Landscape correlates of eastern hemlock (*Tsuga canadensis*) decline due to hemlock woolly adelgid (*Adelges tsugae*): A preliminary assessment.

A Progress Report to the National Park Service

December 1999

John A. Young, David D. Morton, Nissa M. Thomsen US Geological Survey Biological Resources Division Leetown Science Center Kearneysville, WV 25430

Abstract:

Eastern hemlock (*Tsuga canadensis*) is in decline in many parts of its range in the eastern US due primarily to infestation by an exotic insect pest, the hemlock wooly adelgid (*Adelges tsugae*: HWA). In Shenandoah National Park, HWA rapidly killed many stands of hemlock after first appearing in 1989. However, in some stands the impact has been less severe, and hemlock remains largely healthy. At present, few investigators have examined the mechanisms that produce this discontinuous impact, although landscape factors are suspected of playing a role. In an effort to address possible landscape correlates to hemlock decline, we conducted a preliminary analysis of 6 years (1993-1998) of hemlock health estimates in comparison to measures of terrain, stand isolation, and potential dispersal corridors at the stand level. We found that elevation, terrain shape, and distance to streams all exhibited relatively strong correlation with hemlock decline, although the relationship varied by year. There appears to be preliminary evidence suggesting that environmental conditions are either controlling HWA or making hemlock stands more susceptible to decline. We are using the results of this preliminary analysis to guide more detailed efforts aimed at modeling hemlock stand vulnerability as a result of site, landscape, and regional factors.

Introduction:

Eastern hemlock (*Tsuga canadensis*) occurs in cool, moist, hillside and ravine environments in Mid-Atlantic (US) National Parks. In recent years, eastern hemlock forests have been in decline, primarily due to defoliation by hemlock woolly adelgid (*Adelges tsugae*: HWA), an exotic insect that feeds on hemlock sap. HWA was first introduced into the eastern U.S. in the 1950's

(McClure, 1987) and has since spread north and west to infest eastern hemlock stands in Connecticut, New Jersey, Pennsylvania, Maryland, Virginia, and West Virginia. In areas of intense infestation, defoliation by HWA has resulted in almost total eastern hemlock mortality. In some areas, infestation, defoliation, and tree mortality have advanced at such a rapid pace that near complete elimination of hemlocks trees from some forests has been observed within a span of only 3 or 4 years (McClure, 1991). In other areas, HWA is present in large numbers, but only minor defoliation has been observed (Evans, 1995).

Whether this inconsistency in eastern hemlock decline is due to landscape, site, or genetic factors has yet to be determined. However, the impact of HWA on eastern hemlock has the potential for significant disturbance to the ecology of mid-Atlantic highland forests. Since eastern hemlock forms an important component of riparian forests communities in many areas of the mid-Atlantic highlands, stream communities may be particularly impacted. These disturbances may manifest themselves as changes in energy inputs, micro-climatic environments, or physical habitat structure available to birds, fish, and aquatic macro-invertebrate communities. Snyder et al. (1998) found that streams draining eastern hemlock forests support 37% more aquatic invertebrate taxa on average than comparable streams draining hardwood forests in Delaware Water Gap National Recreation Area. In addition, occurrence and abundance of brook trout (*Salvelinus fontinalis*) were higher in hemlock dominated stream environments than in hardwood areas (Snyder et al., 1998). Since several avian species favor eastern hemlock for over-wintering habitat (Benzinger, 1994), disturbances to avian communities may be equally evident.

In this report, we describe a preliminary assessment of hemlock decline using field-based crown health observations, landscape assessments, and statistical models conducted for Shenandoah National Park. The goal of this assessment was to determine if landscape-level factors are correlated with hemlock stand mortality due to HWA. Although at present little is known regarding host susceptibility to HWA, the patchy nature of eastern hemlock decline suggests that landscape-level environmental factors may be influencing the rate of decline by moderating populations of HWA directly (through temperature controls or barriers to dispersal), or by controlling tree health and resistance. In addition, wind, birds, deer, and human activities, disperse HWA (McClure, 1990). All of these factors are moderated to some extent by landscape structure.

This assessment is described as preliminary because the available data on hemlock decline in SHEN is not detailed enough for a complete examination of the mechanisms that operate to induce tree mortality due to HWA. The most serious limitation is the lack of spatial precision in the measured response (hemlock decline), and the undesirable, but unavoidable noise introduced into the analysis by this lack of precision. Despite this limitation, the observed relationships are intriguing and demonstrate the need for further analysis in this area. In an ongoing study, we are using geographic information systems and satellite remote sensing to map hemlock decline in a more precise manner. Additional statistical modeling will address the relationship between satellite

remote sensing derived estimates of hemlock decline, and additional site, landscape, and regional environmental factors.

Setting:

This study was conducted in Shenandoah National Park, Virginia (SHEN), one of the most heavily visited National Park Service units in the eastern U.S. Shenandoah National Park is 78,800 ha in size and is dominated by mixed deciduous forest. Primary forest components (and area) as reported by Teetor (1988) are Chestnut oak (38,100 ha), Red oak (with Ash and Basswood components) (19,010 ha), and Poplar (12,070 ha). Smaller stands of Black locust (7,910 ha), Pine (4365 ha), and Eastern hemlock (445 ha) occupy the remaining forested area (Teetor, 1988). Although eastern hemlock forests occupy less than 1% of the forested area in the park, they are recognized as important natural and cultural resources by park personnel and the public. Eastern hemlock trees in SHEN provide shading along stream corridors, unique habitats for animals, and recreational opportunities for visitors. In addition, some of the oldest trees in the park are eastern hemlocks that occur in the Limberlost area (Teetor, 1988).

Shenandoah National Park was chosen for this research because of the severe and rapid decline of eastern hemlocks in many stands due to HWA since it was first observed in the park in 1989. The observed patchiness in decline since infestation by HWA, and the availability of multiple years of field observations on eastern hemlock make this area ideal for investigations of possible landscape linkages to eastern hemlock decline.

Background:

Landscape pattern and structure play an important role in governing the spread and severity of insect pathogens in forest ecosystems by directly influencing pathogen populations and dispersal capabilities, and indirectly by influencing host tree health and distribution (Castello et al. 1995, Perry, 1988). Powers, et al. (1999) used landscape analysis to evaluate Douglas-fir bark beetle dynamics and host tree susceptibility at multiple scales and found that landscape-scale phenomena were more strongly correlated with beetle kill events than individual tree health factors. Only a few researchers to date have investigated eastern hemlock decline in relation to landscape factors. Bonneau (1997) found that eastern hemlock stands located on cold, moist, north or northeast aspects were generally healthier than stands in drier or more exposed areas of Connecticut. He also noted that hemlock trees in poorer growing environments and those that were also under attack by the hemlock looper (*Lambdina fiscellaria fiscellaria* and *L. fiscellaria athasaria*) were less able to survive infestation by HWA (Bonneau 1997).

Geographic information systems provide useful tools for studying the interaction between insect pests and landscape structure. Digital landscape data (eg. maps) have been used to assess how environmental factors such as slope, topographic position, soils, and moisture regimes combine to form distinct eco-physiographic environments on the landscape (Bailey, et al. 1993, Band 1989, Coughlan and Running 1989). Digital elevation models have been shown to be useful for

quantifying landscape characteristics such as drainage basin area, flow pathways, topographic position, soil moisture, solar radiance, and a number of other geomorphologic parameters (Moore et al. 1991, Jenson 1991, Martz and Garbrecht 1993, Skidmore 1990, Carter 1988, Jenson and Dominique 1988). Specific topographic features such as ridges, gullies, coves, and saddles can be determined from elevation models to assess microhabitat conditions over large areas (Skidmore 1990). Other researchers have used geospatial technologies (eg. geographic information systems and remote sensing) to evaluate forest health impacts of insect defoliators (Bonneau et al., *in press*, Royle and Lathrop 1997, Franklin et al. 1995). Clearly these technologies provide powerful tools for assessing landscape influences on forest health, especially in topographically diverse environments.

Methods:

Crown health surveys were conducted by SHEN personnel following park protocols and consisted of field assessments in hemlock stands where randomly selected eastern hemlock trees were assigned a visually derived crown health rating and canopy position indicator (Table 1). Randomly selected trees in each of 97 separate eastern hemlock stands were visually assessed for crown condition by SHEN forest health technicians (Figures 1-A, 1-B, 1-C). Normally between 75 and 100 hundred eastern hemlock trees in each stand were surveyed, unless there were fewer than 100 trees available, in which case all of the trees in a stand were surveyed (Table 2.). In some cases, several hundred trees were surveyed in a stand (see Appendix 1). Each tree surveyed was assigned to a canopy position and crown health class, and observations were tabulated in a database. Due to time limitations, all 97 stands were not visited each year.

We summarized the crown health database by stand by counting the number of trees in each crown health class/canopy position combination. Total trees surveyed and percentages of the stand in each crown health class were then computed by stand for each of the six years of data availability. In order to assess the relationship between crown condition and landscape variables at the stand level, we developed a weighted crown damage index (WCDI) for each stand. WCDI was calculated by multiplying the numeric value for crown health rating (CH) [1,2,3, or 4] by the number of trees found (N) in each health class, and dividing by the total number of trees in each stand as follows:

$$WCD = ((CH1 * N1) + (CH2 * N2) + (CH3 * N3) + (CH4,5 * N4,5)) / \dot{a}$$
 trees in stand

Classes 4 and 5 were combined to represent dead trees due to the difficulty in determining the cause of tree mortality from visual estimates. After 1993, SHEN personnel included a class "3X" to further define trees that were still alive, but suffered heavy defoliation. This class was assigned a value of 3.5 and inserted into the formula above to compute the weighted mean damage index. The resulting index provides a single estimate of overall crown damage per stand, tracks the crown health class (ie. ranges from "0" or no damage, to "4" or severe damage), and can be used as a dependent variable in multivariate analysis of stand-level landscape associations. However,

due to the differing measurement scales, the 1993 survey cannot be directly compared to surveys in later years.

Crown health surveys were field based and are not spatially explicit. That is, no explicit location was recorded for trees being surveyed. Instead, generalized stand boundaries were used to describe the area where the survey was conducted. SHEN field personnel sketched survey stand boundaries on 1:24,000 scale USGS topographic maps. These maps were digitized and edited by USGS-BRD personnel. Counts of trees in each health class and the computed weighted crown damage index were attached to the resulting GIS maps as attributes by stand number. The resulting map of crown health survey areas was used to summarize landscape variables and to relate crown damage from HWA to landscape attributes. Inaccuracies in delineation of the areas surveyed introduces the greatest amount of uncertainty into this analysis since the locations of surveyed trees were not recorded in the field, and the stand boundaries were generated *post hoc*. While preliminary analysis made use of these generalized boundaries, efforts are being made to fine-tune the delineations using ancillary sources of information (eg. maps of coniferous vegetation). Subsequent analysis will make use of hemlock tree condition on a pixel-by-pixel basis using time-sequenced satellite image interpretations.

Landscape variables

We summarized landscape information using GIS (Arc/Info: ESRI, Inc.) with a database provided by SHEN personnel. Primary data layers provided were a digital elevation model (DEM) of the park, maps of streams, roads, trails, and vegetation. The DEM was derived from standard USGS 1:24,000 scale digital elevation files where each cell represents a 900m² ground area (30 m by 30 m). We used the DEM to produce maps of elevation, slope, aspect, terrain shape, and relative solar illumination using various algorithms available in the Arc/Info software package (ESRI, Inc. Redlands, CA). Slope (degrees) was generated from the elevation matrix for each cell and measures the maximum rate of change in elevation from each cell to its neighbors (ESRI, Inc. 1994). Conceptually, a plane is fitted over a 3x3 window of cells surrounding the cell of interest and the slope of the plane is calculated (Burrough, 1986).

Aspect was generated from digital elevation models by measuring the direction of the maximum rate of change (slope) calculated for a 3x3 window surrounding each cell of the DEM. The output of the aspect function is a compass bearing from 0-359 degrees for each cell (ESRI, Inc. 1994). In order to make this measure useful in multivariate analysis, aspect was translated to a measure of "northness" by a cosine transform such that aspect varied from -1 (south) to 1 (north) (Roberts, 1986).

A measure of terrain shape was calculated from the digital elevation model following methods outlined in McNab (1989). McNab's "terrain shape index" quantifies the local convexity or concavity of a terrain surface. We adapted the terrain shape index for GIS by calculating the difference between elevation at the center of a moving window and the mean elevation of

surrounding cells in the window. Negative terrain shape values indicate a locally concave surface (e.g. a ravine) while positive values indicate a locally convex surface (e.g. a ridge or hummock). Values near zero indicate a locally flat surface. By varying the size of the window used to calculate the index, different scales of convexity and concavity can be measured. We used a circular moving window of 150m radius (eg. 5 cells on the DEM) to calculate a measure of terrain shape. This window size was chosen after experimentation because it captured the prominent features at the scale of interest for the study area.

A measure of relative incident light striking the surface (e.g. solar illumination) was calculated from the DEM using the "hillshade" function in Arc/Info. This function allows for calculation of surface areas in direct sunlight, shade, and shadow given the elevation and azimuth of a light source (e.g. the sun). We calculated the sun's position and height above the horizon at the summer and winter solstice for our study area using tables provided by Marsh (1983). A mean relative solar illumination value was calculated by taking the by-cell mean of these two surfaces. This calculated surface provided a measure of mean solar illumination during the year at each cell relative to other cells on the matrix (values range from 0-255).

Additional measures were developed to assess the relationship between crown health and natural and man-made corridors. We used GIS distance functions to create maps of distance to roads, trails, and streams. In this process, lines representing roads, trails, and streams were converted to a binary representation where presence or absence of the linear feature is recorded on each cell of the map as 1 or 0 respectively. Subsequently, each cell coded as zero is re-coded with the distance (in meters) of the closest non-zero cell. The result of this operation is a continuous surface recording the relative distance within the stand from the linear feature.

Terrain variables were summarized using a cell-based representation of survey stand boundaries at the same cell size and extent as the elevation map. For each stand, the range, mean, and standard deviation of each terrain variable was summarized from cell counts of those cells falling within a given survey stand boundary. Prior to statistical analysis, each terrain variable was assessed for normality and transformed if necessary. All variables were normally distributed except for the distance-based measures (distance to streams, roads, and trails). These variables were transformed using a log transformation to achieve normality.

Due to the generalized nature of the stand boundaries, large areas are incorporated into data summaries although only a few hemlock trees may actually be have been surveyed within the stand. The resulting stand-based landscape summaries potentially incorporate more landscape variance than is actually associated with hemlock growing environments. We assumed that this introduced "noise" or error tends to mask the relationship between landscape variables and hemlock decline. We are attempting to back-calculate the areas actually surveyed using ancillary information, but we present results only of the generalized stand boundaries for this preliminary analysis.

Statistical analyses:

The goal of this preliminary statistical analysis was to examine potential relationships between GIS derived landscape features and stand-level maps of hemlock crown condition. Our aim was to use exploratory data analysis to identify potential avenues for further research as we collect additional data on the rate and nature of hemlock defoliation from remote sensing and field investigations. We assessed bivariate correlations between individual landscape variables and crown damage using scatter plots with fitted regression lines and simple correlation analysis. We used regression tree-based models to assess potential interactions among predictor variables and to determine overall model fit when these interactions are considered. Classification and regression tree models (sometimes referred to by the acronym CART) are non-parametric exploratory modeling techniques that do not assume any distribution in the predictor variables (which can be both categorical and continuous variables). These models are fitted by recursively splitting the dataset into homogeneous units based on the independent variables (Clark and Pregibon, 1993). The result is a tree or mobile graph showing the partitioning of the data set (on the dependent variable), and the "proportional reduction in error" value (similar to a multiple squared R value). When the dependent variable is categorical, these models are termed "classification trees"; when the dependent variable is continuous, the models are termed regression trees. CART models are useful as exploratory tools because they can uncover "nonadditive behavior" or interactions among variables easier than can linear models (Clark and Pregibon, 1993).

Predictor variables used in the regression tree analysis were stand area (AREA), stand perimeter (PERIMETER), mean stand elevation (ELEV_MEAN), mean stand solar illumination (SOLX_MEAN), mean stand northness or aspect (NIDX_MEAN), mean stand slope (SLP_MEAN), mean stand terrain shape (TP_MEAN), log transformed distance to trails (LOG_DTR), log transformed distance to roads (LOG_DRD), log transformed distance to streams (LOG_DSTR). Since crown health surveys were not conducted in the same stands from year to year (or on the same trees), we analyzed each year independently.

Results:

Stands surveyed for hemlock crown health were on average, moderately defoliated (as measured by the weighted crown damage index) even at the beginning of the study (Figure 2). Summaries of field surveys by crown health class and canopy position are given in Appendix A. Overall, crown damage increased in surveyed stands from 1993-1998, with many stands in the severely damaged to dead (3.5-4.0) range. The mean WCDI for all stands remained essentially unchanged from 1994-1997, but increased in 1998 (Table 3). The range and variance of crown damage across all stands increased in successive years. Mean values of the weighted crown damage index show that stands are moderately to heavily defoliated park-wide (μ =2.7-2.9), corresponding to trees with less than 50% of their crowns intact. It appears that the WCDI increased dramatically

from 1993 to 1994, however this is most likely an artifact of the different measurement scale that was used prior to 1994 (no class 3X).

We found that several landscape variables summarized within our generalized stand boundaries are correlated with the weighted crown damage index. Simple bivariate (Pearson) correlations show relatively strong negative correlations between mean stand crown damage (as measured by the WCDI) and elevation, terrain shape, and (log) distance to streams (Table 4). The strongest bivariate correlations occur between crown damage from 1994-1998 and terrain shape (-0.6-0.8). Terrain shape is negatively correlated with the weighted crown damage index, suggesting that stands with more concave (-) terrain shapes (eg. ravines or gullies) are more heavily impacted than stands with more convex (+) terrain shapes (eg. hillsides or ridges). Elevation and distance to streams are also consistently negatively correlated with stand crown damage and the correlation increases in successive years. These findings suggest that stands at higher elevations are less impacted than those at lower elevation, and stands that are closer to streams are more impacted than stands more distant to streams. However, these simple correlations obscure the fact that there are many outliers in the relationship that influence the fit, as is evidenced in Figures 3, 4, and 5.

Regression tree analysis shows substantial conditional interaction among terrain variables in predicting level of crown damage (Figures 6-11). Generally, the factors that were correlated with crown damage from the simple correlation analysis were also important in the regression tree models. Mean stand elevation, terrain shape, and distance to streams all are important factors in the regression tree models, but are conditional on levels of northness (or aspect), slope, distance to roads, area or perimeter. Overall model fit (e.g. proportional reduction in error) ranged from 32.8 % (0.328) of variation in weighted crown damage explained by these landscape factors in 1997, to 67.1 % (0.671) of variation explained from 1995 observations. As an example of interpretation of the tree based models we can look at the results from 1995 (Figure 8) which show that mean stand elevation was the most important factor influencing crown damage in hemlocks. Stands with elevations less than 977 m had higher WCDI values (μ =2.859) than those stands with mean elevations greater than 977 m ($\mu = 1.858$). Among the observations with higher WCDI values (right side of split), stands with mean elevations between 658 and 977 m had lower levels of impact ($\mu = 2.712$) than those stands whose mean elevation was less than 658 m ($\mu =$ 3.022). Within these resulting groups, smaller stands had heavier damage (AREA $< 90,820 \text{ m}^2$) as well as stands with more northerly facing slopes (NIDX_MEAN>0.338).

Significantly, interactions among variables and overall model fit differed by year. In some years (1996, 1997, and 1998) distance to roads was an important factor although stands that were further from roads were more impacted than those closer to roads (a finding somewhat in opposition to expectations) (Figures 9-11). In addition, there is no clear pattern to the strength of the model fit in successive years. However, a model that can explain greater than 50 % of the variation in crown damage based on landscape variables (eg. 1995 and 1998) certainly deserves

closer investigation.

Discussion:

The data used in this analysis was collected for a different purpose than that which is presented here. This data was originally collected to give managers a park-wide estimate of the health of hemlock trees in Shenandoah National Park. Surveys were designed for quick estimates of tree health on numerous trees in as many eastern hemlock stands as could be visited. Since time was limited, locations of individual trees were not recorded and therefore trees surveyed in one year may not have been surveyed in the next. In addition, not all of the 97 potential hemlock stands selected for surveys were visited each year. The limits imposed by past data collection severely limit the ability to conduct *post hoc* assessments of hemlock decline using this data. Nevertheless, by summarizing this data using generalized boundaries of survey areas, we were able to show some preliminary relationships between hemlock crown damage (presumably from hemlock wooly adelgid), and landscape characteristics of the areas where surveys were conducted.

Interpretation of analysis results using this data is made difficult due to the amount of noise (eg. error) present in summaries of landscape variables over large areas. Substantial variation in area exists among the stand boundaries (Table 5). Summaries of landscape variables over these large areas incorporate more landscape variation than should be associated with hemlock environments, and this undoubtedly influences the ability to discriminate landscape influences on eastern hemlock decline.

Given the spatial uncertainties in data collection, the fact that we observed relationships between hemlock crown damage and landscape factors can be interpreted in one of two ways. Either the relationships are completely spurious and would happen by chance given enough data, or there is a relationship and we are observing a weakened signal due to noise. The fact that some relationships can be consistently observed between years, such as the negative correlation between crown damage and elevation, adds support to the latter interpretation. This interpretation also supports anecdotal observations by park biologists of lighter damage in high elevation hemlock stands (Akerson, Shenandoah National Park, *pers. comm.*).

Assuming that the relationships observed are real, can they be explained in ecologically meaningful terms? Fewer impacts at higher elevations could be evidence of a temperature control on hemlock woolly adelgid populations as suggested by Parker, et. al. (1996). Heavier impacts in ravine landforms and in areas close to streams could be explained by birds acting as vectors for dispersal along stream corridors (McClure, 1990). Stands further from roads show heavier impacts, but are less likely to be treated for HWA. In order to assert these ecological interpretations with confidence, more confirmatory analysis needs to be conducted using more precise measurements of hemlock decline. In addition, other relevant factors that might assist dispersal of HWA or influence hemlock tree health need to be considered.

Regression tree models appear to provide an excellent avenue for analysis of the relationship between hemlock decline and landscape structure. Regression tree models uncovered interactions between landscape variables that would not have been apparent using linear regression modeling. This technique will also be valuable for creating predictive models of areas on the landscape likely to be most heavily impacted so that management activities can be better directed without reliance on extensive field surveys. One output of CART models is a set of "decision rules" that can be directly translated into map form using GIS to classify areas according to their potential for hemlock decline.

Future Directions:

The analysis presented here is the first step in fully assessing the potential influences of landscape structure and function on hemlock health. In an ongoing study (Young, et. al., 1998), we are using time-sequenced satellite imagery to assess hemlock decline, which should result in more spatially accurate estimates of hemlock decline rates that can analyzed in relation to landscape structure. We are also continuing to investigate other landscape factors that may serve as potential explanatory variables for hemlock decline. Some of the additional factors we are investigating are:

Moisture regimes: to determine if eastern hemlock in water stressed environments are more or less susceptible to decline.

Gypsy Moth defoliation history: to investigate interactions between previous severe gypsy moth defoliation and hemlock decline.

Geology and soil characteristics: to determine if acid deposition may be influencing tree health in sensitive environments.

Air quality characteristics: to assess the effect of chronic air quality degradation on hemlock health.

Stand isolation: to determine if hemlock stands that are isolated are less susceptible to infestation and decline due to HWA.

Vegetation composition: to determine if hemlock occurring in mixed-species stands are less susceptible to decline than those occurring in "pure" stands.

These variables are being collected using a combination of field surveys and GIS analysis. We will summarize this information using methods similar to those described above using GIS analysis.

Early signs from this analysis are encouraging. There appears to be a significant interaction

between landscape structure and hemlock decline in Shenandoah National Park. However, much work remains to uncover the mechanisms responsible for this interaction. We are optimistic that relationships between hemlock decline and landscape structure will be made clearer through the use of more precise maps of the rate and location of hemlock decline. Hopefully, this will allow us to provide better estimates of vulnerable areas in Shenandoah National Park and other National Park units that are threatened from the hemlock wooly adelgid. This information should be invaluable for assessing potential biological impacts to bird, amphibian, and mammal communities that depend on eastern hemlock for some portion of their life cycle.

Acknowledgements:

This research was funded by the US Geological Survey, Biological Resources Division, "Exotics in the East" research program. Gary Hunt and Mary Willeford-Bair collected hemlock crown health field survey data for 1993-1998 in Shenandoah National Park under the direction of James Akerson. Dan Hurlbert provided GIS data layers for Shenandoah National Park. Craig Snyder and David Smith provided statistical advice and direction.

Literature Cited:

Bailey, R.G., M.E. Jensen, D. Cleland, P.S. Bourgeron. 1993. Design and use of ecological mapping units. In: M.E. Jensen and P.S. Bourgeron, eds. Eastside Forest Ecosystem Health Assessment, Volume II: Ecosytem Management: Principles and Applications. Portland, Oregon: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Band, L.E. 1989. Automating topographic and ecounit extraction from mountainous forested watersheds. AI Applications. Vol. 3, No. 4.

Benzinger, J. 1994. Hemlock decline and breeding birds - I: hemlock ecology. Rec. N. J. Birds 20(1):2-12.

Bonneau, L.R. 1997. An examination of the decline of hemlock health associated with infestation by the hemlock woolly adelgid, A*delges tsugae*, in hemlock forests of southern Connecticut. Unpublished Master's Thesis, University of Connecticut. 118 pp.

Bonneau, L.R., D.L. Civco, and K.S. Shields. *In press*. Use of satellite image data to identify changes in hemlock health over space and time. *Submitted to*: Biological Invasions. 20 pp.

Burrough, P.A. 1986. Principles of Geographical Information Systems for Land Resources Assessment. Clarendon Press. Oxford, UK. 194 pp.

Carter, J.R. 1988. Digital representations of topographic surfaces. Photogrammetric Engineering and Remote Sensing. Vol. 54, No. 11. pp. 1577-1580.

Castello, J.D., D.J. Leopold, and P.J. Smallidge. Pathogens, patterns, and processes in forest ecosystems. BioScience. Vol. 45, No. 1. pp. 16-24.

Clark, L.A., and D. Pregibon. 1993. Tree-based models. In Chambers, J.M. and Hastie, T.J., editors, Statistical Models In S. Chapman and Hall, New York. 377-419.

Coughlan, J.C. and S.W. Running. 1989. An expert system to aggregate biophysical attributes of a forested landscape within a geographic information system. AI Applications. Vol. 3, No. 4. pp. 35-43.

Evans, R.A. 1995. Hemlock ravines at Delaware Water Gap National Recreation Area: Highly valued, distinctive, and threatened ecosystems. Delaware Water Gap National Recreation Area 30th Anniversary symposium. Milfor, PA. 11 pages.

ESRI, Inc. 1994. Cell-based modeling with GRID. Environmental Systems Research Institute,

Redlands, CA. 481 pp.

Franklin, S.E., R.H. Waring, R.W. McCreight, W.B. Cohen, and M. Fiorella. 1995. Aerial and satellite sensor detection and classification of western spruce budworm defoliation in a subalpine forest. Canadian Journal of Remote Sensing. Vol. 21, No. 3. pp. 299-308.

Jenson, S.K. and J.O. Dominique. 1988. Extracting topographic structure from digital elevation data for geographic information system analysis. Photogrammetric Engineering and Remote Sensing. Vol. 54. No. 11. pp. 1593-1600.

Jenson, S. K. 1991. Applications of hydrologic information automatically extracted from digital elevation models. Hydrological Processes. Vol 5. pp. 31-44.

Marsh, W.M. 1983. Landscape Planning: Environmental Applications. John Wiley and Sons. New York. 356 pp.

Martz, L.W. and J. Garbrecht. 1993. Automated extraction of drainage network and watershed data from digital elevation models. Water Resources Bulletin. Vol. 29, No. 6. pp. 901-908.

McClure, M.S. 1987. Biology and control of hemlock woolly adelgid. Bulletin of the Connecticut Agricultural Experiment Station 851, New Haven.

McClure, M.S. 1990. Role of wind, birds, deer, and humans in the dispersal of hemlock woolly adelgid (Homoptera: Adelgidae). Environmental Entomology. Vol. 19, No. 1. pp. 36-43.

McClure, M.S. 1991. Density-dependent feedback and population cycles in *Adelges tsugae* (Homoptera: Adelgidae) on *Tsuga canadensis*. Environmental Entomology. Vol. 20, No. 1. pp. 258-264.

McNab, W. H. 1991. Terrain Shape Index: Quantifying effect of minor landforms on tree height. Forest Science. Vol. 35, No. 1. pp.91-104.

Moore, I.D., R.B. Grayson, and A.R. Ladson. 1991. Digital terrain modeling: A review of hydrological, geomorphological, and biological applications. Hydrological Processes. Vol. 5. pp. 3-30.

Parker, B.L., M. Skinner, S. Gouli, T. Ashikaga, and H. B. Teillon. Survival of hemlock woolly adelgid (Homoptera: Adelgidae) at low temperatures. Forest Science. Vol.44, No. 3. pp. 414-420.

Perry, D.A. 1988. Landscape patterns and forest pests. The Northwest Environmental Journal.

Vol. 4. pp. 213-228.

Powers, J. S., P. Sollins, M.E. Harmon, and J.A. Jones. 1999. Plant-pest interactions in time and space: A Douglas-fir bark beetle outbreak as a case study. Landscape Ecology. Vol. 14. pp. 105-120.

Roberts, D.W. 1986. Ordination on the basis of fuzzy set theory. Vegatatio. Vol 66. pp. 123-131.

Royle, D.D. and R.G. Lathrop. 1997. Monitoring hemlock forest health in New Jersey using Landsat TM data and change detection techniques. Forest Science. Vol. 43, No. 3. pp.327-335.

Skidmore, A.K. 1990. Terrain position as mapped from a gridded digital elevation model. Int. J. Geographical Information Systems. Vol. 4, No. 1. pp. 33-49.

Snyder, C. D., J. A. Young, D. R. Smith, D. P. Lemarie, R. Ross, and R. Bennett. 1998. Influence of eastern hemlock on aquatic biodiversity in Delaware Water Gap National Recreation Area. Report to the National Park Service. US Geological Survey. 73 pp.

Teetor, A. 1988. Identification and mapping of vegetation communities in Shenandoah National Park, Virginia. Final Report MAR-34. Shenandoah National Park. USDOI. 62 pp.

Young, J., F. van Manen, and R. Ross. 1998. Modeling stand vulnerability and biological impacts of the hemlock wooly adelgid. Study Plan Number 2055. U.S. Geological Survey, Leetown Science Center, Kearneysville, WV 25430. 32 pp.

Crown Health Indicator		Canopy Position Indicator		
Value	Meaning	Value	Meaning	
1	>90% crown intact	D	Dominant	
2	50-89% crown intact	С	Co-dominant	
3	< 49% crown intact	Ι	Intermediate	
3X *	< 15% crown intact	S	Suppressed	
4	dead from HWA			
5	dead from other			

<u>Table 1</u>. Crown health (left) and canopy position (right) designations applied to surveyed eastern hemlock trees in Shenandoah National Park from 1993-1997.

* not used in 1993 survey.

		Number	of trees/s	tand
Year	# Stands	Median	Max	Min
1993	66	75	209	15
1994	57	150	908	14
1995	60	75	189	19
1996	80	75	150	4
1997	78	81	180	1
1998	94	100	200	1

Table 2. Number of Eastern hemlock trees surveyed per stand in Shenandoah National Park, by year (1993-1998).

Table 3. Weighted Crown Damage Index values by year (park-wide). Statistics are summarized across all stands (N) for each year.

	WCDI93*	WCDI94	WCDI95	WCDI96	WCDI97	WCDI98
N of cases	66	57	60	80	78	94
Minimum	1.100	1.730	1.290	1.000	1.000	1.160
Maximum	3.280	3.470	3.530	3.940	3.940	3.900
Range	2.180	1.740	2.240	2.940	2.940	2.740
Mean	2.354	2.797	2.775	2.756	2.742	2.972
Standard Dev	0.493	0.348	0.443	0.629	0.630	0.579

*Stands surveyed in 1993 were recorded using a different measurement scale than those surveyed from 1994-1998.

Terrain Variable	1993* n = 66	1994 n = 57	1995 n = 60	1996 n = 80	1997 n = 78	1998 n = 94
Elevation	0.185	-0.536	-0.656	-0.550	-0.677	-0.760
Northness	0.595	-0.142	-0.272	-0.170	-0.254	-0.262
Slope	-0.092	-0.083	-0.187	-0.072	-0.124	-0.002
Terrain Shape	0.058	-0.644	-0.658	-0.684	-0.746	-0.803
Solar Radiance	-0.501	0.185	0.323	0.224	0.330	0.298
Distance to Roads (log)	-0.337	0.073	-0.011	-0.014	-0.003	-0.009
Distance to Trails (log)	-0.136	0.097	0.035	0.365	0.303	0.169
Distance to Streams (log)	0.034	-0.447	-0.516	-0.526	-0.708	-0.741

<u>Table 4</u>. Pearson correlation coefficients between individual landscape variables and weighted crown damage index (WCDI) by year, based on generalized stand boundaries.

*Stands surveyed in 1993 were recorded using a different measurement scale of crown damage than those in 1994-1998.

<u>Table 5</u>. Area (m^2) and perimeter (m) of generalized survey boundaries within which landscape variables were summarized.

	Area	Perimeter
N of cases	97	97
Minimum	10325.594	369.540
Maximum	722971.250	9942.694
Mean	101804.290	1828.061
Standard Dev	97786.129	1416.582



Figure 1-A. Eastern hemlock crown health survey areas, Shenandoah National Park, North District.



Figure 1-B. Eastern hemlock crown health survey areas, Shenandoah National Park, Central District.



Figure 1-C. Eastern hemlock crown health survey areas, Shenandoah National Park, South District.

<u>Figure 2</u>. Park-wide weighted crown damage estimates summarized by year. In these box plots, the horizontal line within the box represents the median value, the length of the box represents the range within which 50% of the observations fall. The vertical lines represent observations within 1.5 * the interquartile range. Asterisks are outlier values.

Weighted Crown Damage by Year

<u>Figure 3.</u> Weighted Crown Damage Index vs. terrain shape for all stands by year. This plot shows the bivariate correlation between crown damage and terrain shape. Individual symbols represent stands sampled each year. The fitted line is a simple linear regression by year.

<u>Figure 4</u>. Weighted crown damage index vs. elevation for all stands by year. This plot shows the bivariate correlation between crown damage and elevation. Individual symbols represent stands sampled each year. The fitted line is a simple linear regression by year.

<u>Figure 5</u>. Weighted crown damage index vs. (log) distance to streams for all stands by year. This plot shows the bivariate correlation between crown damage and distance to streams. Individual symbols represent stands sampled each year. The fitted line is a simple linear regression by year.

<u>Figure 6.</u> Regression tree model showing the relationship between weighted crown damage index in **1993** and landscape variables. Predictor variables used in this analysis were stand area (AREA), stand perimeter (PERIMETER), mean stand elevation (ELEV_MEAN), mean stand solar illumination (SOLX_MEAN), mean stand northness or aspect (NIDX_MEAN), mean stand slope (SLP_MEAN), and mean stand terrain shape (TP_MEAN). Each "branch" of the tree diagram shows partitioning of the dataset and the predictor variable most responsible for minimizing the variance among observations in the resulting split. Overall fit of this model was **0.486 (48.6% of variation explained)**.

<u>Figure 7.</u> Regression tree model showing the relationship between weighted crown damage index in **1994** and landscape variables. Predictor variables used in this analysis were stand area (AREA), stand perimeter (PERIMETER), mean stand elevation (ELEV_MEAN), mean stand solar illumination (SOLX_MEAN), mean stand northness or aspect (NIDX_MEAN), mean stand slope (SLP_MEAN), and mean stand terrain shape (TP_MEAN). Each "branch" of the tree diagram shows partitioning of the dataset and the predictor variable most responsible for minimizing the variance among observations in the resulting split. Overall fit of this model was **0.489** (**48.9** % of variation explained).

Figure 8. Regression tree model showing the relationship between weighted crown damage index in **1995** and landscape variables. Predictor variables used in this analysis were stand area (AREA), stand perimeter (PERIMETER), mean stand elevation (ELEV_MEAN), mean stand solar illumination (SOLX_MEAN), mean stand northness or aspect (NIDX_MEAN), mean stand slope (SLP_MEAN), and mean stand terrain shape (TP_MEAN). Each "branch" of the tree diagram shows partitioning of the dataset and the predictor variable most responsible for minimizing the variance among observations in the resulting split. Overall fit of this model was **0.671 (67.1% of variation explained**).

<u>Figure 9.</u> Regression tree model showing the relationship between weighted crown damage index in **1996** and landscape variables. Predictor variables used in this analysis were stand area (AREA), stand perimeter (PERIMETER), mean stand elevation (ELEV_MEAN), mean stand solar illumination (SOLX_MEAN), mean stand northness or aspect (NIDX_MEAN), mean stand slope (SLP_MEAN), and mean stand terrain shape (TP_MEAN). Each "branch" of the tree diagram shows partitioning of the dataset and the predictor variable most responsible for minimizing the variance among observations in the resulting split. Overall fit of this model was **0.443** (**44.3** % of variation explained).

Figure 10. Regression tree model showing the relationship between weighted crown damage index in **1997** and landscape variables. Predictor variables used in this analysis were stand area (AREA), stand perimeter (PERIMETER), mean stand elevation (ELEV_MEAN), mean stand solar illumination (SOLX_MEAN), mean stand northness or aspect (NIDX_MEAN), mean stand slope (SLP_MEAN), and mean stand terrain shape (TP_MEAN). Each "branch" of the tree diagram shows partitioning of the dataset and the predictor variable most responsible for minimizing the variance among observations in the resulting split. Overall fit of this model was **0.328 (32.8 % of variation explained)**.

Figure 11. Regression tree model showing the relationship between weighted crown damage index in **1998** and landscape variables. Predictor variables used in this analysis were stand area (AREA), stand perimeter (PERIMETER), mean stand elevation (ELEV_MEAN), mean stand solar illumination (SOLX_MEAN), mean stand northness or aspect (NIDX_MEAN), mean stand slope (SLP_MEAN), and mean stand terrain shape (TP_MEAN). Each "branch" of the tree diagram shows partitioning of the dataset and the predictor variable most responsible for minimizing the variance among observations in the resulting split. Overall fit of this model was **0.593** (**59.3** % of variation explained).

