicknesses were sampled at various heights. Three types of cubic volumes were computed for each sample tree. Regression equations were developed to predict these volumes as functions of d.b.h., total height, and species. The following three volumes are all in cubic feet:

TVOL Total aboveground volume of wood and bark, including the stump, but excluding foliage.

CV4 Volume of wood from a 1-foot stump to a 4-inch small-end outside bark diameter. Excludes the bark and foliage. This volume is referred to as WVOL in Pillsbury and Kirkley (1984).

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CV9 Volume of wood from a 1-foot stump to a 9-inch small-end outside bark diameter. Excludes the bark and foliage. Every segment included must be from straight merchantable sections at least 8-feet long. This sawlog volume is referred to as SVOL in Pillsbury and Kirkley (1984).

Table 1.—*Species list.*

FIA code	Common name	Scientific name
312	Bigleaf maple	*Acer macrophyllum*
361	Pacific madrone	*Arbutus menziesii*
431	Giant chinkapin	*Castanopsis chrysophylla*
631	Tanoak	*Lithocarpus densiflorus*
801	Coast live oak	*Quercus agrifolia*
805	Canyon live oak	*Quercus chrysolepis*
807	Blue oak	*Quercus douglasii*
811	Engelmann oak	*Quercus engelmannii*
815	Oregon white oak	*Quercus garryana*
818	California black oak	*Quercus kelloggii*
821	California white oak	*Quercus lobata*
839	Interior live oak	*Quercus wislizeni*
981	California laurel	*Umbellularia californica*

FIA = Forest Inventory and Analysis.

The differences in volume between the primary bole and the entire tree including forks and branches can be substantial, yet most taper-based approaches to volume modeling would ignore the contributions of the forks and branches. An indication of the magnitude of the differences in approaches can be obtained by comparing Pillsbury and Kirkley's (1984) predictions with predictions derived from primary-bole data. For an oak in the deep South with a d.b.h. of 24 inches and height of 90 feet, Clark and Souter (1996) estimate primary-bole CV4 and CV9 as 97.9 and 94.9 cubic feet, respectively. Greater CV4 volumes are predicted by the Pillsbury and Kirkley equations for all the species they considered, with a median prediction of 130 cubic feet. Another difference is that the CV9 to CV4 ratio is almost 1 in the foregoing primary-bole example, and is much smaller for the Pillsbury and Kirkley equations. For example, in Oregon white oak, the predicted CV4 and CV9 are 159 and 86 cubic feet, respectively, implying some 73 cubic feet of volume between 4 inches and 9 inches in diameter. That difference corresponds to about 24 pieces of wood that taper from 9 inches to 4 inches in outside bark diameter; the computation here assumes that each such piece is 3 cubic feet, which is the difference between CV4 and CV9 in the example from Clark and Souter. Hence, Oregon white oak seems to have significant amounts of volume apart from the principal bole, and that volume can be distributed among many different braches.

Algorithm

An algorithm has been developed that predicts multiple wood pieces for a tree of a given species, d.b.h., and total height. Each predicted piece has a predicted length and predicted inside bark taper function. Outside bark diameters are obtained by using the inside to outside bark diameter relationships in Pillsbury and Kirkley (1984). The merchandizing of the individual pieces can be performed to any standards after the piece sizes and their profiles have been predicted.

The method makes explicit use of the TVOL and CV4 equations from Pillsbury and Kirkley (1984) in addition to their bark thickness relationships. It also uses several newly developed empirical equations, and makes use of profile equations developed for the primary boles of white oak in the South (Clark *et al*. 1991), and of bigleaf maple in British Columbia (Kozak 1994). The full algorithm and coefficients are presented by Flewelling (2004). The coefficients were set for each species by an optimization procedure with an objective of a close agreement between the three predictions from the volume equations and the corresponding volumes inferred from the taper equations for the inferred wood segments.

A single example is given to illustrate the algorithm. Consider a Pacific madrone with a d.b.h. of 17 inches and a total height of 50 feet. The algorithm predicts the taper curves for the segments listed in table 2. The summed TVOL and CV4 in the table are in exact agreement with predictions from the Pillsbury and Kirkley (1984) equations. The summed CV9, 22.66 cubic feet, falls short of the 27.70 cubic feet predicted by the volume equation. The profile for each segment is a scaled copy of a portion of the predicted bole profile for a white oak with the same d.b.h. and total height. The lower bole segment has a diameter-scale factor set such that the scaled inside bark diameter at breast height, plus the double bark thickness from the Pillsbury and Kirkley equation, equals the desired d.b.h.

Table 2.—*Counts and predicted volumes of wood segments predicted for Pacific madrone with a d.b.h. of 17 inches and a total height of 50 feet. Volumes of the segments are per piece.*

Segment	Count	Length (ft)	TVOL (ft^3)	CV4 (ft^3)	CV9 (ft^3)
Lower main	1.00	20.5	26.10	22.66	22.66
Upper main	1.00	29.5	6.41	5.86	0.00
Large branches	2.48	20.3	4.41	4.03	0.00
Small branches	13.25	7.3	0.21	0.00	0.00
Total	17.73		46.29	38.52	22.66

d.b.h. =diameter at breast height.

The upper bole segment has a diameter-scale factor set at .8254, and an implying discontinuity in the profile at 20.5 feet. The large branch segments use the same diameter scale factor as for the upper bole, and a height-scale factor of .6878. The small branch segments have large-end outside bark diameters of 4 inches; their profiles are the same as for the small-diameter end portions of the large branch segments. The scale factors and the length of the lower bole segment are from species-dependent equations that depend on d.b.h., total height, and species.

Results

The algorithm has been tested for the full range of d.b.h.s and heights in the Pillsbury and Kirkley (1984) data. TVOL is always recovered exactly. CV4 is usually recovered exactly. The predicted trends of CV9 versus d.b.h. and total height are similar to those from the volume equations, with discrepancies that are usually not more than 10 percent for trees with d.b.h.s more than 15 inches. For lesser d.b.h.s, the percentage discrepancies can be larger. The results are plausible for d.b.h.s as low as 4.5 inches, and for heights as low as 20 feet.

Discussion

Sawlog volume equations and taper equations make predictions that are essentially different and sometimes incompatible at the level of an individual tree. For the smaller tree sizes, the volume equation prediction of CV9 is often for a value that is smaller than the lowest possible volume of an 8-foot sawlog. Arguably the volume equation may be ill conditioned. On the other hand, for d.b.h.s of about 10 inches the volume equation may be predicting a CV9 value that is a valid expectation, even though that may be less than the minimum volume of a single 8-foot sawlog. The taper equations can predict zero volume, or an amount of volume that corresponds to a sawlog of 8 feet or more, but they can not predict intermediate CV9 volumes. This is one of several reasons for differences in CV9 predictions between the volume equations and the algorithm.

The three volume equations do fall into the correct rank order within the range of the data. They are not, however, always in reasonable accord. In the more extreme extrapolations, TVOL may be predicted to be less than CV4. Hence, any taper system that is forced to exactly replicate the equation-predicted volumes would sometimes produce absurd results or totally fail.

One weakness of this project is that none of the original data were available. If the three volume statistics for each tree had been available, the optimization procedure could have minimized the errors between volumes inferred from the taper equations and actual volumes, which would have been a more satisfactory approach as it would bypass any lack of fit in the Pillsbury and Kirkley (1984) equations. The lack of original data also precluded any check on the reasonableness of the predicted numbers and sizes of branches.

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Sample-Based Estimation of Tree Species Richness in a Wet Tropical Forest Compartment

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Abstract.—Petersen's capture-recapture ratio estimator and the well-known bootstrap estimator are compared across a range of simulated low-intensity simple random sampling with fixed-area plots of 100 m^2 in a rich wet tropical forest compartment with 93 tree species in the Western Ghats of India. Petersen's ratio estimator was uniformly superior to the bootstrap estimator in terms of average error (bias) and mean absolute error. The observed richness always had the largest negative bias. A large negative bias of 25 percent persisted even when approximately 10 percent of the area was sampled. Estimated confidence intervals had poor coverage rates. A proposed variance estimator for the observed richness performed well.

Introduction

Obtaining an unbiased and precise estimate of the number of forest tree species (*S*) currently growing in a region, State, or country poses a challenge. The number of species observed in a statistically valid sample is downwardly biased, and historic data and tree distribution maps may not reflect current realities (Guralnick and Van Cleve 2005).

A forest survey would ideally provide an unbiased and precise estimate of *S* for the populations of interest. Research into the species estimation problem was pioneered by Arrhenius (1921), Fisher *et al.* (1943), and Good and Toulmin (1956). We now have a plethora of estimators and estimation procedures (Bunge and Fitzpatrick 1993, Walther and Moore 2005). Rare species, easily missed in typically low-intensity forest survey sampling, exert a disproportionate influence on the results (Link 2003, Mao and Colwell 2005). Samples with a poor representation of rare species cannot be expected to yield reliable estimates of *S*.

Can we expect a typical low-intensity forest survey to provide an acceptable estimate of *S*? Experience with sample-based estimation of *S* for tree species is limited. Schreuder *et al.* (1999) assessed 10 modifications of Chao's and Lee's nonparametric estimators by resampling two large data sets with 4,060 forest inventory plots from Missouri and 12,260, from Minnesota, respectively. Sample sizes in the order of 500 to 700 were deemed necessary to keep bias below 15 percent. Sample sizes of 80 produced a negative bias of about 40 percent. Palmer (1990) performed resampling with very small circular plots of 2 m^2 in the Duke Forest (North Carolina, United States) and found that the nonparametric second-order jackknifed and that the bootstrap estimators performed best in terms of accuracy and precision. Hellmann and Fowler (1999), in a similar resampling study with 25 m^2 plots, found the second-order jackknifed estimator to be the best for low-intensity sampling (< 10 percent of area sampled). Gimaret-Carpentier *et al.* (1998a) found Chao's estimator(s) to be superior to the generalized jackknifed estimator for estimating richness in a wet, species-rich tropical forest.

The objective of this study is to introduce and assess the performance of Petersen's ratio estimator of richness (Thompson 1992) in low-intensity simple random sampling with fixed-area plots in a wet, species-rich tropical forest compartment. Petersen's ratio estimator, which rests on a minimal set of assumptions, is easy to calculate and lends itself to a bootstrap estimation of sampling errors, but has so far not been used for the purpose of tree species-richness estimation. The bootstrap estimator serves as a reference benchmark as it is a widely known and equally simple estimator (Bunge *et al.* 1995, Schreuder *et al.* 1999).

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Material and Methods

Data from a 28-ha forest compartment in the Kadamakal Reserve Forest (Kadagu District, Karnatiaka State, India) near the village of Uppangala in the Western Ghats mountain range (lat. 12º30'N by long. 75º39'W; 500–600 m ALT) are used for this study. The forest type is Dipterocarpus indicus–Kingiodendron pinnatum–Humboldtia brunonis (Pascal 1982). Five strips with a width of 20 m, oriented north-south, 100 m apart, and 180- to 370-m long, were stem mapped (Pascal and Pélissier 1996). Species and spatial location were determined for all trees with a diameter at breast height (d.b.h.) ≥ 30 cm. Pascal and Pélissier (1996) found 1981 such trees (635 trees per ha), representing 93 species (*S* = 93).

The five 20-m-wide survey lines, totaling 1,560 m in length, were subdivided into 312 100 m^2 rectangular (5 m by 20 m) plots. Simple random sampling (SRS) with sample sizes *n* = 10, 15, ..., 30 plots without replacement was simulated. Accordingly, between 3.2 and 9.6 percent of the area was sampled. The area sampled is denoted by A_s. Sampling, followed by estimation of species richness (*S*), was repeated 2,000 times for each sample size.

Let S_{OBS} be the number of species encountered in *n* sample plots. Encountered species are labeled by an index *i* $\left(i = 1,\ldots,S_{OBS}\right)$. The sample data consist of a size $S_{OBS} \times n$ binary matrix δ with element $\delta_{ij} = 1$ if the *i*th species occurred in the *j*th plot and zero (0) otherwise. A design-unbiased estimator of the sampling variance of S_{OBS} is not available. The distribution of S_{OBS} has been assumed Poisson with a mean and a variance equal to S_{OBS}. Instead $S_{OBS}^2 \times \left(\sum_{i=1}^{S_{OBS}} \delta_{i\bullet}\right)^{-1}$ is proposed as an estimator of the sampling variance on the grounds that $\left(\sum_{i=1}^{S_{OBS}} \delta_{i\bullet}\right) \times S_{OBS}^{-1}$ is the average number of plots per unique species in the sample.

To arrive at Petersen's capture–recapture ratio estimator of richness, we first consider the n sample plots as composed of two independent half-samples. Let $S_{OBS}^{(1)}$ be the number of species found in the first half and $S_{OBS}^{(2)}$ the number of species in the second half. We have $S_{OBS} = S_{OBS}^{(1)} + S_{OBS}^{(2)}$. Some species are seen in both half-samples; let this number be denoted by $S_{OBS}^{(1)\cap(2)}$. Petersen's capture–recapture estimator (Thompson 1992) of S is then

$$\hat{S}_{PET} = \eta \times \frac{S_{OBS}^{(2)}}{S_{OBS}^{(1)\cap(2)}} \times S_{OBS}^{(1)} \tag{1}$$

where η is a multiplier that scales the estimate from the half sample to the complete sample of size *n*. Here $\eta = \left(S_{OBS}^{(1)} + S_{OBS}^{(2)}\right) / S_{OBS}^{(1)}$. In case $S_{OBS}^{(1)\cap(2)} = 0$, a modification suggested by Chapman (Seber 1982) would be used. To avoid estimating SPET from a single arbitrary data split, we computed $\hat{\bar{S}}_{PET}$ as the average of $\hat{S}_{PET}^{i}, i = 1,2,\ldots,1\,000$ where $\hat{S}_{PET}^{i}$ is an estimate based on the *i*th random split of the n sample records. The variance of $\hat{S}_{PET}$ was estimated as $Var\left(\hat{S}_{PET}^{i}\right)$.

Smith and van Belle (1984) first suggested a bootstrap estimation of *S*. A bootstrap sample of size *n* is drawn with replacement from the *n* observed sample records. Let S_{BOOT}^{r} be the number of unique species in the *r*th such bootstrap sample. The difference, $\Delta S_{BOOT} = S_{BOOT}^{r} - S_{OBS}$, is a bootstrap estimate of bias (Efron and Tibshirani 1993); thus

$$E_r\left(S_{BOOT}^{r} - S_{OBS}\right) = \Delta S_{BOOT} = \sum_{i=1}^{S_{OBS}} (1 - p_i)^n \tag{2}$$

with expectation taken across all possible size *n* bootstrap samples. ΔS_{BOOT} is an estimate of the number of species "missed" in the sample (bias). From equation (1) we obtain the bootstrap estimator of *S*:

$$\hat{S}_{BOOT} = S_{OBS} + \widehat{\Delta S}_{BOOT} \tag{3}$$

A variance estimator for $\hat{S}_{BOOT}$ conditional on S_{OBS} is

$$\widehat{\operatorname{var}}\left(\hat{S}_{BOOT}\right) = \sum_{i=1}^{S_{OBS}} \left(1 - q_i^{\,n}\right) q_i^{\,n} + \sum_{i=1}^{S_{OBS}} \sum_{j \neq i}^{S_{OBS}} q_{ij}^{n} - q_i^{n} q_j^{n} \tag{4}$$

where q_i is the proportion of sample plots that do not contain the *i*th species and q_{ij} is the proportion that contains neither the *i*th nor the *j*th species.

The two richness estimators either explicitly or implicitly assume an infinite population size. To take the finite population size into consideration (Valliant *et al.* 2000), we corrected the estimates in equations (1) and (3) by

$$\hat{S}'_M = S_{OBS} + (1 - f_{pc})(\hat{S}_M - S_{OBS}) \tag{5}$$

where $f_{pc} = A_s \times A^{-1}$ with $M = \{PET, BOOT\}$. This correction ensures that $f_{pc} \rightarrow 1$ means $\hat{S}'_M \rightarrow S_{OBS}$ as required. A corresponding correction was applied to estimators of sampling variance.

The performance of S_{PET} and S_{BOOT} will be assessed by their average error (estimate of bias), precision (actual and average of estimated sampling errors), accuracy as estimated by the mean absolute difference (*Mad)* between an estimate and the true value, the proportion of estimates within 10 percent of the true value ($\delta 10$), and finally the coverage rate of estimated 95 percent confidence intervals $(pCI95)$.

Results

Observed richness had, as expected, the largest negative average error (estimate of bias), as detailed in table 1. Even with 10 percent of the area sampled, the bias was –56 percent. The average relative error of the observed richness declined at a decreasing rate as sample size increased. S_{PET} was clearly a better estimator than S_{BOOT} in terms of its average relative errors (bias), which were roughly half of those associated with S_{BOOT}. The rate of decline in the average relative error was similar for the three estimators.

Relative standard errors of the richness estimates were about 4 to 5 percent for n = 10 and 3 to 4 percent for n = 30 (table 1). Hence, the decline in the standard error for an increase in n was much slower than $-2^{-1}n^{-1.5}$, as expected for conventional forest inventory estimates of population totals, namely averages. Average estimates of precision for *PET* were quite conservative: about three times larger than the empirically estimated errors (table 1). In contrast, those for *BOOT* were somewhat liberal (too small) at n = 10, but at larger sample sizes ($n \geq 20$) they matched the empirical estimates to within 0.5 percent. The proposed variance estimator for OBS appears attractive inasmuch as the observed and the average of the estimated errors were within 0.5 percent of each other.

Mean absolute differences (table 2) were dominated by the bias component; as such, the results largely mirror those detailed above for the average error. The fraction of estimates within 10 percent of the actual value of 93 was low for *PET* (≤ 8 percent) for all sample sizes. It was 0 for both *OBS* and *BOOT*. Estimated 95 percent confidence intervals of *BOOT* and *OBS* estimates of richness failed to include the actual value (table 2). Results were not much better for *PET*, with coverage rates increasing from just 15 percent at n = 10 to 34 percent at n = 30.

Table 1.—*Mean error (estimate of bias) of richness estimates. Actual (s.e.) and average of estimated sampling errors ($\overline{s.e.}$) are in parentheses (s.e./$\overline{s.e.}$). Errors are in percent of true richness S = 93. Means are across 2,000 replicate samples.*

Estimator	Sample size (A_s/A×100)				
	10 (3.2)	15 (4.8)	20 (6.4)	25 (8.0)	30 (9.6)
S_{obs}	– 75 (4/4)	– 69 (4/4)	– 64 (4/4)	– 60 (4/4)	– 56 (4/4)
$\hat{S}_{PET}$	– 46 (4/11)	– 38 (4/11)	– 34 (4/10)	– 29 (3/0)	– 25 (3/9)
$\hat{S}_{BOOT}$	– 69 (5/3)	– 62 (4/3)	– 57 (4/3)	– 57 (3/3)	– 48 (3/3)

Table 2.—*Mean absolute error (*Mad*) of richness estimates.* Mad *is in percent of true richness (93). Percent of estimates within 10 percent of true value (δ_{10})and coverage rates of estimated 95 percent confidence intervals (pCI_{95})are in parentheses (δ_{10} / pCI_{95}).*

Estimator	Sample size (A_s/A×100)				
	10 (3.2)	15 (4.8)	20 (6.4)	25 (8.0)	30 (9.6)
S_{obs}	75 (0/0)	69 (0/0)	64 (0/0)	60 (0/0)	56 (0/0)
$\hat{S}_{PET}$	46 (2/15)	38 (3/21)	34 (3/21)	29 (5/28)	25 (8/34)
$\hat{S}_{BOOT}$	69 (0/0)	62 (0/0)	57 (0/0)	57 (0/0)	48 (0/0)

Discussion

Low-intensity forest inventories do not provide estimates of tree species richness on a routine basis. Given the importance that is attached to notions of species richness and biodiversity, however, it would seem reasonable to expect that forest inventories would provide such an estimate. While it is generally recognized that the observed number of species will be downwardly biased, it is probably less appreciated that almost any estimator of species richness will be an improvement over the observed richness. It is generally accepted that there is no universally best estimator of *S*. The choice must be based on documented performance (Chao and Bunge 2002). Because an overestimation of richness can have a negative impact on credibility, an estimator unlikely to produce an inflated estimate is warranted. At low-intensity sampling both Petersen's and the bootstrap estimator are unlikely to produce an inflated estimate. Palmer (1990, 1991) and Hellmann and Fowler (1999) have already confirmed this property of S_{BOOT} . The uniform superiority of Petersen's estimator vis-á-vis the bootstrap estimator holds promise, but it needs to be corroborated by additional studies before one can draw any general conclusion.

Because the study site had many rare and just a few common species we cannot *a priori* expect to obtain very good estimates of richness from low-intensity forest inventory sampling. Condit *et al.* (1996) suggest that a sample of at least 1,000 individually sampled trees, or about 10 percent of a population, is needed in wet, tropical species-rich forests before a sample-based estimate of species richness is within 15 percent of the actual value.

Our study reiterated the importance of choosing a suitable estimator of richness. It is well known that the performance of an estimator depends not only on the statistical sampling designs but also on the population structure and spatial distribution of species (Brose *et al.* 2003, Colwell *et al.* 2004, Keating *et al.* 1998). Only an extensive assessment of a larger suite of estimators in diverse environments and across a series of conventional low-intensity forest inventory designs will allow a resolution to the question of whether we can hope to obtain estimates of tree species richness that are both reasonably accurate and reasonably precise from low-intensity forest inventories. The test designs would have to include sampling with plots of different size, as the effect of plot size is expected to depend strongly on both the estimator and the spatial distribution of species in the population of interest (Condit *et al.* 1996, Gimaret-Carpentier *et al.* 1998b).

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Estimating Tree Species Richness From Forest Inventory Plot Data

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Abstract.—Montréal Process Criterion 1, Conservation of Biological Diversity, expresses species diversity in terms of number of forest dependent species. Species richness, defined as the total number of species present, is a common metric for analyzing species diversity. A crucial difficulty in estimating species richness from sample data obtained from sources such as inventory plots is that no assurance exists that all species occurring in a geographic area of interest are observed in the sample. Several model-based and nonparametric techniques have been developed to estimate tree species richness from sample data. Three such approaches were compared using data obtained from forest inventory plots in Minnesota, United States of America. The results indicate that an exponential model method and a nonparametric jackknife method were superior to the nonparametric bootstrap method.

Introduction

Of the international forest sustainability initiatives, the Montréal Process (1998) is geographically the largest, involving 12 countries on 5 continents and accounting for 90 percent of the world's temperate and boreal forests. The Montréal Process prescribes a scientifically rigorous set of criteria and indicators that have been accepted for estimating the status and trends of the condition of forested ecosystems. A criterion is a category of conditions or processes and is characterized by a set of measurable quantitative or qualitative variables called indicators that, when observed over time, demonstrate trends. The Montréal Process includes seven criteria (McRoberts *et al.* 2004) of which Criterion 1, Conservation of Biological Diversity, focuses on the maintenance of ecosystem, species, and genetic diversity. Of the indicators associated with Criterion 1, one of the most intuitive is Indicator 6, Number of Forest Dependent Species. When the emphasis is on the number of tree species, this indicator is characterized as tree species richness.

Because species richness relates only to the presence or absence of species, regardless of distribution or abundance, estimation of species richness is difficult apart from a complete census. Complete tree censuses, however, are not practical for the naturally regenerated, mixed species, uneven aged forests that occur in much of the world. As a result, estimation of tree species richness must depend on sample data. Unfortunately, although tree species richness is an intuitive measure, it is difficult to estimate using sample data because no assurance exists that all species in a geographic area of interest have been observed in the sample, particularly rare or highly clustered species.

The objective of the study was to compare one model-based and two nonparametric approaches for estimating tree species richness from forest inventory plot data.

Data

Forest inventory data are widely recognized as an excellent source of information for estimating the status and trends of forests in the context of the Montréal Process or the Ministerial Conference for the Protection of the Forests of Europe (McRoberts *et al.* 2004). The national forest inventory of the United States of America is conducted by the Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture Forest Service. The program collects and analyzes inventory data and reports on the status and trends of

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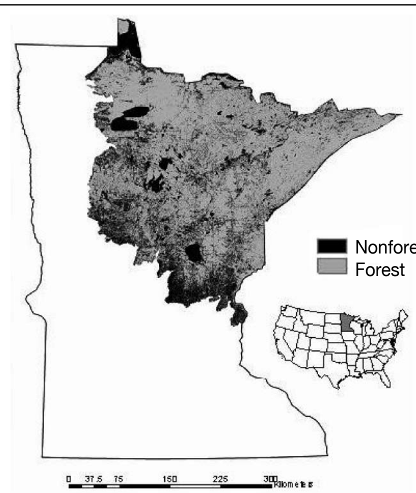
the Nation's forests. The national FIA sampling design is based on an array of 2,400-ha (6,000-ac) hexagons that tessellate the Nation. This array features at least one permanent plot randomly located in each hexagon and is considered to produce an equal probability sample (Bechtold and Patterson 2005, McRoberts *et al.* 2005). The sample was systematically divided into five interpenetrating, nonoverlapping panels. Panels are selected for measurement on approximate 5-, 7-, or 10-year rotating bases, depending on the region of the country, and measurement of all accessible plots in one panel is completed before measurement of plots in a subsequent panel is initiated. The national FIA plot consists of four 7.32-m (24-ft) radius circular subplots that are configured as a central subplot and three peripheral subplots with centers located at 36.58 m (120 ft) and azimuths of 0°, 120°, and 240° from the center of the central subplot. All trees on these plots with diameters at breast height of at least 12.5 cm (5.0 in) were measured and the species identifications were recorded.

The study area was in Minnesota, United States of America, and consisted of the geographic intersection of Bailey's ecoprovince 212 (Bailey 1995) and Mapping Zone 41 of the Multiresolution Land Characterization Consortium (Loveland and Shaw 1996) (fig. 1). Forests in the study area are generally naturally regenerated, uneven aged, and mixtures of conifer and deciduous species. Data for 3,300 plots with centers in the study area and observed between 1999 and 2003 were available.

Figure 1.—*Study area.*



Methods

Several model-based and nonparametric approaches have been proposed for estimating tree species richness from sample data. All these approaches extrapolate information from the distribution of the species observed in the sample, S_o, to estimate the total number of species, S_t .

Exponential Model

Model-based approaches are generally based on empirical species accumulation curves (Soberón and Llorente 1993) depicting the relationship between the total number of species observed and the cumulative area of the sample. Nonlinear statistical models with horizontal asymptotes are fit to the empirical curves, and the estimates of the asymptotes are considered estimates of S_t. The exponential model

$$E\left(S_o\right) = b_1\left[1 - \exp\left(b_2 A^{b_3}\right)\right] \tag{1}$$

where E(.) is statistical expectation, S_o is the number of species observed, A is the cumulative area of the sample, and the βs are parameters, is a flexible curve, although admittedly it has no biological basis for describing a species accumulation curve. With this model, β_1 corresponds to the asymptote, and its estimate provides an estimate of S_t. The covariance matrix of the model parameter estimates is estimated as

$$\hat{V} = \hat{\sigma}_\varepsilon^2 \left(Z'Z\right)^{-1} \tag{2}$$

where $\hat{\sigma}_\varepsilon^2$ is the residual variance estimated by the mean squared error, the elements of the Z matrix are $z_{ij} = \frac{\partial f}{\partial \beta_j}\left(A_i\right)$, and f is the statistical expectation function of the model.

Bootstrap

For a sample of size n, Smith and van Belle (1984) describe the bootstrap procedure (Efron 1979) using five steps:

1. Construct the empirical cumulative probability function with density n^{-1} at each of the n plot observations.

2. Draw a sample of size n with replacement from the empirical cumulative probability function.

3. Define

$$I_j^i = \begin{cases} 0 & \text{if the } j^{th} \text{ species is not observed in the } i^{th} \text{ sample drawn in Step 2} \\ 1 & \text{if the } j^{th} \text{ species is observed in the } i^{th} \text{ sample drawn in Step 2} \end{cases}$$

and calculate the i^{th} estimate of S_o as $\hat{S}_o^{Bi} = \sum_{j=1}^{S_o} I_j^i$.

The statistical expectation of $\hat{S}_o^{Bi}$ is

$$E\left(\hat{S}_o^{Bi}\right) = \sum_{j=1}^{S_o} E\left(I_j^i\right) = \sum_{j=1}^{S_o}\left[1-\left(1-\frac{Y_j}{n}\right)^n\right] = S_o - \sum_{j=1}^{S_o}\left(1-\frac{Y_j}{n}\right)^n$$

where Y_j is the number of plots in the bootstrap sample from Step 2 for which the j^{th} species is present. The bias in $\hat{S}_o^{Bi}$ is

$$E\left(\hat{S}_o^{Bi} - S_o\right) = -\sum_{j=1}^{S_o}\left(1-\frac{Y_j}{n}\right)^n,$$

so that the bootstrap estimate of S_t is

$$\hat{S}_t^{Bi} = S_o + \sum_{j=1}^{S_o}\left(1-\frac{Y_j}{n}\right)^n.$$

4. Repeat Steps 2-3 N times.

5. Calculate the bootstrap estimate of S_t as

$$\hat{S}_t^B = \frac{1}{N}\sum_{i=1}^{N}\hat{S}_t^{Bi} \qquad (3)$$

The variance of $\hat{S}_t^B$ is given by Smith and van Belle (1984) as

$$Var\left(\hat{S}_t^B\right) = \sum_{j=1}^{S_o}\left(1-\frac{Y_j}{n}\right)^n\left[1-\left(1-\frac{Y_j}{n}\right)^n\right] + \sum_{j \neq k}\sum\left[\left(\frac{Z_{jk}}{n}\right)^n - \left(1-\frac{Y_j}{n}\right)^n\left(1-\frac{Y_k}{n}\right)^n\right] \qquad (4)$$

where, for the original sample, Y_j is the number of plots for which the j^{th} species is observed and Z_{jk} is the number of plots for which the j^{th} and k^{th} species are jointly absent.

Jackknife

For a sample of size n, Smith and van Belle (1984) describe how the Jackknife estimate of S_t may be obtained in five steps:

1. Remove the observations corresponding to the i^{th} plot, and let r_i be the number of species that were observed only on the i^{th} plot.

2. Using only observations from the remaining plots, calculate the i^{th} jackknife estimate of S_o as $\hat{S}_o^{Ji} = S_o - r_i$.

3. Calculate the pseudovalue
$\theta_i = nS_o - (n-1)\hat{S}_o^{Ji} = S_o + (n-1)r_i$.

4. Repeat Steps 1-3 for each of the n plots.

5. Calculate the jackknife estimate of S_t as

$$\hat{S}_t^J = \frac{1}{n}\sum_{i=1}^{n}\theta_i = S_o + \frac{n-1}{n}\sum_{i=1}^{n} r_i = S_o + \frac{n-1}{n}R \qquad (5)$$

where $R = \sum_{i=1}^{n} r_i$.

The variance of $\hat{S}_t^J$ is

$$Var\left(\hat{S}_t^J\right) = \left(\frac{n-1}{n}\right)^2 Var\left(\sum_{i=1}^{n} r_i\right) = \left(\frac{n-1}{n}\right)^2 nVar\left(r_i\right) \qquad (6)$$

$$= \frac{(n-1)^2}{n}\left(\frac{1}{n-1}\right)\sum_{i=1}^{n}\left[r_i^2 - \left(\frac{R}{n}\right)^2\right] = \left(\frac{n-1}{n}\right)\sum_{i=1}^{n}\left[r_i^2 - \left(\frac{R}{n}\right)^2\right]$$

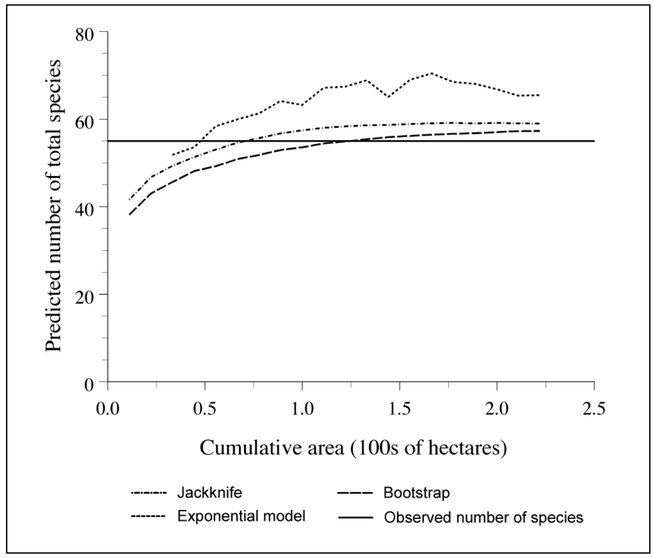
The above jackknife estimates are characterized as first order, because the observations from only a single plot are removed. Second-order jackknife estimates based on removing two plots simultaneously may also be calculated, but for this application preliminary analyses indicated they were not substantially better than first-order estimates.

Analyses

All three approaches were evaluated to determine sample sizes necessary to produce defensible estimates of S_t. The issue is whether $\hat{S}_t$ continues to increase as the sample size increases.

If so, the sample size is inadequate. If the sample size is adequate, the graph of $\hat{S}_t$ versus the cumulative sample area should reach and maintain an approximately constant value. For all three methods, samples sizes (i.e., number of plots) from 165 to 3,300 in steps of 165 were considered, and 250 samples of each size were randomly drawn. For the exponential model, the order in which plots of a particular sample are considered affects the species accumulation curve and, as a result, $\hat{S}_t$ and Var($\hat{S}_t$). To compensate, the plots in each sample were randomly reordered 1,000 times, the mean species accumulation curve was determined, and the exponential model was fit to the mean curve. For the nonparametric bootstrap and jackknife methods, the order of the plots in the sample is not an issue. For all three methods, the means of $\hat{S}_t$ and $\sqrt{Var\left(\hat{S}_t\right)}$ over the 250 samples were calculated for each sample size.

Figure 2.—*Estimates of total number of species.*



Results and Discussion

For all three methods, 250 samples were sufficient to stabilize the means of the estimates of $\hat{S}_t$ and $\sqrt{Var\left(\hat{S}_t\right)}$. In addition, on the basis of comparisons of residual error estimates, 1,000 random reorderings of the samples were sufficient to eliminate individual sample deviations in the mean species accumulation curves. Graphs of $\hat{S}_t$ versus the cumulative sample area for the three methods indicate that the sample size of 3,300 plots, representing 221.92 ha of sample area, is adequate for the jackknife and exponential model methods but possibly not for the bootstrap method (fig. 2). For the total sample size of 3,300 plots, $\hat{S}_t \pm \sqrt{V\hat{a}r\left(\hat{S}_t\right)}$ was 65.46 ± 0.10 for the exponential model, 57.30 ± 1.68 for the bootstrap approach, and 59.00 ± 1.68 for the jackknife approach. All three methods produced estimates of S_t that were greater than $S_o = 55$, as should be expected.

In general, for a given sample size, the precision of the exponential model estimate of S_t was greater than the bootstrap and jackknife estimates which were comparable. For all three methods, the precision increased with greater sample sizes.

The exponential model and jackknife methods appear preferable to the bootstrap method because estimates using the former two methods stabilize with increasing sample size, while estimates using the latter method appear to be continuing to increase. Because the true number of species in the study area is unknown, it is uncertain as to which, if any, of these three methods produces superior estimates. This preliminary study suggests that additional model forms should be considered, that additional samples may be required to obtain a more definitive comparison of the methods, and that the comparisons should be made for other geographical areas.

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Defining Stem Profile Model for Wood Valuation of Red Pine in Ontario and Michigan With Consideration of Stand Density Influence on Tree Taper

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Abstract.—As part of the Canada-United States Great Lakes Stem Profile Modelling Project, established to support the local timber production process and to enable cross-border comparisons of timber volumes, here we present results of fitting Zakrzewski's (1999) stem profile model for red pine (*Pinus resinosa* Ait.) growing in Michigan, United States, and Ontario, Canada. The model was fitted as a system of simultaneous equations using a three-stage least squares regression method. Influence of stand density on red pine tree taper was explored using data from a spacing trial in Ontario.

Introduction

Twenty years ago, Reed and Green (1984: 977) wrote: "In the past, when merchantability standards were relatively stable, separate individual tree volume equations were developed for each set of merchantability limits. With rapidly changing standards, this approach becomes infeasible." This conclusion is still valid. A properly developed timber product estimation system should allow for the development of compatible and mathematically tractable models that are fitted with sound statistical procedures and are responsive to ever-changing utilization standards. The latter need is more and more important in an increasingly global timber trade network. Questions about the comparability of lumber prices and timber harvest structures (chiefly proportions of saw logs and pulp logs in harvested wood) between U.S. and Canadian timber markets highlight the rising importance of developing valid cross-border comparisons.

Stem profile models can provide a robust and systematic way for linking the raw commodity (wood) to wood products and thus should be useful for understanding differences in wood pricing systems and assessing potential growing timber stock value differences among markets. For example, the commercial software BUCK (http://www.forestyield.com) allows for consistent calculation of various product mixes (e.g., dimensional lumber and pulp wood volume) from raw wood volume, using an array of data inputs transformed via stem profile modelling. Consistent and tractable volume estimation can be accomplished in two steps: (1) develop stem profile models that can define the cross-sectional area and volume of tree stems or logs and (2) use analytic geometry and user-specific input variables describing wood product dimensions and sawing variables, such as saw blade width, to develop precise and consistent estimates of sawn volume (fig. 1) (for example, see information on the system Optitek [Forintek Canada Corp. 1994]). Step 2 can be accomplished with little error once Step 1 is accomplished. If board foot/cubic meter conversion factors were based on a common taper model, for example, conversions within a region of interest would be consistent. Further, once a common stem profile model is accepted to model raw volume, changes in utilization standards can be rapidly accommodated, allowing for computation of precise board (or other wood product) units, unlike typical board foot rules (Freese 1973) that confound assumptions regarding stem taper with peculiarities in sawing technology and assumptions about the size of trees that will be merchandized. Hence, a critical step in developing compatible estimates within a region of interest is developing a regionally valid stem profile model on which scaling conversions can be based. Losses in recoverable timber products caused by presence of cull or stem deformities could be accounted for during forest inventory procedures.

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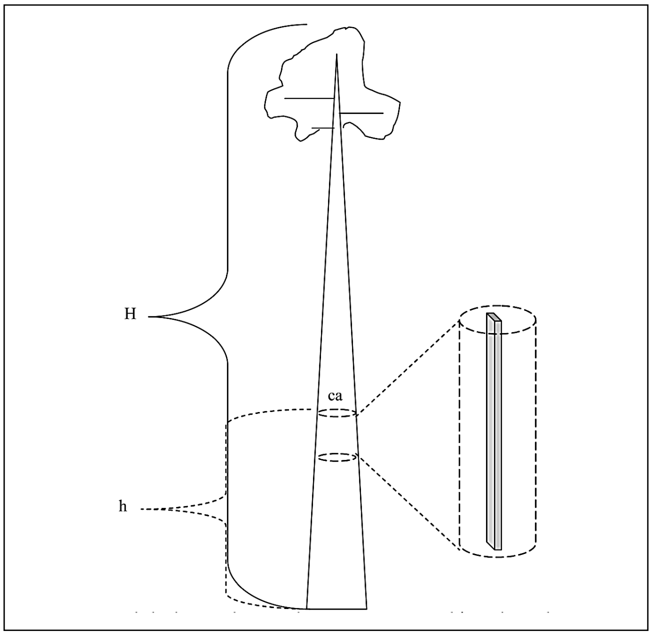
Figure 1.—*Stem profile models allow for the cross-sectional area (*ca*) of a tree stem or log to be assessed at any points along the stem length (h or H the total height of the tree), allowing precise estimates of stem volume. Once the cubic foot volume of a section of tree is defined by a stem profile model (dashed cylinder), the quantity of wood products of any dimension (shaded board) can be derived using analytical geometry and input variables describing the technique for wood processing (e.g., saw blade kerf).*



The Great Lakes Stem Profile Modelling Project (GLSPMP) was established by the Ontario Ministry of Natural Resources, Ontario Forest Research Institute, in partnership with Michigan, Minnesota, and Wisconsin Departments of Natural Resources, the U.S. Department of Agriculture (USDA) Forest Service, and the support of Michigan State University, to improve local timber product estimates and to enable cross-border comparisons of productivity potential of forest sites within the region of interest. The objective of the project is to create a regional Stem Analysis Database Management System and to provide valid stem profile models for major commercial tree species for the Great Lakes Region. During the current softwood lumber dispute, Zakrzewski's (1999) taper model was verified by the U.S. Department of Commerce and extensively used to process timber measurement data from Ontario in support of cross-border comparisons of harvest structures. Here, we present results of fitting that stem profile model for red pine (*Pinus resinosa* Ait.) from Ontario and Michigan, using data and models developed as part of the GLSPMP. Volume tables most commonly used for red pine are those by Fowler (1997) in Michigan and Honer *et al.* (1983) in Ontario; however, the models used to produce the tables do not describe tree stem taper. We wanted to demonstrate the feasibility of developing statistically and legally defensible estimates of timber product volume across regional political borders. Our specific objective was to suggest one model for the both regions and examine the conditions under which one model is applicable.

The second objective of the presented study is to explore influence of a stand density on red pine taper using data from a spacing trial in Ontario referred to here as the Stiell trial. This influence has already been suggested in the literature, and accounted for either explicitly through including stand density measures into taper model (e.g., Sharma and Zhang 2004), or implicitly by accepting density-related tree slimness measures into the model (e.g., Zakrzewski 1999). Red pine was used to examine spacing effects on taper due to the availability of data and because red pine is genetically very uniform (Mosseler *et al.* 1992). Sharma and Zhang (2004) examined black spruce, jack pine, and balsam fir. Only black spruce required a density term.

Methods and Data

Stem Profile Models Specification

In the presented study Zakrzewski's (1999) stem profile model was defined. In taper-density relation study, Kozak's (2004) model was also used to examine consistency of the results. Zakrzewski's (1999) stem profile model is based on geometric foundations and describes either outside bark or inside bark cross-sectional areas (ca_z) along relative stem height locations z:

$$ca_z = K \frac{z^2 + \beta z^3 + \gamma z^4}{z - s} \tag{1}$$

where z is defined by height location h of a cross-sectional area relative to total tree height H ($z = 1 - h / H$) and K is a tree-specific constant value calculated as:

$$K = \frac{C\,(z_0 - s)}{z_0^2 + \beta z_0^3 + \gamma z_0^4}$$

where C is a cross-sectional area, either outside or inside bark, respectively. For describing outside bark or inside bark cross-sectional areas along tree stem, determined by input diameter d_0 of height location h_0 (thus, $C = \pi\, d_0^2/40{,}000$), commonly d.b.h.; i.e., outside bark diameter D at breast height (BH). Therefore, $z_0 = 1 - h_0 / H$; β, γ and s are model constants. The equation may feature one, two, or no points of inflection, analytically calculable, without segmentation. In equation (1), s = 2 can be used as a predefined constant (Zakrzewski and MacFarlane 2006). A simple transformation of equation (1) provides an equation that describes diameters d_z along the tree stem:

$$d_z = (40{,}000\ ca_z / \pi)^{0.5}.$$

The presented model is mathematically tractable, meaning that after integrating ca_z (eq. 1) over h, the exact volume of a total stem (VOL), or any section of a stem, can be obtained. Total stem volume is calculated as:

$$\begin{aligned} VOL = KH[\frac{1}{2} + \frac{1}{4}\gamma + s^2 \ln(s-1) + s^3\gamma + s^3\beta \ln(s-1) + s^2\beta \\ + s^4\gamma \ln(s-1) + \frac{1}{2}s^2\gamma + s + \frac{1}{3}s\gamma \\ + \frac{1}{3}\beta + \frac{1}{2}s\beta - s^4\gamma \ln(s) - s^2 \ln(s) - s^3\beta \ln(s)] \end{aligned} \tag{4}$$

The model (eq. 1) can be analytically solved to locate any reasonable merchantability (diameter) limit on a particular stem (Zakrzewski 1999).

Kozak' s model 02 (eq. [4] in Kozak 2004) model was used for comparison.

$$\hat{d}_i = a_0 D^{a_1} H^{a_2} X_i^{\,b_1 z_i^4 + b_2\left[1/e^{D/H}\right] + b_3 X_i^{0.1} + b_4\left[1/D\right] + b_5 H^{Q_i} + b_6 X_i} \tag{5}$$

Where:

$\hat{\boldsymbol{d}}_{\boldsymbol{i}}$ = predicted inside bark diameter at height h_i from ground (cm)

$$\begin{aligned} \boldsymbol{X_i} &= \left[1.0 - \left(\boldsymbol{h_i}/\boldsymbol{H}\right)^{1/3}\right] \Big/ \left[1.0 - \boldsymbol{p}^{1/3}\right] \\ \boldsymbol{Q_i} &= \left[1.0 - \left(\boldsymbol{h_i}/\boldsymbol{H}\right)^{1/3}\right] \\ \boldsymbol{p} &= 1.3/\boldsymbol{H} \end{aligned} \tag{6}$$

Kozak's model is one of the most flexible functions describing tree stem profiles (9 coefficients) and has low multicolinearity. The limitations of the above function come chiefly from a lack of full mathematical tractability of the model.

Data

Two data sets were used in the presented studies: one was used for defining a general stem profile model acceptable for Ontario and Michigan, another one was Ontario-specific and used for exploring influence of density on red pine's taper.

The data used for fitting general red pine stem profile models in this study consisted of measurements on 210 sample trees from Ontario and 128 sample trees from Michigan, for a total of 338 stems with 3,215 inside and outside bark diameters measured along the stems. The data were collected in Ontario by Honer (MacLeod 1978) and in Michigan by Van Dyck (2005). In both cases, d.b.h. was measured at 1.37 m. D.b.h.s in Ontario's data ranged from 6.5 to 65.5 cm, and in Michigan's data from 12.9 to 41.7 cm; heights ranged from 7.7 to 34.5 m, and from 8.5 to 26.1 m, respectively. The data were from red pine plantations, but information about planting densities was not available.

The Stiell trial data come from the Petawawa Research Forest from a spacing trial initiated by Will Stiell and described in Penner *et al.* (2001). Briefly, in 1953, a red pine spacing trial was established on abandoned fields near Chalk River, Ontario (46°00'N, 77°26'W) to examine the effects of initial planting density on the growth and yield of red pine. The experiment consists of two plantations (blocks 109 and 110) a few hundred metres apart. Block 109 is approximately 3.2 ha and block 110 is approximately 14.3 ha. The soil in one block is a deep fine to medium aeolian sand whereas the other block has medium water-laid sand with an aeolian sand cap. The soil moisture on both is similar and, as a result, both areas are considered to be in the same productivity class (Berry 1964). The study site was of high productivity for red pine with a site index of 24.4 m at 50 years (Stiell and Berry 1973).

Bareroot seedlings were machine planted in the spring of 1953 at square spacings of 1.2, 1.5, 1.8, 2.1, 2.4, 3.0, and 4.3 m. The average size of an area planted at a particular spacing was 1.6 ha.

In the fall of 2002, 50 growing seasons from establishment, 73 trees were selected from the buffers for destructive sampling, representing the range of d.b.h.s in the PSP (table 1) from the buffers. The diameter outside bark and bark thickness was measured at 0.3, 0.8, 1.0, 1.3, and every subsequent 2 m along the bole to the base of the live crown and then every 1 m in the live crown for an average of 16 measurements along the stem.

Model Fitting and Validation Methods

There are a few optional approaches to defining equation (1). One can use a traditional regression fitting technique, either nonlinear or linear fit to benefit from the intrinsic linearity of equation (1). Use of the regression procedures and their respective weaknesses (Gregoire *et al.* 2000) can be, however, avoided. If an individual tree total height, diameter at known tree height, and a tree stem volume or volume of a height location specific section of the stem are known, the coefficient β of equation (1) can be calculated analytically (Zakrzewski 2004) for that tree (in such case it is required that $s = 2$ or substituted with H, and coefficient γ set to 1). This approach was applied to "translate" Gevorkiantz and Olsen (1955) volume tables into stem profile models for Michigan State inventories. In fact, there is no need to transform the one-equation taper model fitted for one endogeneous variable (e.g., diameter) to predict response of a different variable (e.g., volume). A system of simultaneous equations may be fit, duly recognizing that many variables in the system may be interdependent, and thus, the classical least squares rules could be biased (Judge *et al.* 1988). We chose this method to define the general stem profile model for Ontario and Michigan, so equation (1) has been transformed to predict four individual tree measures:

(1) Outside bark cross-sectional areas along tree stem ca_{ob}.
(2) Cross-sectional areas of bark along tree stem ca_{bark}.
(3) Height location of randomly selected inside bark diameter h_{diam} (the equation defining this height is not shown here, but is presented in Zakrzewski [1999]).
(4) Inside bark volume of a stem section vol_{log} of variable length (0.45 to 31 m, 9 m average) including possibility for total tree volume.

Outside and inside bark cross-sectional areas were based on 5 to 11 sectional diameter measurements per stem; most often 8 to 10. Inside bark cross-sectional area ca_{ib} was not an endogeneous variable in the system; however, a bark cross-sectional area model (right-hand side of the equation) was formulated as the difference between outside bark cross-sectional area and a form of equation (1) describing inside bark cross-sectional areas. Accepting one set of coefficients of equation (1) to define bark thickness along a stem was a deliberate simplification.

From a range of relative height locations between 2 m and 80 percent of the total tree height, inside bark diameters were randomly selected. Height location of these diameters h_{diam} was the endogeneous variable in the system of equations.

To define inside bark volume of variable length logs (vol_{log}, endogeneous variable in the system), height location of the base of the log and the location of the top cross-sectional area of the log were selected randomly for each stem. For about 10 percent of tree stems, log volume was defined as total tree volume (with no stump). Volumes were calculated as a sum of sectional volumes estimated using Smalian's formula (Avery and Burkhart 1994). The ultimate objective of fitting the model was to ensure acceptable predictions of tree stem parameters of interest to users of the model; i.e., a combination of low bias and high precision of predictions. Three-stage least squares (3SLS) was applied to account for both a simultaneity bias and

Table 1.—*Stiell trial spacing data are summarized by initial spacing.*

Initial spacing (m)	Number of trees	Quadratic mean d.b.h. (cm)	Top height (m)	Volume (m^3)
1.5 x 1.5	8	18.6	20.9	0.31
1.8 x 1.8	17	19.2	21.1	0.32
2.1 x 2.1	18	22.5	24.5	0.48
2.4 x 2.4	15	25.6	24.5	0.62
3.0 x 3.0	15	29.0	24.9	0.78

d.b.h. = diameter at breast height.

contemporaneous correlation (LeMay 1990, Van Deusen 1988). SAS Institute's PROC MODEL was used to fit the system of equations with 3SLS algorithms.

In the presented study, autocorrelation of errors was not accounted for during the model fitting procedure.

Similar to the task of model fitting, the model performance test requires examining both the method and the data. The fitted equation (1); i.e., a general model for Ontario and Michigan, was applied to obtain prediction errors for the 338 trees described above (following Kozak and Kozak 2003). An equivalence test (Wellek 2003) was applied to examine optional regions of indifference for estimates of stem volumes. Traditionally, a null difference hypothesis would assume that the respective mean errors produced by model predictions are equal to 0, and the respective tests indicate whether sufficiently strong evidence exists to question this equality. The hypothesis we examined was different: namely, we insisted that the mean tree volume prediction error is not equal to 0. Such a hypothesis can be rejected if existing differences fall in the user-specified region of indifference. This subjectivity allows a practical evaluation of the modelling tool and helps decide if the expected errors are negligible for the model's user (Robinson and Froese 2004). The region of indifference was defined as ε, a measure relative to standard deviation of prediction errors. Using this measure, a noncentrality parameter of *F*-distribution was calculated as $\psi 2 = n\,\varepsilon^2$, and then a cut-off statistic $\acute{C}$ was generated for comparison with the *t*-value. The value of cut-off is the square root of the α-quantile of the noncentral *F* distribution with degrees of freedom $\nu_1 = 1$ and $\nu_2 = n - 1$. The cut-off value $\acute{C}$ can be easily obtained using the SAS software (function FINV): $\acute{C}$ = sqrt(FINV($\alpha, \nu_1, \nu_2, \psi^2$)). If the *t*-value is smaller than the cut-off value, the hypothesis of dissimilarity can be rejected (we used $\alpha = 0.05$).

To look at spacing effects, equation (1) was fit using ordinary least squares nonlinear regression (PROC NLIN), predicting inside bark cross-sectional from d.b.h. (outside bark) and total height. A combined model was fit to trees from all spacings and then separate models were fit by spacing. Kozak's model (Eq. [5]) was modified to predict cross-sectional area and then fit to the same data for comparisons with equation (1).

Results

Results of Fitting the General Model

The 3SLS coefficients for the proposed regional stem profile model and associated statistics are presented in table 2. The constant $s = 2$ was used in the model, thus only two regression coefficients were estimated. Coefficient γ for red pine was significantly different from unity; however, setting this coefficient to 1 would be conceivable without affecting the predictive power of the model. Points of inflection for red pine were determined to occur on the average at 29 and 70 percent of the trees' relative length. The system weighted statistics for R^2 were 96 percent for outside bark cross-sectional areas (root mean squared error [RMSE] = 0.0109 m^2), 93 percent for height location of given diameter (RMSE = 1.28 m), 98 percent for log volume (RMSE = 7.2 percent), and 25 percent for bark cross-sectional area (RMSE = 0.00006 m^2). Reported goodness of fit measures were calculated using McElroy's (1977) multi-equation analog of Buse's (1973) result (Judge *et al.* 1985).

Using the coefficients of the model, inside bark diameter prediction errors were calculated using the same data set used for the model fitting (table 3). Lack of fit statistics indicated a negative bias (mean error of prediction in table 3) in diameter predictions in the bottom 30 percent of relative height ranging from -0.6 to -0.1 cm, and in the top 30 percent, ranging from -0.7 to -0.3 cm. In the middle of the stems, bias was positive, ranging from 0.05 to 0.6 cm. Standard deviation of errors ranged from 0.8 to 2.9 cm in the top of stems. When the data were split into Michigan and Ontario subsets, the average standard deviation of diameter prediction errors for Ontario (2 cm) was twice that for Michigan (1 cm). Residuals of the

Table 2.—*Stem profile model 3SLS coefficients.*

Coefficient	Coefficient estimate	Coefficient standard error
β	– 1.8412	0.010
γ	0.9516	0.009

3SLS = three-stage least squares.

Table 3.—*Model performance statistics (absolute and relative (%) errors) for the proposed regional red pine stem profile model.*

Region	Variable	N	Mean error	Standard error of mean	Standard deviation of error	MIN error	MAX error
Combined	dob_z [cm]	3,215	– 0.16	0.03	2.09	– 11.34	9.61
	dib_z [cm]		– 0.13	0.03	1.79	– 11.05	8.42
	h_{diam} [m]	338	0.17	0.02	1.28	– 3.55	5.16
	Vol_{log} [%]		– 0.69	0.72	13.28	– 71.25	34.57
	Vol_{tot} [%]		0.14	0.51	9.43	– 61.04	21.63
Ontario	dob_z [cm]	2,218	– 0.27	0.05	2.34	– 11.34	9.66
	dib_z [cm]		– 0.28	0.04	2.02	– 11.05	8.42
	h_{diam} [m]	210	0.13	0.03	1.41	– 3.55	5.16
	Vol_{log} [%]		– 1.48	1.08	15.71	– 71.25	34.57
	Vol_{tot} [%]		– 0.95	0.74	10.81	– 61.04	21.63
Michigan	dob_z [sq. m]	997	0.08	0.04	1.36	– 7.09	6.73
	dib_z [cm]		0.18	0.03	1.06	– 6.19	5.42
	h_{diam} [m]	128	– 0.26	0.03	0.93	– 2.69	4.01
	Vol_{log} [%]		0.61	0.68	7.71	– 33.69	26.43
	Vol_{tot} [%]		1.94	0.54	6.22	– 21.81	12.72

equations were strongly correlated in case of cross-sectional area outside bark and cross-sectional area of bark (93 percent). Due to the model formulation, predicted diameter outside bark (d_{ob}) is always larger than diameter inside bark. In terms of bark thickness, the standard deviation of prediction errors was, on average, about 0.35 cm. Not unexpectedly, bark thickness was significantly underestimated at the bottom part of stems.

While tree sizes along tree stems are a major focus in stem profile modelling, predictions of wood volumes are ultimately of most interest to forest practitioners. Using the obtained coefficients, total tree (without stump) volume (Vol_{tot}, table 3) predictions were examined (input variables were the same as those used for model fitting). For the whole data set, relative error was, on average, 0.14 percent, with standard deviation of 9.43 percent relating to individual tree predictions. For Michigan, respective values were 1.94 percent and 6.22 percent, and for Ontario 0.95 percent and 10.81 percent. Average relative error in log volume (Vol_{log}, table 3) was 0.69 percent, with standard deviation 13.28 percent. For Michigan, respective values were 0.61 percent and 7.71 percent, and for Ontario 1.48 percent and 15.71 percent. Bias was negligible.

Results of Fitting the Stand-Density-Specific Model

Both models fit the data well (table 4, fig. 2) with the Kozak model having lower bias. The combined model (all spacings in a common model) was compared to separate models (fig. 2b) by spacing by comparing the error sums of squares for the combined model to the pooled error sums of squares from the separate models.

$$F = \frac{\left(SSE_{combined} - \sum_{spacing} SSE_{spacing}\right) \Big/ \left(dfe_{combined} - \sum_{spacing} dfe_{spacing}\right)}{SSE_{combined} \big/ dfe_{combined}}$$

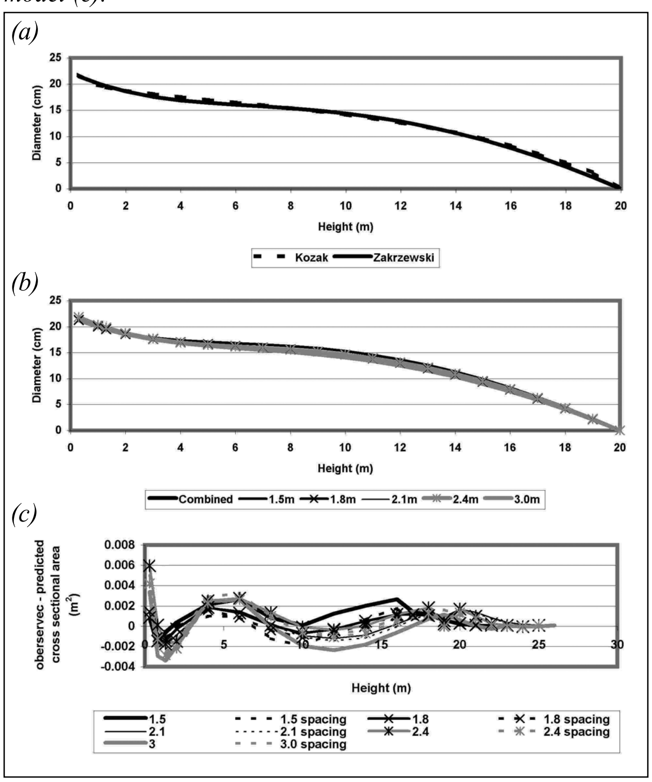
For both the Zakrzewski and the Kozak model, the hypothesis of a common taper model across all spacings was rejected (p < 0.0001 for both models). When the narrowest and widest spacings were removed, a common model fit the data as well as separate spacing models indicating a single model is adequate for spacings of 1.8 to 2.4 m. Spacings of 1.5 and 3.0 m are better predicted using separate models. As seen in figure 2b, the narrower spacings have larger cross-sectional areas above breast height for the same d.b.h. and total tree height, leading to higher volume. This is similar to the results of Sharma and Zhang (2004) for black spruce.

Table 4.—*The error sums of squares and degrees of freedom are given by spacing for the Zakrzewski model and the Kozak model.*

Model	Spacing	N	d.b.h. (cm)	Total height (m)	Diameter inside bark (d.i.b.) (cm)	Combined		Separate	
						Predicted d.i.b. (cm)	Mean d.i.b. error (cm)	Predicted d.i.b. (cm)	Mean d.i.b. error (cm)
Zakrzewski	1.5	108	18.74	21.15	12.43	12.38	0.52	12.77	0.13
	1.8	236	19.39	21.10	12.88	12.62	0.26	12.68	0.20
	2.1	296	22.60	24.50	14.83	14.57	0.26	14.65	0.19
	2.4	214	25.61	24.62	16.87	16.49	0.41	16.69	0.21
	3	202	28.95	24.79	19.41	19.23	– 0.02	18.94	0.28
Kozak	1.5	108	18.74	21.15	12.43	12.74	0.17	12.92	– 0.01
	1.8	236	19.39	21.10	12.88	12.95	– 0.07	12.93	– 0.05
	2.1	296	22.60	24.50	14.83	15.13	– 0.30	14.91	– 0.08
	2.4	214	25.61	24.62	16.87	16.88	0.02	16.98	– 0.08
	3	202	28.95	24.79	19.41	19.38	– 0.16	19.33	– 0.11

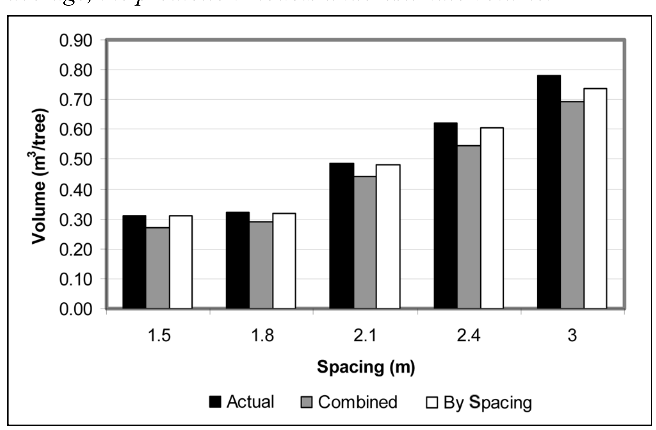
d.b.h. = diameter at breast height; d.i.b. = diameter inside bark.

Figure 2.—*The Kozak and Zakrzewski models for all spacings combined are compared for a tree with a total height of 20 m and a d.b.h. of 20 cm (a). The predictions are very close with the Kozak model having increased flexibility due to the inclusion of additional parameters. The combined model is compared to separate models by spacings for the Zakrzewski model (b). The errors along the stem are given by spacing for the Zakrzewski model (c).*



Although the taper model was fit to cross-sectional area, stem volume is key variable of interest. The Zakrzewki taper model was used to predict total stem volume and compared to the actual volume (fig. 3). The actual volume was calculated using Smalian's formula using the taper data. The taper model consistently underestimated total volume regardless of whether separate models were calibrated by spacing or whether the combined model was used. The taper model errors vary along the stem (fig. 2c) but the influence of cross-sectional area errors on volume are much greater near the base of the stem. This illustrates one of the benefits of a tractable model. Volume errors can be minimized directly by fitting the volume form of the taper model or volume and cross-sectional area errors can be minimized simultaneously.

Figure 3.—*The volume predictions are given by spacing for the combined model and separate models by spacing. Note, on average, the prediction models underestimate volume.*



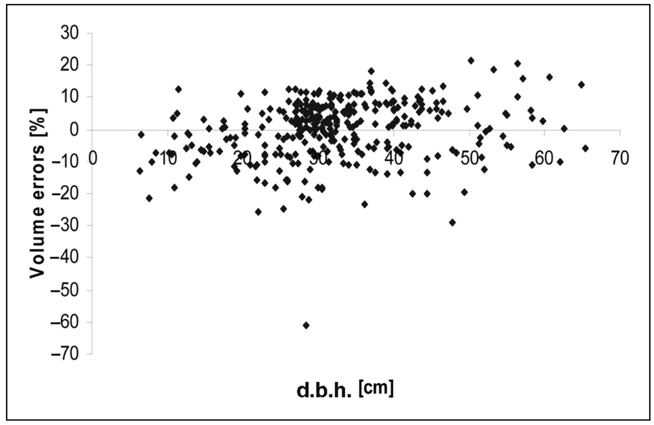
Validation of the Performance of the Models

From the results presented in table 3, it is evident that the stem profile model yields acceptably low errors in log and tree volume prediction. For the purpose of cross-border comparisons, however, we must ask if we can use the same set of coefficients (the same stem profile model) to estimate wood volume in Michigan and Ontario. The answer is conditional based on user-specified criteria of equivalence.

Equivalence tests, introduced to forestry by Robinson and Froese (2004), provide foresters with a sound and practical foundation to address the issue of model suitability for a desired purpose. Hypothesized dissimilarity between the observations and the model predictions is rejected if the existing differences fall in the region of indifference specified by model users from Michigan and Ontario. If the hypothesis is rejected, further efforts to improve the precision of the model's predictive power could be considered as a purely academic exercise, or worth pursuing only for tasks demanding higher accuracy and precision.

To test the scenario of inside bark total tree stem volume prediction (Vol_{tot}) being more practical for model application, an estimate of inside bark diameter at the *BH* level was used as the model's input. To reduce d.b.h. (outside bark diameter) to the inside bark diameter at the *BH* level, the double bark thickness was predicted from the sample tree based regression model. The resulting volume errors were similar to those obtained using variable location input diameters. Tree volume errors were plotted against d.b.h. values and did not show any consistent pattern (fig. 4).

Figure 4.—*Inside-bark tree volume prediction errors estimated for red pine data from Michigan and Ontario using proposed regional stem profile model.*



d.b.h. = diameter at breast height.

To evaluate the presented results, a paired *t*-test of equivalence was performed. Normal probability plots indicated normality of distribution of errors for the joint data sets and for the individual regions. The criteria (suggested acceptable errors of 0.03 or 0.06 m^3) were used to test the base for the rejection of dissimilarity hypothesis. Those were translated to different values of ε depending on the estimate of standard deviation of the volume prediction errors (ε values are obtained by dividing a criterion value by the respective standard deviation). Results indicate that the fitted model is acceptable if the model users in Michigan and Ontario can tolerate expected errors of total stem volume estimates not greater than around 50 percent of expected standard deviation of errors, i.e., 0.06 m^3 (table 5). In practical terms, this can be expressed as around 4.7 percent volume error for a larger number of stems (a half of relative standard deviation reported in table 3 for the combined regions).

Table 5.—*Statistical summary of equivalence test (at α = 0.05) for red pine total tree volume prediction errors.*

Region	Criterion (m^3)	N	Mean error	Standard deviation	ε	*t*-value	Cut-off value $\bar{C}$	Hypothesis of dissimilarity
Combined	0.06	338	0.027	0.120	0.495	4.10	7.41	Rejected
	0.03				0.247		2.90	Not rejected
Ontario	0.06	210	0.033	0.150	0.399	3.28	4.12	Rejected
	0.03				0.199		1.25	Not rejected
Michigan	0.06	128	0.015	0.039	1.501	4.40	14.76	Rejected
	0.03				0.750		6.72	Rejected

Conclusions

As part of the Great Lakes Stem Profile Modelling Project, the general stem profile model developed by Zakrzewski (1999) was fitted for red pine in Michigan, United States, and Ontario, Canada, and its predictive performance examined. Results indicate much greater variability in red pine stem profiles in Ontario than in Michigan, which relates to differences in the data sets (perhaps stand density) defined by characteristic differences in stem form among species, across ecosystems, and under different growing conditions. While local variation in tree stem form can be accounted for by fitting (localizing) models (e.g., MacFarlane [2004] used ecological classification systems to define ecologically referenced height-diameter models), suitable regional models may be adequate for defining equivalent comparisons across larger regions (e.g., species neutral, composite volume equations developed by Gevorkiantz and Olsen [1955]).

Our results suggest that cross-border comparisons of timber inventories can be directly addressed using regional stem profile models. The fact that in this study stem profile model error was generally insensitive to the use of variable location input diameters demonstrates how the taper model can accommodate measurements taken from any reasonable portion of a stem or log, an important consideration in a model developed to combine data from different forest.

The Zakrzewski model and Kozak's taper model led to similar conclusions about the effect of tree density (stems/ha) on taper. Based on the data used here, for moderate initial spacings (1.8 to 2.4 m), a single taper model is adequate. For narrower (1.5 m) and wider (3.0 m) spacings, separate taper models should be calibrated or the taper model modified to explicitly incorporate the density effect. Fitting only the cross-sectional area formulation of the taper model led to underprediction of volume, on average. A mathematically tractable taper model allows fitting of volume directly either on its own or simultaneously with cross-sectional area.

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Modeling Forest Bird Species' Likelihood of Occurrence in Utah With Forest Inventory and Analysis and Landfire Map Products and Ecologically Based Pseudo-Absence Points

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Abstract.—Estimating species likelihood of occurrence across extensive landscapes is a powerful management tool. Unfortunately, available occurrence data for landscape-scale modeling is often lacking and usually only in the form of observed presences. Ecologically based pseudo-absence points were generated from within habitat envelopes to accompany presence-only data in habitat classification models (HCM) for the northern goshawk (*Accipiter gentilis atricapillus*). We built models at two resolutions, using predictor variables derived from 250-m Forest Inventory and Analysis map products, 30-m U.S. Department of Agriculture Landfire map products, and digital elevation models. Cross-validation provided an assessment of models' predictive capabilities. Use of ecologically based pseudo-absence points to accompany extant presence points in HCM can be a powerful asset for species conservation.

Introduction

Species habitat classification models (HCMs) and their associated habitat suitability maps are valuable assets to species monitoring, conservation, and land-use planning, particularly across broad landscapes where intensive surveying and monitoring is difficult. Species metapopulations are often spread across broad landscapes, justifying management across spatial extents which approximate their population ranges. Recent advances in statistical modeling, Geographic Information System (GIS), and remote sensing have enabled researchers to more accurately model species-habitat relationships in a spatial context (Levin *et al.* 1997, McNoleg 1996, Scott *et al.* 2002). In addition, the creation of broad-scale continuous map products that portray land-cover variables have become valuable resources for species habitat modeling, particularly across large spatial extents.

The U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis (FIA) program recently created map products of forest attributes across the central Utah highlands at 250-m resolution (table 1) (Blackard *et al.* 2004). Similar map products of forest attributes have been created by the USDA Landfire program as well, although at a finer resolution of 30-m (table 2) (Keane *et al.* 2002, Landfire 2005). When spatially intersected with species occurrence data (i.e., spatially explicit presence/absence points), spatial map products produce predictor variables useful in species HCMs. The statistical model underlying HCMs can then distinguish (i.e., classify) suitable habitat from nonsuitable habitat. Generalized linear models (GLMs), generalized additive models, and classification trees (Breiman *et al.* 1984) are among the most frequently used techniques. GLMs are a popular choice because they have proven to be robust and stable (Brotons *et al.* 2004; Engler *et al.* 2004; Guisan *et al.* 1999, 2002; Manel *et al.* 1999; Pearce and Ferrier 2000; Thuiller *et al.* 2003).

Landscape-scale studies often lack absence data due to the amount of resources needed to collect absence data points

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across an extensive study area. In addition, occurrence databases containing recent and historical data (e.g., from censuses, field studies, museum and herbaria records) usually contain only presences. This lack of absence data precludes the use of many statistical techniques in HCMs. Two basic methods exist for handling the problem of presence-biased datasets: (1) using profile-type models, which incorporate the presence-only bias into the model and control its effects on the resulting predictions (e.g., Hirzel et al. 2002, Stockwell and Peterson 2002b, Zaniewski *et al.* 2002), and (2) generating pseudo-absence points to be used in place of unknown absence data (e.g., Engler *et al.* 2004, Guisan and Thuiller 2005, Stockwell and Peterson 2002b, Zaniewski *et al.* 2002).

Profile-type models contrast attributes of presence-only data with background levels of environmental variables across the study area. Factor analysis (Hirzel *et al.* 2002), fuzzy set theory (Busby 1991, Chicoine *et al.* 1985, Robertson *et al.* 2004), artificial intelligence methods (Stockwell and Noble 1991), and statistical mechanics (Phillips *et al.* 2006) are modeling techniques used in profile-type models. Unfortunately, several drawbacks exist for profile-type models, including overprediction (e.g., Ecological Niche Factor Analysis [ENFA]—Brotons *et al.* 2004, Engler *et al.* 2004), and assumptions that all predictor variables are equally important in determining species' distribution (e.g., Fuzzy Envelope Model—Robertson *et al.* 2004), that the presence data is unbiased (e.g., ENFA—Hirzel *et al.* 2002), that the presence-only data originates only from source habitat (e.g., Maxent—Phillips *et al.* 2006), and difficulty in interpretation and statistical assessment. An alternative to profile-type models is to generate so-called pseudo-absences to pair with known presences (Ferrier and Watson 1997, Stockwell and Peters 1999, Stockwell and Peterson 2002b, Zaniewski *et al.* 2002). Traditional techniques of generating pseudo-absence points involve randomly selecting pseudo-absences from broadly defined species ranges, such as an entire study, and excluding locations where presence points exist. To constrain pseudo-absence point selection, Stockwell and Peters (1999) suggested creating a pseudo-survey region that confines the extent from which the pseudo-absence points can be generated.

This study improves on existing pseudo-absence point generation techniques by incorporating biological knowledge concerning the species-habitat relationship to constrain the region from which pseudo-absence points are selected. The northern goshawk (*Accipiter gentilis atricapillus*), considered a management indicator species in many national forests of the Intermountain West, was chosen as a study species because of its well-documented habitat associations (Brotons *et al.* 2004), and sufficient recent and extant presence points in Utah, but lack of absence points. The objectives of this study were (1) to develop methods to incorporate species' ecology into the generation of pseudo-absence points, (2) to apply these methods to produce HCMs and output likelihood of occurrence maps for northern goshawk nest sites and nest areas across Utah's central highlands, and (3) to test the utility of FIA and Landfire vegetation map products for wildlife habitat applications.

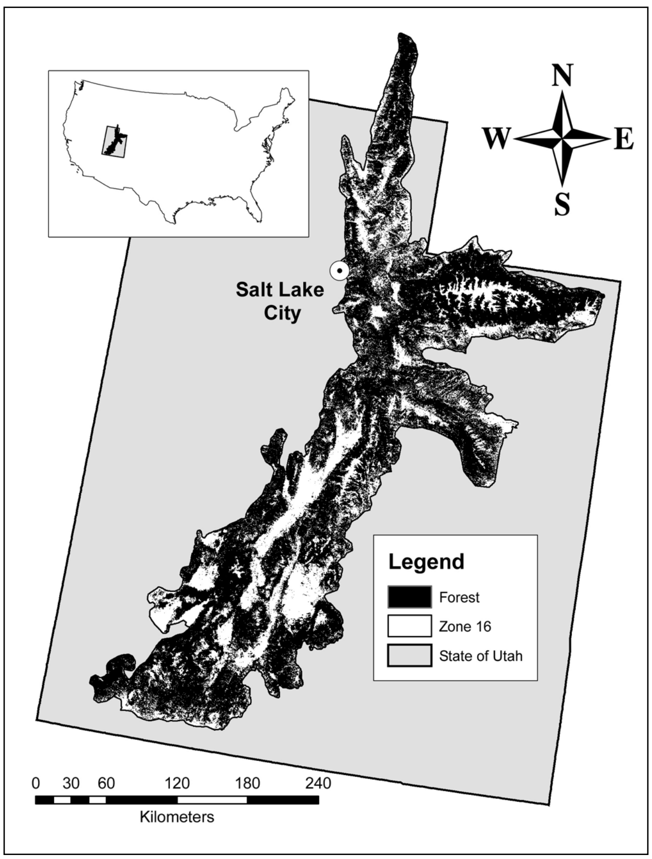
To incorporate biological knowledge, and constrain the region from which pseudo-absence points are randomly selected, spatial habitat envelopes based on known goshawk habitat associations were created. We define a habitat envelope as an ecological representation of a species, or species feature's (e.g., nest), observed distribution (i.e., realized niche) based on a single attribute, or the spatial intersection of multiple attributes. No existing computer programs (e.g., GARP) were employed to assure complete control over the generation of habitat envelopes and the selection of ecologically based pseudo-absence points. Known ecological associations of northern goshawk nest location to habitat variables were translated into increasingly complex habitat envelopes. Pseudo-absence points were then paired with extant presence points and used in logistic regression to model the likelihood of occurrence of northern goshawk nest site (at 30-m resolution) and nest area (at 250-m resolution) as a function of habitat predictor variables. Models were evaluated with accuracy metrics via 10-fold cross-validation. Top models were translated into likelihood of occurrence maps across the study area, creating habitat suitability maps for each resolution. These envelope-based models were then compared to traditional models based on current practices for generating pseudo-absences, which involve selection of absences from broadly defined species ranges.

Methods

Study Region

The study occurred in forested regions of Zone 16, comprising the Wasatch and Uinta mountain ranges in Utah, southeast Idaho, and southern Wyoming (fig. 1). The zone is approximately 55 percent forested. Elevation ranges from 386 m to 3,978 m (1,266 to 13,051 ft). Zone 16 was selected because FIA and Landfire map products are complete for this region, thereby providing a large set of digital predictor layers for modeling purposes.

Figure 1.—*Zone 16 study region.*



Study Species

The northern goshawk is the largest accipiter in North America, is an apex predator, and is holarctic in distribution (Squires and Reynolds 1997). Homerange is approximately 2,400 ha, and consists of three components: nest area (~12 ha), post-fledging area (~170 ha), and the foraging area (~2,200 ha) (Reynolds *et al.* 1992). Multiple nest areas exist within a home range (Reynolds *et al.* 1994), and multiple (satellite) nests occur within each nest area (Reynolds *et al.* 2005, Squires and Reynolds 1997). In general, large trees (> 40.6 cm diameter at breast height) (Beier and Drennan 1997) arranged in a clump (Graham *et al.* 1999) with dense canopy cover (Beier and Drennan 1997, Bright-Smith and Mannan 1994, Graham *et al.* 1999, Reynolds *et al.* 1992, Stephens 2001) are preferred for nesting.

For modeling purposes, nest site is defined as the habitat immediately surrounding the nest (nest tree to 0.10 ha area surrounding the nest tree) (Reynolds *et al.* 1982, Squires and Reynolds 1997). Nest area is defined as habitat around the nest, 10 to 12 ha area in size that includes the nest tree, adult roosts, and prey plucking sites (Newton 1979, Reynolds *et al.* 1992). Nest site habitat characteristics were derived from the spatial intersection of 30-m resolution (0.09-ha) predictor variables with nest presence points (for suitable nest sites) and nest pseudo-absence points (for unsuitable nest sites) in a GIS (Zarnetske 2006). Nest area habitat characteristics were derived from the spatial intersection of 250-m resolution (6.25-ha) predictor variables with nest presence points (for suitable nest areas) and nest pseudo-absence points (for unsuitable nest areas) in a GIS (Zarnetske 2006). Hereafter, 30-m resolution (representing nest sites) and 250-m resolution (representing nest areas) models using habitat envelopes are referred to as "30-m habitat envelope models" and "250-m habitat envelope models," respectively. Models using traditional techniques of generating pseudo-absence points are referred to as "30-m traditional models" and "250-m traditional models."

Predictor Variables

The FIA plot-based inventories of forested land across Zone 16 were combined with 250-m MODIS imagery using regression tree modeling techniques to produce a suite of vegetation map products (Blackard *et al.* 2004) (tables 1 and 2). Landfire 30-m resolution map products for Zone 16 were created with plot inventories (including FIA plot data), biophysical gradients, and 30-m Landsat Thematic Mapper imagery using regression tree modeling as well (Keane *et al.* 2002, Landfire 2005)

Table 1.—*Descriptions of continuous spatial map products from Landfire and FIA.*

Variable	Abbreviation	Description
Landfire map product		
Canopy bulk density	CBD	kg/m
Canopy base height	CBH	m to live canopy
Forest canopy cover	FCC	% canopy cover
Forest height	FHT	m
Herbaceous canopy cover	HCC	% canopy cover
Herbaceous height	HHT	m
Shrub canopy cover	SCC	% canopy cover
Shrub height	SHT	m
Elevation	ELEV	m
Slope	SLP	% rise
Transformed aspect	TASP	0-1
FIA		
Stand age	AGE	age (yrs)
Basal area	BA	m²/ha
Forest biomass	BIO	tons/ha
Crown cover	CC	% crown cover
Forest growth	GRW	m³/ha
Quadratic mean diameter	QMD	cm
Stand density index	SDI	ha
Trees per hectare	TPH	trees > 2.54 cm DBH per ha
Forest volume	VOL	m³/ha
Weighted height	WHT	m (weighted by larger trees)
Elevation	ELEV	m
Slope	SLP	% rise
Transformed aspect	TASP	0-1

(tables 1, 2). Zone 16 Landfire map products included forested and nonforested areas; for modeling and comparison with FIA map products, nonforested regions in Landfire map products were excluded. Elevation (m), slope (%), and aspect (degrees) derived from 30-m and 250-m digital elevation models (DEMs) originating from the U. S. National Elevation Dataset. Aspect was rescaled to a scale from 0 to 1, where high values were assigned to north-northeast facing slopes (Roberts and Cooper 1989):

$$TASP = [1-\cos(aspect-30)] / 2.$$

FIA map products and the 250-m DEM were restricted to use in the 250-m models while Landfire map products and the 30-m DEM were restricted to use in the 30-m models.

Table 2.—*Descriptions of categorical spatial map products from Landfire and FIA. All units were converted to the metric system for consistency.*

Variable	Abbreviation
Landfire map product	
Cover type (dominant cover type)	COV
ponderosa pine	PP
lodgepole pine	LPP
high elevation pine[a]	HEP
Douglas fir	DF
white fir	WF
spruce/fir	SF
pinyon-juniper	PJ
juniper	J
riparian and other hardwoods	RH
aspen/birch	AB
Structure (height, forest canopy cover)	STR
forest, height <= 10m, canopy <= 40%	STR1
forest, height <= 10m, canopy > 40%	STR2
forest, height > 10m, canopy <= 40%	STR3
forest, height > 10m, canopy > 40%	STR4
FIA map product	
Forest type (dominant forest type)	FT
rocky mountain juniper[b]	PJ
juniper woodland[b]	PJ
pinyon-juniper woodland	PJ
Douglas fir	DF
ponderosa pine	PP
white fir	WF
Engelmann spruce	ES
Engelmann spruce/subalpine fir	ES/SAF
subalpine fir[c]	ES/SAF
blue spruce[d]	DF
lodgepole pine	LPP
foxtail pine/bristlecone pine[c]	ES/SAF
limber pine[c]	ES/SAF
aspen	QA
deciduous oak woodland	DO
cerocarpus woodland	CW
intermountain maple woodland[e]	DO
misc. western hardwood woodlands[e]	DO

[a] *Reassigned to lodgepole pine.*
[b] *Reassigned to pinyon-juniper woodland.*
[c] *Reassigned to Engelmann spruce/subalpine fir.*
[d] *Reassigned to Douglas fir.*
[e] *Reassigned to deciduous oak woodland.*

Northern Goshawk Nest Presence Points

Recent (1993–2005) northern goshawk nest point locations were obtained from the Ashley, Dixie, Fishlake, Manti-La Sal, Uinta, and Wasatch-Cache National Forests, and the Utah Division of Wildlife Natural Heritage database (n = 564). Only the most recently active nest per northern goshawk territory was selected to reduce spatial autocorrelation (n = 285, 1994–2005) (Reynolds 1983, Speiser and Bosakowski 1991, Woodbridge and Detrich 1994). Four nest locations were associated with Landfire nonforested pixels and six nest locations were associated with FIA nonforested pixels. These locations were eliminated, reducing the total number of nests to 281 for the 30-m models and 279 for the 250-m models.

Ecologically Based Pseudo-Absence Points

Pseudo-absence points for both the 30-m and 250-m habitat envelope models were randomly selected from within ecologically based habitat envelopes. Habitat envelopes represent the spatial extent of a species' gross habitat needs, contain a large percentage of extant presence points, and are derived from single or the intersection of multiple spatial variables. Viable northern goshawk habitat envelopes contained at least 90 percent of extant presence points (≥ 508 of 564). Habitat envelopes were created in a GIS based on existing habitat associations reported from 30 northern goshawk studies in the Western United States (Zarnetske 2006).

These northern goshawk studies provided 30-m resolution nest site and 250-m resolution nest area habitat characteristics during the breeding season. Geometric means (geomeans) of published minima and maxima values of habitat characteristics (i.e., percent canopy closure, tree height) across studies were used to set the lower and upper limits of the habitat envelopes. If minima and maxima habitat characteristics were not reported, the 95 percent confidence interval habitat characteristic values, or values of ± 1 standard deviation (SD) were used instead. If unavailable, standard deviation was calculated as $SD = SE \times \sqrt{(N)}$.

Single variable habitat envelopes were created by extracting the grid cells for a particular habitat variable that fell within geomeans of published minima and maxima. The spatial intersection of two or more envelopes produced multivariable habitat envelopes. Habitat envelopes at each model resolution containing less than 90 percent of all presence points (n < 507) were discarded. Up to three habitat envelopes from each type (1, 2, and 3 variable) which contained the highest percentages of presence points, were chosen for pseudo-absence point generation (tables 3 and 4).

Before selection of pseudo-absence points from habitat envelopes, northern goshawk nest areas and post-fledging areas (a total of 182 ha centered on each nest) for all 564 nests were removed from the habitat envelopes so that pseudo-absence points would not be selected from areas where known nests and defended territories occur (Reynolds *et al.* 1992).

Unbalanced ratios of presence to absence points can affect the accuracy of classification models (Manel *et al.* 2001, Stockwell

Table 3.—*Northern goshawk 30-m nest site habitat envelopes from Landfire map products. "∩" refers to the spatial intersection of multiple single-variable habitat envelopes. All units converted to the metric system for consistency.*

Envelopes	Values	% of all nest points contained (n = 564)	% cover of zone 16 forested area
CONASP	All conifers and aspen[a]	97.7	95.0
ELEV	1,828–3,048 m	96.0	88.0
FHT	8.97–25.6 m	96.9	79.3
CONASP ∩ FHT	All conifers and aspen[a] FHT: 8.97–25.6 m	94.9	60.1
CONASP ∩ ELEV	All conifers and aspen[a] ELEV: 1,828–3,048 m	93.7	84.6
ELEV ∩ FHT	ELEV: 1,828–3,048 m FHT: 8.97–25.6 m	92.8	65.2
CONASP ∩ ELEV ∩ FHT	All conifers and aspen[a] ELEV: 1,828–3,048 m FHT: 8.97–25.6 m	90.9	53.1

[a] *All conifers and aspen, including ponderosa pine, lodgepole pine, high elevation pine, Douglas fir, white fir, spruce/fir, pinyon/juniper, juniper, aspen/birch.*

Table 4.—*Northern goshawk 250-m nest area habitat envelopes from FIA map products. "∩" refers to the spatial intersection of multiple single-variable habitat envelopes.*

Envelopes	Values	% of all nest points contained (n = 564)	% cover of zone 16 forested area
QMD	11.5–77 cm	100.0	99.6
WHT	5–21 m	99.8	81.3
SDI	337–2,021 (in ha)	97.9	90.3
QMD ∩ WHT	QMD: 11.5–77 cm WHT: 5–21 m	99.8	80.9
QMD ∩ SDI	QMD: 11.5–77 cm SDI: 337–2,021 (in ha)	97.9	89.8
SDI ∩ WHT	SDI: 337–2,021 (in ha) WHT: 5–21 m	97.7	74.9
QMD ∩ SDI ∩ WHT	QMD: 11.5–77 cm SDI: 337–2,021 (in ha) WHT: 5–21 m	97.7	74.6
ELEV ∩ QMD ∩ WHT	ELEV: 1,828–3,048 m QMD: 11.5–77 cm	95.9	72.4
QMD ∩ CONASP ∩ WHT	QMD: 11.5–77 cm All conifers and aspen[a] WHT: 5–21 m	95.9	68.5

[a] *All conifers and aspen including pinyon-juniper, Douglas fir, ponderosa pine, white fir, Engelmann spruce, sub-alpine fir, lodgepole pine, and aspen.*

and Peterson 2002a); consequently, the proportion of presence to absence points was balanced to ensure that predicted distributions are as accurate as possible. One hundred sets of pseudo-absence points were randomly selected from each habitat envelope (n = 281 for 30-m habitat envelopes; n = 279 for 250-m habitat envelopes). A one-sample *t*-test compared the distribution of 100 samples against the habitat envelope population to test for biased samples ($P > 0.05$, one-sample *t*-test).

Traditional Pseudo-Absence Points

A set of traditional pseudo-absence points was also generated for each of the 30-m and 250-m traditional models. Instead of generating habitat envelopes, pseudo-absence points were randomly selected from the entire study region (in this case, all forested area within Zone 16). Existing northern goshawk nest areas and post-fledging areas were removed from the study area so that pseudo-absence points would not be assigned within existing territories.

Habitat Envelope Model Creation

One set of pseudo-absence points was randomly selected for each habitat envelope (Zarnetske 2006), paired with the presence points, and modeled as the response using logistic regression in R (R Project 2006). Variables used to create a habitat envelope were not included in the logistic regression models (i.e., QMD was not included as a predictor variable if the pseudo-absence points were generated from the QMD habitat envelope). Some cover types in models at 30-m resolution and some forest types in models at 250-m resolution were so low in occurrences of presences or pseudo-absences that logistic regression could not converge. Consequently, "high elevation pine" was reassigned as "lodgepole pine" within the Landfire cover type. Within FIA forest type, "rocky mountain juniper" and "juniper woodland" were reassigned "pinyon-juniper woodland," "sub-alpine fir," "limber pine," and "bristlecone pine" were reassigned "Engelmann spruce/sub-alpine fir," "blue spruce" was reassigned "Douglas fir," and "intermountain maple woodland" and "misc. western hardwoods" were reassigned "deciduous oak woodland." Decisions to reassign types were based on associated forest cover following Burns and Honkala (1990). In this manner, the presence/pseudo-absence data sets remained balanced and logistic regression was able to converge.

Ten-fold cross-validation was performed to assess model predictive capability, and associated model metrics were calculated (i.e., sensitivity, specificity, kappa, percent correctly classified [PCC], and receiver operating characteristic plot's area under the curve [AUC]). Models produced from the same set of absence points and habitat envelope were ranked according to Akaike's information criterion (AIC) (Akaike 1973), cross-validation error rate, and adjusted deviance (D^2_{adj}) to form a list of top candidate models (4 for each traditional model resolution, 18 for 30-m models, and 33 for 250-m models) (Zarnetske 2006). Because these pooled top models were not nested models containing the same variables, AIC was not an appropriate measure of performance for comparison among models. To determine the top model of each resolution, models were selected first by low cross-validation error rate (all models < 1 percent from the lowest cross-validation error rate), and then by the highest D^2_{adj}. If D^2_{adj} was equal for two or more top models, the more parsimonious model was chosen as the top model (tables 5 and 6).

Traditional Model Creation

Traditional models were created following the same methodology as described above for the habitat envelope with exceptions noted here. One set of pseudo-absence points was randomly selected for each resolution, paired with the presence points, and modeled as the response with predictor variables using logistic regression in R (Zarnetske 2006). All traditional models per resolution were ranked according to AIC. Top candidate models were each assessed for fit (D^2_{adj}) and predictive capability (sensitivity, specificity, kappa, PCC, AUC) on the training data, and internally validated by 10-fold cross validation. Models were ranked and the top model per resolution was chosen following the methodology above (tables 5 and 6).

Table 5.—*Top habitat envelope and traditional models from the list of competing top models. Only significant cover types and forest types are shown. Direction of variable influence is indicated by "+" or "–" preceding the variable. AIC and ∆AIC are reported but these models cannot be compared with AIC because they contain different sets of pseudo-absence points.*

Model name	Model	AIC	∆AIC
30-m resolution			
TRAD30-4	+CBH*** –HCC* +FHT*** –SLP***	583.40	4.68
CONASP ∩ ELEV3	+CBH*** +FHT*** –SLP***	546.95	2.96
250-m resolution			
TRAD250-3	+ FT(–PJ*** +DF* +PP*** +WF*** +LPP*) +GRW –SLP***	584.10	3.28
QMD3	+FT(–PJ*** +DF* +PP*** +WF***) +GRW*** –SLP***	542.53	3.80

AIC = Akaike information criterion.
** P < 0.05; ** P < 0.01; *** P < 0.001*
Forest type codes: PJ = pinyon/juniper, DF = Douglas fir, PP = ponderosa pine, WF = white fir, LPP = lodgepole pine.

Table 6.—*Top models' fit and predictive capability statistics. ( ) = standard error. Error rate represents 10-fold cross-validation error rate.*

Model name	D^2_{adj}	Sensitivity	Specificity	Kappa	PCC	Error rate	AUC
30-m resolution							
TRAD30-4	0.74	0.81	0.74	0.56	0.78	23.39	0.82 (0.02)
CONASP ∩ ELEV3	0.69	0.84	0.77	0.62	0.81	19.46	0.85 (0.02)
250-m resolution							
TRAD250-3	0.72	0.78	0.70	0.48	0.74	27.03	0.82 (0.02)
QMD3	0.67	0.83	0.76	0.59	0.79	22.68	0.84 (0.02)

AUC = area under the curve; PCC = percent correctly classified.

Habitat Suitability Maps

Top habitat envelope 30-m and 250-m models' coefficients were translated into likelihood of occurrence GIS maps across forested regions of Zone 16 using StatMod extension (Garrard 2002) in ArcView 3.2 (ESRI 2005) (figs. 2 and 3). Maps depict likelihood of occurrence of nest site (30-m) or nest area (250-m) ranging from 0 to 1, where 0 to 0.25 is very unsuitable habitat (light grey), 0.25 to 0.50 is unsuitable habitat (grey), 0.50 to 0.75 is suitable habitat (dark grey), and 0.75 to 1.0 is highly suitable habitat (black).

Results

Top habitat envelope models always outperformed top traditional models in terms of model fit and predictive capability (table 6). Slope was always significantly negative in all top candidate models (table 5). Top traditional and habitat envelope 30-m models all contained forest height variables (i.e., CBH and FHT) that were significantly positive. Top traditional and habitat envelope 250-m models all contained FT either within the habitat envelope or as a predictor variable. At both resolutions, four-variable habitat envelope models always had the lowest AIC scores, but similar three-variable models were usually within $\Delta AIC < 2$, suggesting that addition of a fourth predictor variable did not improve models significantly (Zarnetske 2006).

The top 30-m traditional model (TRAD30-4) had four parameters and included a negative association with HCC, a significantly negative association with SLP, and a significantly positive association with both CBH and FHT (table 5). The top 250-m traditional model (TRAD250-3) was the most parsimonious of top competing models with low cross-validation error rates. This model had 12 parameters, including a positive association

Figure 2.—*Likelihood of goshawk nest site occurrence across Zone 16 based on top 30-m habitat envelope model.*

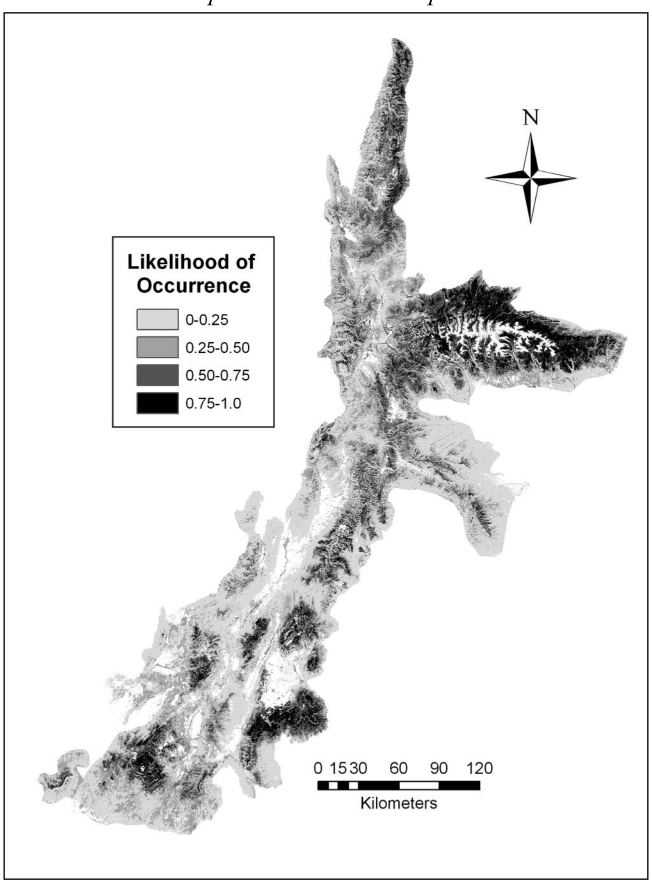
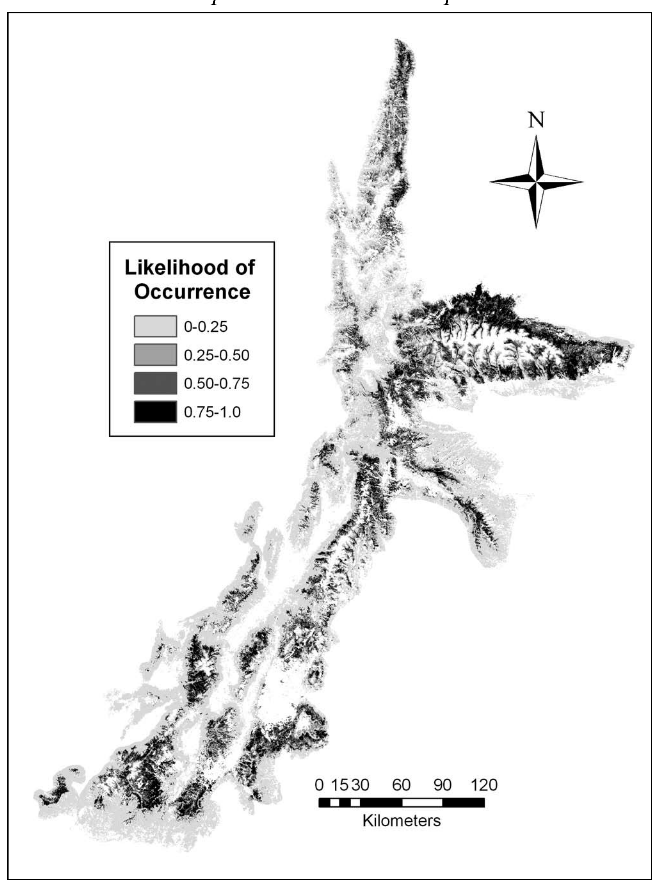


Figure 3.—*Likelihood of goshawk nest area occurrence across Zone 16 based on top 250-m habitat envelope model.*



with forest types appropriate for northern goshawk nest areas (i.e., ponderosa pine, white fir, lodgepole pine), a negative association with low suitability forest types (pinyon/juniper), a significantly positive association with GRW, and a significantly negative association with SLP (Zarnetske 2006).

The CONASP ∩ ELEV habitat envelope produced the pseudo-absence points used in the top 30-m habitat envelope model. These pseudo-absences were less variable than those used in the top 30-m traditional model for most variables. CONASP ∩ ELEV3 was the most parsimonious of competing models with only three parameters (CBH, FHT, SLP). QMD3 was the top 250-m habitat envelope, and pseudo-absence points in this model were also less variable than those used in TRAD250-3 for most variables (Zarnetske 2006).

Discussion

The ecology of the species-habitat relationship was successfully incorporated into the generation of ecologically based pseudo-absence points by creating habitat envelopes. This method can be a powerful asset for extracting information from extant species occurrence databases, which are often underutilized because traditional modeling techniques require both presence and absence points. Rare, threatened, and sensitive species such as the northern goshawk can benefit from the production of landscape-scale habitat suitability maps using ecologically based pseudo-absence points. These habitat suitability maps provide information for species range shift studies, censuses, reserve designs, species reintroduction, habitat restoration, and biodiversity conservation. Ecologically based pseudo-absence points can be applied to any species, ecosystem, data resolution, and spatial extent, given some *a priori* knowledge concerning the species-habitat relationship. In addition, the use of readily available software (e.g., Program R and ArcGIS) allows easy application and the flexibility to work with user-defined data structures and map products.

Representation of underlying ecological relationships will always improve when observed and measured biological relationships are incorporated into modeling and extrapolation (Belovsky *et al.* 2004). The consistent improvement in model fit and predictive capability of habitat envelope models is a testament to using ecologically-based pseudo-absence points over traditional pseudo-absences. In addition, reliance on sound statistical modeling with pseudo-absences may be more appropriate than obscure profile-type models that are difficult to interpret and assess for model fit and predictive capability. In cases where field-collected absences are suspected to be false (Graham *et al.* 2004; Hirzel *et al.* 2001, 2002), ecologically based pseudo-absences could provide more robust absences.

Incorporating ecology into pseudo-absence point generation should also decrease the chance of a biologically inappropriate top model because habitat envelopes already constrain the regions of pseudo-absence point generation to preferred habitat. Pseudo-absences from habitat envelopes will be less variable on average than those generated from an entire study area due to the reduced region from which they are selected. In this study, this allowed the statistical models to improve classification of northern goshawk highly suitable and moderately suitable habitat, and to create more statistically and ecologically robust models. The distinction of highly suitable from moderately suitable is essential to species conservation and habitat management, particularly for rare, threatened, and sensitive species susceptible to habitat fragmentation and degradation. Researchers interested in well-studied species such as the northern goshawk will be able to focus on highly suitable habitat within the range of suitable habitat. Lesser-known species will still benefit from ecologically based pseudo-absence points because presumably some aspect of their habitat association is known (i.e., they prefer forested over nonforested areas).

A successful habitat envelope will maximize the percent of presence points contained while at the same time reducing the area from which pseudo-absence points are selected. Based on the high number of presence points contained, the reduced area from which pseudo-absence points are selected, and the high model fit and predictive capability statistics, the CONASP ∩ ELEV habitat envelope appears to be the best habitat envelope at 30-m resolution for the northern goshawk. The top 250-m habitat envelope model included the same parameters (FT, GRW, SLP) as the top traditional model, and almost the same area as the entire study region (99 percent of the study region). The similarity in model parameters and spatial extent caused more heterogeneous ecologically based pseudo-absence points than expected, but the top 250-m habitat envelope model was still an improvement in model fit and predictive capability over the top 250-m traditional model. High AUC values from these top habitat envelope models indicate that the models have useful application across the study area because they are insensitive to threshold cut-off values (Fielding and Bell 1997, Swets 1988), and have few false positives. Due to the immense resources needed to census goshawk metapopulations across an area the size of Zone 16, false positives would be detrimental to census efforts. The high sensitivity, specificity, kappa, and PCC, and low cross-validation error rate for both top habitat envelope models suggests that sampling high likelihood of occurrence sites may lead to the discovery of new nest sites and nest areas.

Northern goshawk habitat associations were pooled from the entire Western United States, consisting of a variety of forested ecosystems. If more northern goshawk habitat studies were available for regions similar to Utah's central highlands (i.e., Intermountain West field studies), and only this habitat information was considered in creating habitat envelopes, more two- and three-variable habitat envelopes could have provided robust sets of pseudo-absence points. In addition, the entire study area already represents a habitat envelope of sorts because it is constrained to forests in Zone 16. If traditional models were produced over all of Zone 16 (i.e., 55 percent forest and 45 percent nonforest), they would better reflect the current methods of generating pseudo-absence points.

The models contain error from a variety of sources. As models themselves, each FIA and Landfire map product contributes spatial and classification error. Because FIA and Landfire map products of Zone 16 incorporate plot-based inventory data and satellite imagery spanning from 1998–2003, certain cells within the map products may inaccurately reflect current conditions (Blackard *et al.* 2004, FIA 2005, Landfire 2005). DEMs and spatial error associated with nest points are additional sources of error. No known methods exist to incorporate the inherent error of spatial layers into statistical classification models.

The assumptions that habitat is saturated (Capen *et al.* 1986), and that the species modeled is in equilibrium with its environment (Austin 2002), are often ignored in broad-scale habitat modeling because knowing the locations of all individuals or the individuals' attribute (i.e., a nest) is nearly impossible across a broad landscape, particularly at one time step. It is probable that not all northern goshawk territories in Zone 16 have been identified and that some of the nests used in the models are in sink habitats. Some nests used in modeling may be in sink habitat due to incomplete nest activity information. Most large-scale species occurrence datasets include data collected by a variety of survey methods and do not have complete data point attribute information.

The likelihood of occurrence of nest sites and nest areas across Zone 16 reflects environmental habitat variables only. Prey abundance, nest productivity, and interannual climatic variability are important variables driving nest success in addition to appropriate habitat type (Doyle and Smith 1994, Keane 1999, Reynolds *et al.* 2006, Salafsky *et al.* 2005, Wiens *et al.* 2006). These variables were not available for each nest location across Zone 16; consequently, northern goshawk nest placement does not necessarily correlate directly with nest productivity. It is for this reason that the nest site and nest area habitat suitability maps should be used as guides to locate new highly suitable habitat, and new nests and territories. Intensifying sampling in highly suitable areas while decreasing sampling effort in low suitability areas should increase sampling efficiency.

As new nests are located, the model can be adjusted to incorporate more recently active nests. Ideally, a northern goshawk HCM would use 1 year's nest activity information across Zone 16 so that unoccupied known nests could be treated as absences and occupied nests could be treated as presences. On a landscape scale such as Zone 16, this could be achieved on a per-season basis by identifying successful nests (i.e., those that produced fledglings) during existing routine national forest nest monitoring, determining competitor presence and prey abundance through distance sampling (following Salafsky *et al.* 2005), using spatial habitat data such as FIA and Landfire map products, incorporating disturbance extents and severity ratings (such as timber sale, fire, and beetle kill), and recording weather extremes and climatic events in proximity to each nest. In this manner, data collected on a per-year basis would allow for per-breeding season analysis of suitable and successful nesting habitat. The likelihood of occurrence of active nests could be modeled following Reich *et al.* (2004), but using pseudo-absence points to accompany known presence points. If these assessments continue for several years in a row, the variability between years will be captured and a more complete assessment of across-landscape habitat suitability and nest success will be clear.

Researchers and conservationists will gain insight into the level of habitat saturation throughout Zone 16 through yearly monitoring of new nests found with the help of this model, and monitoring existing nests for activity. Combining this knowledge of nest activity with age of adult breeders would help determine the stability of the Zone 16 population (Kenward *et al.* 1999, Reynolds *et al.* 2006, Reynolds and Joy 2006). Sympatric species such as the sharp-shinned hawk (*Accipiter striatus*), spotted owl (*Strix occidentalis*), and barred owl (*Strix varia*), have similar nesting habitat requirements to the northern goshawk (Bildstein and Meyer 2000, Gutiérrez *et al.* 1995, Mazur and James 2000) and will likely benefit from northern goshawk habitat conservation. If possible, northern goshawks should be assessed on a bioregional scale, incorporating population demographics across the Western United States (Woodbridge and Hargis 2006). HCMs using ecologically based pseudo-absence points with FIA and Landfire map products to locate new territories and nests across the Western United States will assist this bioregional assessment.

Conclusions

FIA and Landfire map products will be useful in habitat assessments to a range of species, particularly rare, threatened, and sensitive species. As alteration to U.S. landscapes continue, it is becoming increasingly important to insure connectivity among ecosystems and available habitat for species' metapopulations across entire ecoregions. The production of these map products across the ecoregions of the United States will greatly assist species habitat assessments, land-use planning, and ecosystem conservation over broad spatial extents. Ecologically-based pseudo-absence points in combination with extensive land cover map products such as FIA and Landfire have the potential to assist a wide variety of species' habitat assessments and increase the utility of database presence points.

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Challenges of Working With FIADB17 Data: The SOLE Experience

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Abstract.—The Southern On Line Estimator (SOLE) is an Internet-based Forest Inventory and Analysis (FIA) data analysis tool. SOLE is based on data downloaded from the publicly available FIA database (FIADB) and summarized by plot condition. The tasks of downloading, processing, and summarizing FIADB data require specialized expertise in inventory theory and data manipulation. The FIADB is an important FIA product that should be made as easy to use and as error free as possible. Some of the errors that have been found in the FIADB are outlined here along with the incremental steps made toward improving it over the past year.

Introduction

The Southern On Line Estimator (SOLE) (http://ncasi.uml.edu/SOLE/) is an Internet-based database analysis tool developed cooperatively by the National Council for Air and Stream Improvement (NCASI) and the U.S. Department of Agriculture Forest Service Southern Research Station. SOLE performs tabular, chart, linear model, and map analyses on annual Forest Inventory and Analysis (FIA) data made publicly available through the FIA database (FIADB).

SOLE's data is based on publicly available annual FIA data downloaded from the FIADB data download facility and summarized by plot condition. This largely automated process requires a comprehensive program that must be modified to accommodate changes in the FIADB. This paper illustrates some of the challenges that NCASI has faced in using the FIADB by giving several examples of major events that have impacted the utility of the FIADB.

FIADB Revisions

The FIADB has undergone several revisions. The East/Westwide databases were consolidated into FIADB Version 1.0 in 2001 (Miles *et al.* 2001) to produce a consistent structure and repository for FIA data. FIADB1.0 was revised to FIADB1.7 in 2004 (Alerich *et al.* 2004), which substantially changed the database structure. Each of the nine tables carried over from FIADB1.0 doubled in size with new variables describing biological conditions/properties (plot location, forest health data, regional variables, etc.) and database administration (estimation methods, data modification dates, etc.).

The upgrade to Version 1.7 was disjointed because data were released before the supporting documentation. Substantial changes in the database caused users to struggle to understand new variables and tables. The most notable change was the redefinition of condition proportion (CONDPROP, which describes the proportion of a plot defined by a particular suite of site characteristics) to be adjusted over stratum. All values in the CONDPROP field were missing, and close inspection of the condition table revealed five new variants of CONDPROP. An inquiry to the Northeastern regional FIA office confirmed that one of these variants was a close approximation to the old definition of CONDPROP. This approximation was incorporated into SOLE. Documentation explaining this change in FIADB1.7 was released later that month.

In July 2005 FIA upgraded FIADB to Version 2.1 to use the National Information Management System to collect, compile, summarize, and distribute the data. The 2.1 revision was introduced as "development" files (available alongside Version 1.7 data) with a draft user manual. Implementing this newest FIADB data into SOLE has not shown any substantial difference in the database structure or variable definitions. Version 2.1 has since moved into production, yet the user manual and data file names are still labeled as "draft."

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The FIADB Data Dump

FIADB data is delivered via the FIADB data dump, which is the only public access point to access FIADB data. Users navigate to this Web page and select a data file for download. Recent revisions to the FIADB data download facilities have improved on some, but not all, aspects of data delivery. Because the data dump is the singular public gateway to FIA data, complete and accurate documentation is critical.

In 2005, data files began receiving a time stamp when they are uploaded to the FIADB. The intent of the time stamp is for users to determine whether they have the most recent data. Unfortunately, this time stamp is not always accurate. For example, the AL_04 compressed file has a timestamp of April 2005. Downloading and decompressing the file reveals that the individual files were actually modified in November 2005. FIA should ensure that the time stamp is accurate.

Major changes to the FIADB data are not always documented. Georgia's annual data disappeared from the FIADB for several months in 2004. The data file reappeared without explanation. Concurrently, California and Oregon's data had internal formatting errors that prevented proper file import. The Pacific Northwest station confirmed the error, then applied a correction over the next few months. The errors were never noted on the Web site. In December 2005, all annual data from 1998 to 2002 for Indiana and Missouri were removed without explanation. Errors must be carefully and completely explained to enable users to assess the integrity of past analyses.

The latest incarnation of the FIADB data dump, "FIA Data Mart," improves on the former data download facility. State selection has been condensed from multiple pages of text to a single drop down list. Multiple data formats can be selected for each State and a direct link leads to the user guide for each format. Unfortunately, notation of survey type (periodic/annual) has been removed. This information is available only by viewing the summary statistics link on the MapMaker homepage.

NCASI's FIADB Assessment

NCASI created a FIADB Assessment to characterize the following properties of annual FIADB data by State:

1. Plot coordinate type.
2. Number of plots by measurement year.
3. Proportion of plots containing key variables.

Changes in these characteristics are tracked over time. The assessment reports are updated on a quarterly basis and posted at http://ncasi.uml.edu/SOLE/.

Summary

FIA data is essential to monitor the forests of the United States. A tremendous amount of effort goes into collecting, compiling, and delivering data to the public through the FIADB. The public accesses FIADB data through a single portal, thus it is critical that the portal be error free and easy to use. The essential information a user needs to perform an analysis includes survey type, FIADB manual, an accurate time stamp, and explanation of past data errors. All of this information should be accessible from one location.

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Use of FIA Plot Data in the LANDFIRE Project

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Abstract.—LANDFIRE is an interagency project that will generate consistent maps and data describing vegetation, fire, and fuel characteristics across the United States within a 5-year timeframe. Modeling and mapping in LANDFIRE depend extensively on a large database of georeferenced field measurements describing vegetation, site characteristics, and fuel. The LANDFIRE Reference Database (LFRDB) incorporates existing data from numerous sources along with new data targeting specific ecosystems. This article describes the contribution of Forest Inventory and Analysis (FIA) data to the LFRDB. Plot selection, quality assurance procedures, and geoprocessing applied to FIA data in LANDFIRE are discussed. We also describe the use of FIA data as inputs to several modeling and mapping processes. Several characteristics of the FIA sample design and field methods are beneficial to modeling vegetation distributions in LANDFIRE. In addition, tree-level attributes afforded by FIA data are essential to developing canopy fuel layers and are generally unavailable from other existing datasets. Ongoing and potential collaboration between FIA and LANDFIRE is identified.

Introduction

LANDFIRE (Landscape Fire and Resource Management Planning Tools; www.landfire.gov) is a 5-year project begun in 2004 to provide consistent geospatial data on vegetation, fire, and fuel across the entire United States, regardless of ownership. Principal investigators in this multipartner project are the U.S. Department of Agriculture (USDA) Forest Service Missoula Fire Sciences Laboratory, the U.S. Geological Survey (USGS) National Center for Earth Resource Observation and Science, and The Nature Conservancy. LANDFIRE is sponsored by the Wildland Fire Leadership Council, which implements and coordinates the National Fire Plan and the Federal Wildland Fire Management Policy. LANDFIRE has been identified as a data and modeling system key to implementing a national strategy for addressing the Nation's wildland fire problems (U.S. GAO 2005).

Deliverable products from LANDFIRE include more than 20 spatial data layers and a comprehensive set of field-plot data. Spatial layers are raster datasets generated at 30-m^2 resolution and distributed on The National Map Web site (http://gisdata.usgs.gov/website/landfire). Final products will be delivered by Multi-Resolution Landscape Characterization (MRLC) map zone (USGS 2005b), with Western States' map zones scheduled for completion by the end of 2006, Midwestern and Eastern States' by 2008, and those in Alaska and Hawaii by 2009.

A critical element of LANDFIRE is the provision of all spatial data required to run FARSITE (Finney 1998). FARSITE is a widely used fire-spread simulation model. It requires fuel layers in addition to topographic, weather, and wind data. LANDFIRE generates two versions of mapped fire behavior fuel models (Anderson 1982, Scott and Burgan 2005), forest canopy height, canopy cover, canopy bulk density, and canopy base height. Elevation, aspect, and slope products (USGS 2005a) are distributed with the LANDFIRE fuel layers to provide the complete set of FARSITE spatial inputs.

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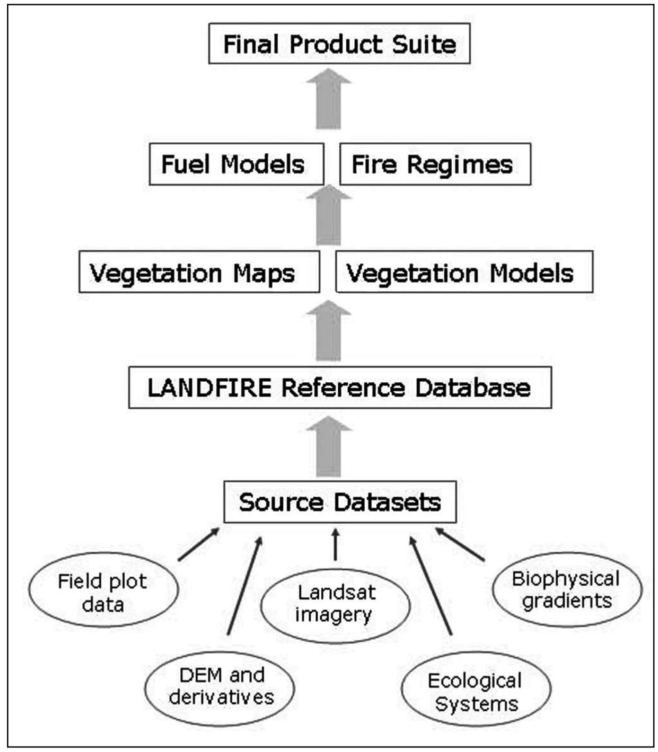
LANDFIRE also provides layers describing fire regimes and vegetation. Fire regime layers include fire regime condition class (FRCC) (Hann *et al.* 2003), FRCC departure, fire regime groups, fire return interval, and fire severity. Vegetation layers include environmental site potential, biophysical settings, existing vegetation type, existing vegetation canopy cover, existing vegetation height, and succession classes.

In this article, we briefly describe the process used to generate the LANDFIRE spatial products, with an emphasis on how Forest Inventory and Analysis (FIA) plot data are used in mapping and modeling.

LANDFIRE Process

LANDFIRE uses an integrative process incorporating satellite imagery, ecosystem simulation, vegetation modeling, and simulated landscape dynamics (Keane *et al.* 2002b, Rollins *et al.* 2004). Mapping is based extensively on a large database of georeferenced field measurements describing vegetation, site characteristics, and fuel. Multiple, independent screening procedures are applied to the plot data at various points in the process for quality assurance (QA). Plot data are associated with numerous additional attributes derived from spatial layers, vegetation classifications, and QA results. Figure 1 shows an overview of information flow in LANDFIRE.

Figure 1.—*Overview of the LANDFIRE process used to generate spatial data layers describing vegetation, fuel characteristics, and fire regimes.*



Source Datasets

Spatial Layers

Three dates of Landsat 7 imagery for each map zone are provided by the MRLC Consortium (USGS 2005b). A digital elevation model (DEM) and selected DEM derivatives are obtained from Elevation Derivatives for National Applications (USGS 2005a). Soil depth and texture layers are derived from the STATSGO database (USDA NRCS 2005b). Ancillary Geographic Information System (GIS) layers include roads (BTS 2005) and the 1992 National Land Cover Dataset (NLCD) (NLCD 1992, USGS 2005c).

LANDFIRE generates 42 simulated biophysical gradient layers (e.g., evapotranspiration, soil temperature, growing degree days) that become potential predictor variables in the mapping process. Biophysical gradients are generated using WX-BGC, an ecosystem simulator derived from BIOME-BGC (Running and Hunt 1993) and GMRS-BGC (Keane *et al.* 2002b). Inputs to WX-BGC are DAYMET interpolated weather data (Thornton *et al.* 1997), soil depth, soil texture, and elevation.

Vegetation Map Unit Classification

LANDFIRE vegetation mapping classification begins with NatureServe's ecological systems (Comer *et al.* 2003), with additional development by NatureServe and LANDFIRE ecologists. Ecological systems are defined by NatureServe as a group of plant community types that tend to co-occur within landscapes that have similar ecological processes, substrates, and/or biophysical gradients. They represent a mid-scale classification, smaller than ecoregions but larger than the associations and alliances at lower levels of the U.S. National

Vegetation Classification (USNVC) (Federal Geographic Data Committee 1997, Maybury 1999). The spatiotemporal scale for ecological systems is specified as tens to thousands of hectares, persisting for 50 or more years. At this spatial scale, ecological systems are mappable using remotely sensed data, while the temporal scale allows successional dynamics to be integrated into the concept of each unit.

Ecological systems provide the basis for map unit classifications of LANDFIRE existing vegetation types, environmental site potential, and biophysical settings. Existing vegetation type represents the vegetation currently present at a given site. Systematic crosswalks will link LANDFIRE existing vegetation type map units with the USNVC, the cover type classifications of the Society of American Foresters (Eyre 1980) and Society for Range Management (Shiflet 1994), and various agency classifications. Environmental site potential represents the vegetation that could be supported at a given site based on the biophysical environment. As used in LANDFIRE, map unit names for environmental site potential represent the natural plant communities that would become established at late or climax stages of successional development in the absence of disturbance. Environmental site potential is an abstract concept and represents neither current nor historical vegetation. Biophysical setting represents the vegetation that can potentially exist at a given site based on both the biophysical environment and an approximation of the historical fire regime. The biophysical settings map is a refinement of the environmental site potential map. As used in LANDFIRE, map unit names for biophysical setting represent the natural plant communities that would become established in later stages of successional development given natural ecological processes such as fire.

Field Plot Data

LANDFIRE obtains existing field data describing vegetation and/or fuel from numerous sources including the USDA Forest Service FIA program and other USDA Forest Service programs, the USGS Gap Analysis Program, Bureau of Land Management, Bureau of Indian Affairs, Department of Defense, Department of Energy, various State natural resource agencies, and university research labs. Vegetation data generally include some combination of the following: cover type, percentage cover by species or lifeform, heights and diameters of individual trees, crown ratios and crown classes of individual trees, and tree density. Fuel data generally include some combination of the following: counts or biomass estimates of fine and coarse woody material, percentage cover of live and dead shrubs and herbs, heights of the shrub and herb layers, and canopy base height. Plot photos are used if available. The data must include a georeference for each sampling point. LANDFIRE also samples a limited number of new field plots targeting systems underrepresented in the existing data.

Acquisition of FIA data begins with selected fields (table 1) from the Condition, Plot, Tree, and Seedling tables in the FIA database (Alerich *et al.* 2004, Miles *et al.* 2001) for all phase 2 plots (Reams *et al.* 2005). Tree canopy cover and understory species composition for each plot are also acquired where available regionally. Plot data are acquired from both the older periodic surveys (McRoberts 2005), as well as the annual inventories conducted since 2000 that use a national standardized plot design (Bechtold and Scott 2005). Down woody material data from FIA phase 3 plots are provided by the USDA Forest Service North Central Research Station (Woodall and Williams 2005). Data acquisition is coordinated with personnel from FIA Spatial Data Services (USDA Forest Service 2005) and designated FIA liaisons to the LANDFIRE project.

LANDFIRE Reference Database

Populating the LANDFIRE Reference Database (LFRDB) involves two phases: (1) compilation of plot records from disparate sources into a common data structure, and (2) associating the plot records with a large number of derived attributes. LFRDB structure and management tools are derived from the Fire Effects Monitoring and Inventory System (Systems for Environmental Management 2005). The compilation phase involves standardizing coordinate information, measurement units and species codes, along with initial QA screening. The second phase involves classifying plots to LANDFIRE existing vegetation type and environmental site potential, and performing spatial overlays to attribute plot records with topographic, gradient, and spectral values.

Table 1.—*FIA variables provided for use in LANDFIRE. Names of tables and national variables are from FIA database.*

Variable	Description	Availability
Plot table		
STATECD	State code	National
CYCLE	Cycle number	National
SUBCYCLE	Subcycle number	National
UNITCD	Unit code	National
COUNTYCD	County code	National
PLOT	Plot number	National
MEASDAY	Measurement day	National
MEASMON	Measurement month	National
MEASYEAR	Measurement year	National
DESIGNCD	Plot design code	National
Condition table		
CONDID	Condition identifier	National
CONDPROP	Condition proportion	National
LANDCLCD	Land class code	National
FORTYPCD	Forest type code	National
CRCOV	Tree crown cover	Regional
DSTRBCD1, DSTRBCD2, DSTRBCD3	Disturbance codes	National
DSTRBYR1, DSTRBYR2, DSTRBYR3	Disturbance years	National
TRTCD1, TRTCD2, TRTCD3	Stand treatment codes	National
TRTYR1, TRTYR2, TRTYR3	Stand treatment years	National
Tree table		
SUBP	Subplot number	National
TREE	Tree number	National
STATUSCD	Tree status code	National
SPCD	Species code	National
DIA	Current diameter	National
HT	Height	National
ACTUALHT	Actual height	National
CR	Compacted crown ratio	National
CCLCD	Crown class code	National
TPACURR	Trees per acre	National
HTTOCR	Height to crown	Regional
UNCR	Uncompacted crown ratio	Regional
Seedling table		
SUBP	Subplot number	National
SPCD	Species code	National
COUNTCD	Seedling count code	National
Other tables		
Various	Understory species composition	Regional

Source: Alerich et al. *2004, Miles* et al. *2001.*

Compilation of FIA Plot Data

The current national design for FIA ground plots uses clusters of four 24-ft radius subplots totaling approximately 1/6th ac. The minimum circle enclosing all four subplots is approximately 1.5 ac. A mapped-plot feature of the design specifies protocols by which field crews delineate areas within subplots recognized as distinct condition classes based on a predetermined set of discrete variables classifying land use, forest type, stand size, regeneration status, tree density, stand origin, ownership group, and disturbance history (Bechtold and Scott 2005). Although the motivation for the current plot design relates to avoiding statistical bias and domain classification problems, the condition-class information also allows users to make assumptions about the degree of heterogeneity in the plot footprint. It should be noted that before implementation of the national core design in the late 1990s, FIA units used a variety of plot designs with different approaches to positioning plots relative to condition-class boundaries (Bechtold and Scott 2005).

At present, LANDFIRE incorporates data from single-condition FIA plots only. Single-condition plots are assumed to have reasonably homogenous vegetation over the area of the plot footprint, and therefore to be more appropriate for associating with specific pixel values in raster datasets, compared with multiple-condition plots in general. Only the most recent measurement is used for plots sampled more than once over time. Initial QA procedures during compilation include linking all species nomenclature to PLANTS database codes (USDA NRCS 2005a), range validation of canopy cover, height values, and dates, and checking coded attributes against lookup tables. Source documentation is maintained to an extent that would allow FIA personnel to trace a record in the LFRDB back to the original internal FIA dataset.

Derived Attributes

Automated sequence tables are used to assign plots to vegetation map units (ecological systems) for existing vegetation type and environmental site potential. The sequence tables encode rule sets for classifying plots based on life form canopy cover values and relative abundance of indicator species. Species composition data for FIA plots are derived from Tree and Seedling records and understory vegetation records where available (e.g., Interior West, Pacific Northwest).

Spatial overlays are performed to associate plot records with approximately 100 raster data layers (fig. 2). These derived attributes become potential predictor variables in the mapping process described below. Coordinates for FIA plots are not stored in the LFRDB. Geoprocessing and spatial analysis are done by designated FIA liaisons to the LANDFIRE project for compliance with FIA confidentiality and security requirements.

LFRDB Summary to Date

LFRDB compilation was complete for eight map zones as of September 15, 2005 (fig. 3). There were 71,664 potentially usable plot records for these eight map zones. Two percent of these plots (1,446) were withheld from mapping for use in accuracy assessment. Overall, 15 percent of plots were from FIA, while 31 percent of plots in woodland and forest cover types were from FIA. Table 2 shows summary characteristics for FIA plots and non-FIA plots as a group. Non-FIA plots tended to be clustered nearer to roads compared with FIA plots that are positioned to provide a broad-scale statistical sample based on a hexagonal frame with spatial intensity of one plot per 6,000 acres in the population of interest (Reams *et al.* 2005).

Figure 2.—*Geoprocessing to generate derived spatial attributes for field plot records.*

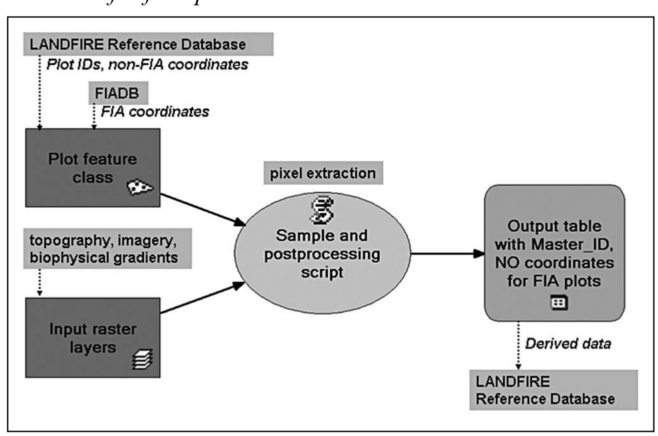
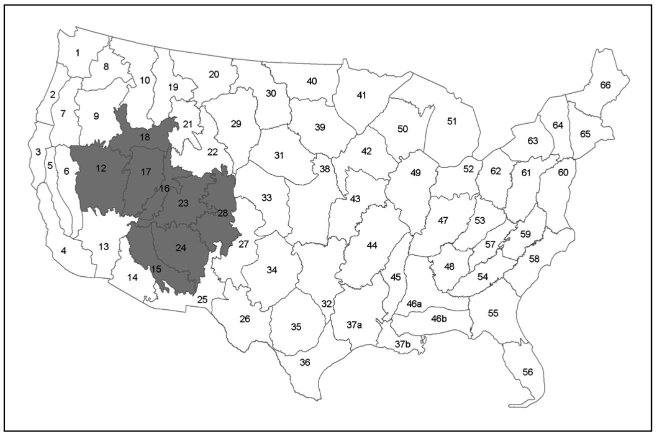


Figure 3.—*LANDFIRE map zones for the coterminous United States. Shading indicates zones for which LFRDB compilation was completed as of September 15, 2005.*



LFRDB = LANDFIRE Reference Database.

Table 2.—*Summary characteristics of FIA plots and non-FIA plots as a group from the first eight map zones[a] of the LFRDB.*

Characteristic	FIA plots	Non-FIA plots
Average distance to nearest road[b]	985 m	396 m
Spatial pattern	Dispersed	Clustered
Temporal span	1978–2004	1984–2004

FIA = Forest Inventory and Analysis; LFRDB = LANDFIRE Reference Database.

[a] Map zones 12, 15, 16, 17, 18, 23, 24 and 28.

[b] Based on U.S. Bureau of Transportation Statistics (2005) roads layer

Vegetation Mapping

Vegetation maps, both existing vegetation type and environmental site potential, are foundational to LANDFIRE fuel and fire regime products. The general approach to mapping is based on classification trees (e.g., Huang *et al.* 2003) using See5 software (www.rulequest.com). Thousands of plots per map zone from the LFRDB are available as training sites for supervised classification. Plots are subjected to two separate QA screening procedures before mapping. Approximately 100 potential predictor variables are associated with plot records, describing topography, biophysical gradients, and spectral reflectance (satellite imagery is not used for mapping environmental site potential or biophysical setting). Classification-tree output from See5 is applied spatially using custom software to produce the vegetation maps.

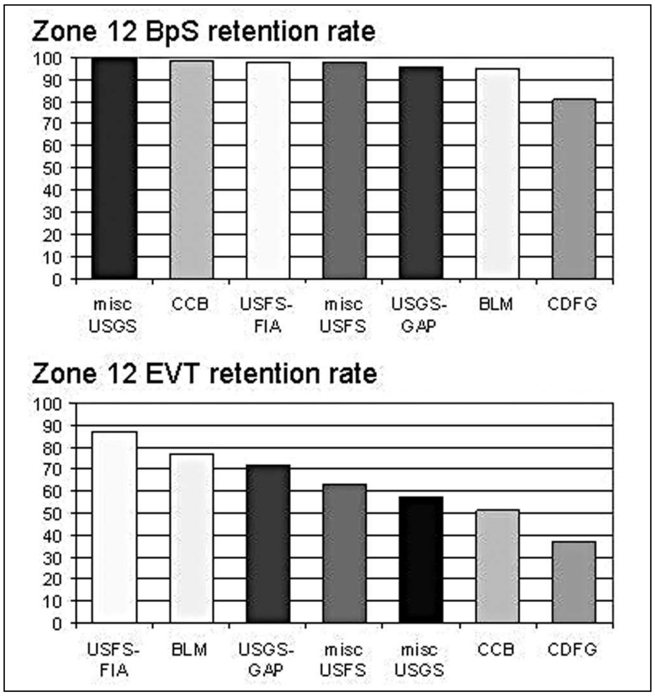
QA Screening Procedures

QA screening of plots before mapping environmental site potential and biophysical setting attempts to identify plots that have been misclassified by the sequence table. Plots could be misclassified due to incomplete species composition data, recent disturbance that affects species composition on the plot, or errors in the sequence table. Initially, a subset of plot records is flagged based on unlikely combinations of environmental site potential and existing vegetation type. The flagged plots are examined further by manually reviewing species composition data and plot photos if available. The process also makes use of disturbance history information if available, including FIA disturbance (DSTRB) and treatment (TRT) codes.

QA screening prior to mapping existing vegetation type examines assumptions inherent to integrating satellite imagery with the plot data. The procedure attempts to reconcile point-in-time differences between plot measurement date and image acquisition date. Initial flagging of plots is based on distance to nearest road, lack of agreement between the plot dominant life form and NLCD, and recent disturbance on the plot if disturbance history data are available. In addition, a threshold value of Normalized Difference Vegetation Index difference produced from MRLC 1992 and MRLC 2001 (USGS 2005b), indicating areas of likely change, is also used to flag potential problem plots. Flagged plots are examined visually, overlaid on satellite imagery.

QA screening represents a significant investment in analyst time before vegetation mapping due to the requirement for manual inspection of plot records in both tabular and spatial contexts. QA attributes in the LFRDB denote which plots were discarded from mapping, reason codes for the discarded plots, and analyst notes. Retention rate is the percentage of plots retained for mapping after QA screening. FIA plots tend to exhibit high retention rates relative to other data sources in the LFRDB (fig. 4).

Figure 4.—*Percentage plot retention by data source following quality assurance screening for existing vegetation type (EVT) and biophysical settings (BpS) mapping in LANDFIRE map zone 12. Data sources are USGS Nevada and Utah Gap Analysis Programs (USGS-GAP), USDA Forest Service FIA program (USFS-FIA), various USDA Forest Service vegetation mapping and related efforts (misc. USFS), Stanford University Center for Conservation Biology (CCB), Bureau of Land Management Ely field office (BLM), California Department of Fish and Game (CDFG), and USGS monitoring effort within the Nevada Test Site (misc USGS).*



Vegetation Models and Fire Regimes

Although vegetation modeling and fire regime mapping are major components of LANDFIRE, they are described here only briefly because they do not use FIA data directly. Vegetation models quantify succession and disturbance dynamics for each biophysical setting (Pohl *et al.* 2005). They are aspatial, state-and-transition models developed through a series of regional expert workshops using Vegetation Dynamics Development Tool (VDDT) software (ESSA Technologies Ltd. 2005). Development of the models involves specifying successional states for each biophysical setting, along with temporal parameters and probabilities for transition pathways between states. Extensive documentation and peer review accompany model development.

The VDDT models, along with maps of biophysical setting and topography, and parameters for fire and climate, are inputs to a spatially explicit Landscape Disturbance and Succession Model (LANDSUM) (Keane *et al.* 2002a). LANDSUM simulates historical vegetation and fire regime characteristics. Output from LANDSUM is used to generate the LANDFIRE fire regime maps. Combined with maps of existing vegetation succession classes, LANDSUM reference condition output is used to generate maps describing vegetation departure (e.g., FRCC).

Fuel Layers

Fuel Loading Models

LANDFIRE fuel loading models contain information about specific live and dead fuel amounts that can be used to predict fire effects such as soil heating, vegetation mortality, and smoke. They are based on a classification comprising 14 fire effects groups. Coarse woody debris, duff, and litter are important discriminants. Development of fuel loading models is informed by FIA phase 3 down woody material (DWM) data (Woodall and Williams 2005), and DWM data from FIA phase 2 plots where available (e.g., Pacific Northwest FIA).

Canopy Fuel Layers

LANDFIRE maps the FARSITE canopy fuel layers, canopy bulk density (CBD), and canopy base height (CBH) directly from field data using methods similar to those described above for vegetation mapping. CBD is the volumetric density of available canopy fuel (kg/m^3), based on dry weight of material greater than 0.25-in diameter. CBH is defined as the lowest height above ground with sufficient fuel to propagate fire vertically, starting where CBD is greater than or equal to 0.012 $kg\ m^{-3}$. CBD and CBH are estimated from plot data using FuelCalc software (Reinhardt *et al.* 2006). FuelCalc implements a set of species-specific biomass equations to estimate CBD and CBH along with available canopy fuel and total canopy weight. Tree-level inputs to FuelCalc are species, diameter at breast height, height, height to base of live crown, crown class, and (plot-level) trees per acre.

FIA data generally afford the required inputs to FuelCalc, whereas most other data sources in the LFRDB do not provide this full set of attributes. A caveat is that height to base of live crown is derived from the tree crown ratio. The FIA national core variable is compacted crown ratio (CR), the percent of the tree bole supporting live, healthy foliage, with the crown visually compacted to fill in gaps, expressed as a percentage of total tree height (Alerich *et al.* 2004). Compacted crown ratio has long been considered an indicator of tree vigor and an important predictor of periodic growth increment in forest growth models (e.g., Wykoff *et al.* 1982). In fire behavior modeling, however, a major interest is on the vertical continuity of fuel from the ground to the crown as a predictor of crown fire risk. Height to base of live crown derived from uncompacted crown ratio is a more appropriate variable for these applications (Monleon *et al.* 2004). Uncompacted crown ratio is available regionally for some FIA plots (e.g., Interior West, Pacific Northwest).

Conclusions

Use of FIA data has clear benefits for LANDFIRE. FIA provides a national, consistent dataset that is continually updated. Data quality is high, resulting in high retention rate for plots subjected to LANDFIRE QA screening procedures. The even spatial distribution of FIA plots is beneficial for mapping at regional scales. Condition-class information from the mapped-plot feature of the national FIA plot design can potentially be exploited to improve integration with remotely sensed data. Furthermore, FIA data contain a rich set of attributes including species composition, stand structure, down woody material, and tree-level inputs for FuelCalc estimation of canopy fuel. The full set of FuelCalc inputs is not generally available from other data sources.

A limitation of FIA data for mapping vegetation and fuel characteristics at a national extent is the regional availability of certain attributes. These include plot-level tree canopy cover, understory species composition, and uncompacted crown ratio. While these attributes are available for FIA phase 2 plots in the Interior West and Pacific Northwest regions, national mapping projects using FIA data may be required to choose between altering methodologies across regions or accepting FIA national core variables for wall-to-wall coverage. Despite this limitation, FIA is more consistent on a national basis compared with other existing datasets in terms of attributes available, sampling design, and field methods.

The collaborative relationship with LANDFIRE also has benefits for the FIA program. LANDFIRE provides a national application of FIA data to wildland fire management through development of an integrated data and modeling system. FIA plots processed by LANDFIRE comprise a value-added data set with potential application to other mapping efforts. LANDFIRE attributes FIA plots with ecological systems classification, quantitative vegetation models, biophysical gradients, predicted fire regime characteristics, and a set of QA attributes relevant to integrating plot data with satellite imagery, vegetation classification, and fuel mapping. Software tools developed for geoprocessing and exploratory data analysis in LANDFIRE also could have broader utility within FIA.

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