REVIEW

Opportunities and Limitations for Image-Based Remote Sensing in Precision Crop Management

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*T*his review addresses the potential of image-based remote sensing to provide spatially and temporally distributed information for precision crop management (PCM). PCM is an agricultural management system designed to target crop and soil inputs according to within-field requirements to optimize profitability and protect the environment. Progress in PCM has been hampered by a lack of timely, distributed information on crop and soil conditions. Based on a review of the information requirements of PCM, eight areas were identified in which image-based remote sensing technology could provide information that is currently lacking or inadequate. Recommendations were made for applications with potential for near-term implementation with available remote sensing technology and instrumentation. We found that both air-craft- and satellite-based remote sensing could provide valuable information for PCM applications. Images from aircraft-based sensors have a unique role for monitoring seasonally variable crop/soil conditions and for time-specific and time-critical crop management; current satellite-based sensors have limited, but important, applications; and upcoming commercial Earth observation satellites may provide the resolution, timeliness, and high quality required for many PCM operations. The current limitations for image-based remote sensing applications are mainly due to sensor attributes, such as restricted spectral range, coarse spatial resolution, slow turnaround time, and inadequate repeat coverage. According to experts in PCM, the potential market for remote sensing products in PCM is good. Future work should be focused on assimilating remotely sensed informa- tion into existing decision support systems (DSS), and conducting economic and technical analysis of remote sensing applications with season-long pilot projects. ©Elsevier Science Inc., 1997

INTRODUCTION

In the late 1970s and early 1980s, a great research effort was focused on the use of multispectral images for crop inventory and crop production. The Large Area Crop Inventory Experiment (LACIE) demonstrated the feasibility of utilizing satellite-based multispectral data for estimation of wheat production (MacDonald and Hall, 1980) based on techniques that are still in use today by crop production forecasters in the USDA Foreign Agricultural Service. The AgRISTARS program conducted by the USDA, NASA, and NOAA extended this methodology to include other crops and regions and expanded the research to encompass larger agricultural issues. The LACIE and AgRISTARS programs not only produced robust methods for regional crop identification and condition assessment, but also defined the physics of relations between spectral measurements and biophysical properties of crop canopies and soils. It was widely recognized that this basic scientific and technical knowledge had great potential to be used by farmers for making day-to-day management decisions.

Bauer (1985) summarized the underlying premise of using optical remote sensing for crop condition assessment. That is, multispectral reflectances and temperatures of crop canopies relate to two basic physiological processes: photosynthesis and evapotranspiration. In both processes, LAI, the ratio of leaf surface area to ground area, is the fundamental canopy parameter, and crop de-

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velopment stage is another crop parameter of major importance. He identified an emerging conceptual framework in which spectral data were used in combination with meteorological, soils, and other crop data to model crop growth, condition, and yield. Jackson (1984) presented a similar view and evaluated current and future remote sensing systems for use within such a framework for farm management. His 20-year vision for an ideal system included a fleet of autonomous satellites providing frequent, high-resolution data with quick turnaround and delivery to users. This vision may soon become reality with the planned launch (1997–1998) of several commercial satellites that are designed to provide multispectral images with 3-day repeat coverage, 1–4 m spatial resolution, and delivery to users within 15 min from the time of acquisition (Fritz, 1996). The synergy of such an imaging system with the scientific algorithms and models developed over the past 30 years could provide detailed crop and soil information to farm managers and crop consultants at a finer temporal and spatial scale than ever before.

Not coincidentally, this pending increase in information supply coincides with advances in farm management technology that will result in an acute demand for crop and soil information. Recent advances in technology for variable-rate production input applications, with concurrent advances in global positioning systems (GPS) and geographic information systems (GIS), have provided powerful analysis tools for farm management. This has been termed "precision crop management (PCM)", defined as an *information- and technology-based agricultural management system to identify, analyze and manage site-soil spatial and temporal variability within fields for optimum profitability, sustainability and protection of the environment* (Robert et al., 1995).

Variable rate technology (VRT), probably the best developed part of the PCM system (Searcy, 1995), applies production inputs at rates appropriate to soil and plant conditions within fields. Variable rate systems have been demonstrated for several materials, including herbicide (Mortensen et al., 1995), fertilizer (Fergusen et al., 1995; Schueller, 1992), insecticide (Fleischer et al., 1996), and seeds. Concurrent advances in GPS technology have provided the moderately priced, accurate positioning system necessary for field implementation of VRT (Palmer, 1995). These advances in location technology have been combined with the ubiquitous use of GIS by PCM workers (Usery et al., 1995) in the most advanced systems for PCM. For example, Hanson et al. (1995) described a herbicide application system mounted on a tractor with a GPS guidance system which was linked to a digital weed map, allowing only weed-infested areas of the field to be sprayed. The weak link in many PCM systems is the availability of such maps of weeds, insect infestations, crop nutrient deficiencies, and other crop and soil conditions. Remotely sensed images ob-

tained with aircraft and satellite-based sensors have the potential to provide such maps for the whole field, not just sample sites, within the time and space requirements of PCM applications.

It is this convergence of technological advances that inspired this review of the potential for image-based remote sensing to provide spatially and temporally distributed information for PCM. In the next section, we reviewed the current and proposed methods for obtaining information for PCM, with particular reference to the published results of the 1994 International Conference on Site Specific Management for Agricultural Systems (Robert et al., 1995). Based on that review, we identified eight areas in which remote sensing technology could provide information that is currently inadequate or completely unavailable. We provided a review of recent advances in RS related to these eight areas. [For a general review of remote sensing for assessing crop conditions, readers should refer to reviews by Jackson (1984), Bauer (1985), and more recently, Hatfield and Pinter (1993).] With consideration of the technical limitations of currently available sensors and advances in image processing techniques, recommendations were made for applications with potential for near-term implementation and applications that deserve further research. An economic analysis of these applications was not attempted, but it should be considered in selecting the applications that are most promising for commercial development.

REVIEW OF CURRENT METHODS FOR OBTAINING INFORMATION FOR PCM

There are three basic types of information required for PCM:

- information on seasonally stable conditions
- information on seasonally variable conditions
- information required to diagnose the cause of the crop yield variability and develop a management strategy

Since the designations of "seasonally stable" and "seasonally variable" are not conventional PCM terminology, we will define them here. Seasonally stable conditions are those that are relatively constant through the crop growing season, such as yield-based or soil-based management units, and only need to be determined preseason and simply updated, when and if necessary. Seasonally variable conditions are those that change continually within the season, such as soil moisture, weed or insect infestations, and crop disease, and need to be determined numerous times during the season for proper management. The first two categories are based on the assumption that the condition of interest (such as soil physical properties, nutrient availability, or weed population) is already defined, and information is needed to spatially quantify the condition. The third category can

encompass both seasonally stable and seasonally variable conditions where the source of variability in crop production is unknown. These three types of information have potential for use of image-based remote sensing and will be addressed individually in the following sub-sections.

One approach to meet some of the information requirements of PCM has been through the use of noninvasive tractor-based sensors which control variable rate applicators in near-real time. Several such sensors have been developed for measuring soil organic matter (Tyler, 1994), soil nitrate levels (Adsett and Zoerb, 1991), and soil clay content and thickness (Sudduth et al., 1995). For real-time crop monitoring, there has been research into the development of weed sensors to discriminate weeds from standing crops (Thompson et al., 1990; Guyer et al., 1993), a tractor-based charged couple device (CCD) camera to discriminate plants from soil and trash for guiding most-beneficial chemical applications (Cai and Palmer, 1994), and a sensor for assessing crop nitrogen status based on an in-field reference of known nitrogen status (Blackmer et al., 1996). Daughtry et al. (1995) proposed a fluorescence technique that allowed discrimination of residue from bare soil, and a commercial prototype that could be mounted on a trailer is currently being built. These vehicle-mounted sensors are mentioned briefly here due to their critical role in PCM; however, this review and further discussion will be limited to satellite- or airborne-based spectral observations, and those PCM applications that seem most promising at the present time.

Mapping Seasonally Stable Management Units

Grain Yield Monitors

One of the more dramatic advances in acquiring spatially variable data for PCM has been the commercial development of combine-mounted grain yield monitors. The data from the monitor are georeferenced using a Differential GPS (DGPS) receiver onboard the harvesting equipment to produce yield maps. Yield maps collected for several growing seasons can provide an integrated expression of relative productivity that is a property of the field and unchanging from year-to-year and from crop-to-crop (Kitchen et al., 1995). Yield maps have been used directly for management of fertilizer application (Schueller and Bae, 1987; Eliason et al., 1995), water application (King et al., 1995), and planting and soil engaging operations (Schueller, 1988), and have important indirect applications in management of weeds, insects, and crop diseases. On the other hand, yield monitors can result in significant errors in yield estimation due to coarse resolution, time lags in moving the grain from the crop to the point of measurement, variations in combine speed, and noise induced by the machine vibration and varying terrain (Lamb et al., 1995).

The production of grain yield maps generally requires that instantaneous grain yields acquired at coarse and/or variant resolutions with DGPS positioning be interpolated to obtain average yields at a given, finer resolution. Generally, geostatistical analysis is used for this interpolation, based on kriging or the simpler inverse distance technique (Murphy et al., 1995). The drawbacks of geostatistical analysis include the need for a large number of samples at close intervals and the assumption of stationarity (i.e., random, not systematic, data variation) which is often untrue for soil and crop properties (Tomer et al., 1995). Consequently, other means for interpolating instantaneous yield measurements to produce a map product have been suggested. Tomer et al. (1995) used digitized aerial infrared photographs and point-based harvest samples with regression analysis to map crop grain yields. Long et al. (1995) compared four methods for deriving yield maps from combine-based yield measurements—interpreting soil survey maps, interpreting aerial photographs, and two kriging-based methods—and found that the aerial method was significantly more accurate than the other three methods for their dryland cropped site. In any case, there is general agreement on the need for improvements in all types of yield mapping methodology for PCM.

Soil Fertility Properties

Farm managers have long known that soil variability influences the productive potential of agricultural lands. Maps of soil fertility and physical attributes are being used in PCM to determine the responsive and nonresponsive parts of fields (Wolkowski and Wollenhaupt, 1995). Nielsen et al. (1995) identified several of the most important soil fertility attributes that could be mapped and managed for improved yield: available soil nitrogen or some other macro or micro plant nutrient, relative position and slope of the terrain, and soil organic matter content. Soil organic matter content has been directly related to the efficacy and rate of fertilizer applications, as well as to crop yield and other soil variables such as phosphorus. Pierce et al. (1995) suggested that soil physical properties or landscape (particularly in their effect on water relations) may be even more important than soil fertility in explaining yield variations. Bell et al. (1995) outlined three approaches for mapping soil variability for PCM. These were based on 1) county soil surveys at 1:12,000 to 1:24,000 scales, 2) geostatistical interpolation techniques (e.g., kriging) to map soil properties from a grid of point samples, and 3) use of soil/landscape models with input from either remote sensing or a digital elevation map (DEM).

County soil surveys have two limitations for use in PCM. First, the typical scales of greater than 1:12,000 cannot be used to delineate within-field soil variability. Spangrud et al. (1995) suggest that scales of 1:6000 to 1:8000 are needed to guide soil specific crop management. Second, soil attributes from county surveys are too

imprecisely measured to adequately represent soil attribute variation that can affect crop yield at the field scale (Moore et al., 1993).

In most cases, information for soil-specific crop management has been obtained through soil sampling in large grids that overlay a field, at optimal grid spacings ranging from 60 to 100 m (Franzen and Peck, 1995). These discrete samples are converted to continuous map format through the statistical technique of kriging, for which the limitations were discussed in the previous subsection. Nielsen et al. (1995) suggested several alternatives to conventional kriging for making soils maps for PCM, including use of spectral and cospectral analysis, state-space analysis, spatial covariance, and fuzzy set analysis.

Another approach for mapping soil management units is based on soil/landscape models, generally combined with DEM information. Verhagen et al. (1995) described a deterministic, mechanistic simulation model that combined soil physical measurements with a water balance module and a crop growth model to distinguish soil horizons with equivalent hydrologic properties and map spatial and temporal variations. Another simulation model, proposed by Roytberg and Chaplin (1995), was used to describe the variability in soil physical condition during tillage based on the soil resistance force, which could be measured with tractor-based tillage transducers. Models based solely on relief and landscape position have been used to map spatial variability of several soil chemical and physical properties (e.g., organic C, pH, soil moisture, depth of A horizon, depth to free carbonates in glaciated landscapes) (Wang et al., 1995; Bell et al., 1995) and have proven useful for managing fertilizer applications (Nolan et al., 1995). One disadvantage of these approaches for PCM is the dependence upon DEM data which are generally acquired from USGS contour maps at 30 m×30 m spatial resolution on which elevation data are rounded to the nearest meter. Such data are too coarse for most precision farming applications. Bell et al. (1995) note that the optimal scale for describing landscape characteristics is unknown and probably depends on climatic conditions; however, a 10 m×10 m grid with submeter elevation accuracy is preferred for many PCM applications. Spangrud et al. (1995) explored the possibility of mapping field elevations with a GPS and evaluated the number and pattern of such measurements needed for PCM.

Mapping Seasonally Variable Management Units

Though many PCM decisions can be made based on seasonally stable management units defined by maps of soil fertility or yield, there are other management decisions that could benefit from seasonally variable information on such conditions as weed or insects infestation, crop stress (due to water or nitrogen), crop disease, or soil moisture. For example, information on within-field soil

moisture variation throughout the season has been shown to be relevant to decisions made about tillage activities (Lindstrom et al., 1995) and nitrogen applications (Huggins and Alderfer, 1995; Sadler et al., 1995).

Generally, commonly used PCM information-gathering techniques (e.g., yield monitors or grid sampling) cannot provide the quick, large-area coverage required for mapping seasonally variable management units. Techniques that have been specifically designed to obtain seasonally variable information for PCM are generally based on evaluation of aerial imagery. For example, Blackmer et al. (1995) used aerial images obtained at a wavelength that was particularly sensitive to canopy N levels (0.55 μm) to map nitrogen-deficient areas within fields of corn. Similar techniques have shown promise for determining nitrogen levels of wheat (Stanhill et al., 1972; Hinzman et al., 1986) and rice (Takebe et al., 1990). In attempts to use geostatistics with point measurements to analyze weed aggregations, Mortensen et al. (1995) cited the benefits of using "sensing" technology to provide spatial maps of weed infestations or guide real-time spray-no-spray decisions. Hanson et al. (1995) identified the advantages of using aerial imagery for mapping weed infestation (e.g., cost, timing, and accuracy) and demonstrated a feasible technique for mapping wild oats in wheat fields. These applications will be explored more fully in the next main section.

Determining Cause of Yield Variability and Management Strategy

Once information on yield variability is available, it must be analyzed for making management and application decisions. The challenges are to distinguish deterministic sources of yield variability from stochastic sources (Searcy, 1995), to develop VRT decision criteria (Kitchen et al., 1995) in the form of decision support systems (DSS), and to understand the relation between crop and soil variability and management strategies (Colvin et al., 1995). Tevis (1995) suggested several options ranging from simply applying a threshold function to a specified attribute layer (Tevis and Searcy, 1991) to using an expert system with several agronomic attribute layers (He et al., 1992). Managing crop and soil conditions that vary in both the spatial and temporal domain will require expert systems to analyze data (determine cause/effect) and make integrated management decisions (Fixen and Reetz, 1995).

McGrath et al. (1995) describe a packaged system for fertility management that includes automated data collection and analysis, an expert system for evaluating data in combination with other information to suggest management options, and automated applicators to carry out the management program. This package has individual submodels for phosphorus, potassium, organic matter, and soil moisture, where static and dynamic informa-

tion is required for each. This modular approach in a GIS environment appears to be the norm for development of expert systems and decision support systems for PCM (Brown and Steckler, 1995). Griffith (1995) foresees a merging of many models to define specialized portions of the behavior of the total production process. Other decision aid models have been developed for managing specific crops such as sorghum (SORKAM, Vanderlip et al., 1995), and cereals (CERES with DSSAT, Hoogenboom et al., 1994; Booltink and Verhagen, 1996).

OPPORTUNITIES FOR IMAGE-BASED RS IN PCM

In the previous section, the state of PCM was reviewed and several opportunities for remote observations were identified. Each of the next subsections relate an issue of PCM information acquisition identified in the previous section to the status of remote sensing technology and theory for that issue. This is not meant to be an exhaustive review of the progress of RS, but rather examples that illustrate some of the more common approaches related to each issue. At the end of each subsection, opportunities are identified wherein RS data could be used to identify or analyze site-soil spatial and temporal variability for PCM.

Discussion was limited to the most commonly used wavelength regions at spatial resolutions of 1 km or less: reflected radiance in the visible, NIR and shortwave infrared (SWIR) wavelengths (0.4–2.6 μm), emitted radiance (3–16 μm), and backscatter of synthetic aperture radar (0.9–25 cm referred to as SAR). Reference is made to some of the more commonly used concepts in RS; these will be defined here, with an appropriate citation for further reading. Spectral vegetation indices (VI) are a ratio or linear combination of reflectances in the red and NIR wavebands that is particularly sensitive to vegetation amount (Jackson and Huete, 1991), or the amount of photosynthetically active plant tissue in the plant canopy (Wiegand et al., 1991); a commonly used VI is normalized difference VI (NDVI) which is the difference of the red and NIR measurements divided by their sum. Hyperspectral RS is the measurement of spectral "signatures" using data of high spectral resolution (e.g., 0.01 μm) within the range of 0.4-2.6 μm (Price, 1990). The "red edge" in hyperspectral RS refers to the transition from low reflectance in the visible region of the spectrum to high NIR reflectance that is particularly sensitive to chlorosis and crop stress (Demetriades-Shah et al., 1990).

Converting Point Samples to Field Maps

Images of surface reflectance, temperature, or radar backscatter may provide a solution to the problems identified in converting point-based samples to continuous soil or yield maps using geostatistics and other conventional

methods. This will be termed "indirect" mapping because some *in situ* data (such as soil or yield samples) is required to relate the spectral data to the physical parameter of interest. In many cases, the best results in applying remote sensing techniques to identify management units will be obtained when the crop is present. Crop plants integrate the effects of the climatic environment, stress (disease, nutrient, and water), and soil properties. These effects are often expressed in the crop canopy achieved (Wiegand and Richardson, 1984). Two techniques show some promise here: image classification (supervised or unsupervised), and cokriging.

Conventional image classification, whether supervised or unsupervised, utilizes a statistical routine (e.g., maximum likelihood) to sort an image into discrete spectral categories. In supervised image classification, on-site measurements of soil or crop conditions are used to "train" the classifier and the product is a map of the desired surface parameter. Unsupervised image classification circumvents the need for training sets by using the image spectral data to define "clusters" that are used to produce a map of spectrally similar classes. The spectral data from sample sites can be extracted and then be related to measured variables at the same sites (yield, available water, salinity, soil nitrogen, etc.) to define the unsupervised class map in the variable of interest (Wiegand et al., 1996). Image classification techniques run quickly and easily on many personal computers, and are underutilized in PCM. Furthermore, recent advances in supervised image classification have decreased the large ground data sets required for accurate map-making. Alternative classifiers, such as artificial neural network or genetic algorithms, require fewer samples than conventional classifiers, though care must still be taken in selecting the composition of the samples (Foody et al., 1995; Clark and Cañas, 1995). There have been suggestions that a fuzzy logic classifier would work best for agricultural fields of high heterogeneity (Blonda et al., 1991).

The limitations of conventional kriging techniques for producing maps of crop and soil conditions from on-site samples have been addressed in the previous section. The use of "cokriging," which links multiple measurements through regression analysis (termed coregionalization), has been suggested as an alternative. Atkinson et al. (1992) found that cokriging with on-site measurements of reflectance and vegetation cover resulted in maps of cover with three times the precision achievable with univariate kriging for a given amount of effort. The use of remotely sensed images with statistical techniques has been suggested to improve map accuracy, reduce the number of soil samples needed, and circumvent the need for annual grid sampling of soil nitrogen levels (Ferguson et al., 1995). Fuzzy set analysis within a GIS environment is particularly conducive to incorporation of aerial images (McBratney and Whelan, 1995).

Thus, we suggest the following:[1]

1. Measurements of soil and crop properties at sample sites combined with multispectral imagery could produce accurate, timely maps of soil and crop characteristics for defining precision management units.

Mapping Crop Yield

Remote sensing has been used operationally for preharvest forecasting of yield. In the simplest approach, final grain yield has been correlated with a single observation of the normalized difference vegetation index (NDVI) or an NDVI time integral at specific times during the season (Tucker et al., 1980; Rasmussen, 1992; Yang and Anderson, 1996). In other applications, NDVI has been used to determine yields (e.g, corn, soybean, or grain) by computing the areas under the predicted growth profile for some selected time periods (Boatwright et al., 1988), monitoring the postanthesis senescence rate (Idso et al., 1980; Potdar, 1990; 1993), and measuring the length of the grain-filling period (Quarmby et al., 1993). Most studies suggest that NDVI can be effective for providing information on germination and vegetative stages, but this information must be combined with input from an agrometeorological model to accurately determine crop yields (Patel et al., 1991; Rudorff and Batista, 1991).

Integrated with models, RS data are generally used to estimate model inputs related to light interception, such as leaf area index (LAI) or percent vegetation cover. The rate of crop growth is then calculated from meteorological data based on an efficiency factor for conversion of radiant energy to biomass (Wiegand et al., 1986a). This information is used to predict yield as a function of biomass growth rates, like those listed in the previous paragraph. In another approach, remotely sensed inputs of instantaneous LAI or evaporation rates are used for within-season model calibration to reinitialize or reparameterize the model and improve yield prediction (Maas, 1988; Moran et al., 1995; Bouman, 1992). The latter approach has the advantage of requiring fewer remotely sensed inputs since the calibrated model is used to estimate crop growth when remotely sensed data are not available.

Thus, we suggest the following:

2a. Multispectral images obtained late in the crop growing season could be used to map crop yields with approaches as simple as regression.

2b. Remote sensing information could be combined with crop growth or agrometeorological models to predict final yield.

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[1] The suggestions listed in this section are numbered for easy cross-reference with the numbers in Figures 1–3 and Table 2.

Mapping Soil Variability

Mapping soils of naturally vegetated areas with RS is often based on the association of vegetation type with soil (Korolyuk and Shcherbenko, 1994); this is not feasible for agricultural sites where crops simply increase the complexity of image interpretation. A more appropriate method for agricultural applications would be to extract information about soil surface conditions directly from radiometric measurements of bare soils. Surface reflectance information has been related directly to variability in loess thickness (Milfred and Kiefer, 1976), soil organic matter (Robert, 1993; Zheng and Schreier, 1988; Baumgardner et al., 1970), soil calcium carbonate content (Leone et al., 1995), soil nutrients (particularly those associated with soil texture and drainage) (Thompson and Robert, 1995), iron oxide content (Coleman and Montgomery, 1987), and soil texture classes (with similar responses to water and fertilizer) (King et al., 1995). Soil thermal information has been linked with variations in soil moisture content (Idso et al., 1975) and soil compaction (Burrough et al., 1985).

Despite the relations among soil reflectance and soil properties, remotely sensed images are not currently being used to map soil characteristics on a routine basis (with the exception of high and medium altitude aerial photographs that serve as base maps in county level soil surveys). This is because the reflectance characteristics of the desired soil properties (e.g., organic matter, texture, iron content) are often confused by variability in soil moisture content, surface roughness, climate factors, solar zenith angle, and view angle. This is particularly true for mapping agricultural soils with varying cultivation practices. In fact, Leek and Solberg (1995) showed that images of surface reflectance acquired during times of greatest plowing activity could be used to map tillage and assist in erosion control.

Kimes et al. (1993) proposed to overcome this confusion by using an expert system to analyze hyperspectral images based on spectral signatures of some soil properties. It worked well for broad classes (e.g., fine versus coarse texture) and was most successful in distinguishing high and low organic matter content soils. In another approach, Muller and James (1994) suggested that the uncertainty in mapping soil particle size caused by differences in soil roughness, moisture, and vegetation cover could be minimized by using a set of multitemporal images for soil classification. Salisbury and D'Aria (1992) reported that thermal infrared band ratios from the upcoming EOS ASTER sensor (range 8–14 μm, resolution 90 m) could be used to discriminate such soil properties as particle size, soil moisture, soil organic content, and the presence of abundant minerals other than quartz.

Remote sensing may also prove useful for mapping more transitory conditions, such as salt-affected soils. There is evidence that salt-affected soils in general show

relatively higher spectral response in the visible and near-IR regions than normal cultivated soils, and strongly saline-sodic soils were found to have higher spectral response than moderately saline-sodic soils (Rao et al., 1995). Verma et al. (1994) found that better results (particularly for discrimination of the similar reflectance properties of salt-affected soils and normal sandy soils) could be obtained by combining reflectance and temperature information. Further, Sreenivas et al. (1995) reported that a combination of optical and SAR data showed potential for detecting saline areas and separating saline soils from sodic soils, particularly under moist soil conditions. Wiegand et al. (1996) have used soil and plant samples, videography or SPOT HRV spectral observations, and unsupervised classification to map soil salinity and yield at salt-affected cropped fields.

For both crop and soil mapping, remotely sensed images should also be considered for revision of maps of "seasonally-stable" management units. By comparing such maps acquired at optimum times within the season (when soils are bare or when crops cover or phenology is optimum), it may be possible to revise management units midseason in response to unexpected changes. The revision process could be as simple as displaying the remote sensing data as a backdrop to a vector map of management units within a GIS and visually assessing differences (Chagarlamudi and Plunkett, 1993) or could be based on automated technology for change detection (Hallum, 1993).

Thus, we suggest the following:

3a. Multispectral images obtained when soils are bare could be used to map soil types relevant to PCM with approaches based on models and/or on analysis of single or multiple image acquisitions.

3b. Maps of spectral variability (obtained under conditions of either bare soil or full crop cover) may prove useful for revision of maps of management units

Monitoring Seasonally Variable Soil and Crop Characteristics

In the previous main section, we identified several seasonally variable soil and crop conditions for which information on variability would be useful for PCM; these included soil moisture content, crop phenology, crop growth, crop evaporation rate, crop nutrient deficiency, crop disease, weed infestation, and insect infestation. RS techniques for monitoring these eight parameters will be discussed in the next paragraphs.

Soil Moisture Content

Attempts have been made to map soil moisture content of agricultural fields based on a simple linear correlation with the backscatter of the SAR signal in long wave-

lengths (e.g., C-band at 5.7 cm or L-band at 21 cm). This direct relation can be strong for bare soil conditions, but there is considerable scatter when fields of variable crop biomass are included in the regression (Benallegue et al., 1994). Thus, most recent works in mapping within-field soil moisture conditions are based on the use of dual-frequency SAR where the combination of long and short (e.g., Ku-band at 2 cm or X-band at 3 cm) wavelengths is used to determine the vegetation-induced attenuation of the long-wavelength signal to improve estimates of soil moisture (Taconet et al., 1994; Prevot et al., 1993; Paloscia et al., 1993; Moran et al., 1997a). There are other issues that must be considered in the use of SAR for mapping soil moisture content for PCM applications. Studies have found that SAR measurement depth is only 0.1–0.2 times the wavelength, and it decreases with moisture content; this translates to about 10 cm measurement depth for the L-band at moderate moisture content (Engman and Chauhan, 1995). Furthermore, the SAR signal is sensitive not only to soil moisture but also to surface roughness (like that associated with differentially tilled agricultural soils) and topography. Engman and Chauhan (1995) suggested that the best application of existing, unifrequency SAR sensors may be for monitoring the temporal change of soil moisture to minimize the influence of variability in roughness, vegetation and topography. Others have suggested that SAR radiative transfer models could be used, with ancillary data provided by remote sensing of non-SAR wavelengths or other sources, to reduce the surface-induced "noise" in the SAR signal and improve soil moisture estimates (Moran et al., 1997b; Wingeron et al., 1995).

Crop Phenology

Knowledge of the stage of the crop development is useful for *time*-specific crop management (TSCM), such as minimizing or maximizing crop stress during crucial periods (e.g., grain filling in wheat, anthesis of corn, or sugar development in cantaloupe). For example, the vegetative, reproductive and senescing phases of wheat crops have been discriminated based on seasonal shifts in the red edge (Railyan and Korobov, 1993), bidirectional reflectance measurements (Zipoli and Grifoni, 1994), measurements of reflected polarized light (Ghosh et al., 1993), and temporal monitoring of NDVI (Boissard et al., 1993).

Crop Growth

The most common approach in remote sensing for measuring or monitoring crop growth is the empirical correlation of VI with such crop variables as LAI, percent vegetation cover, vegetation phytomass and fraction of absorbed photosynthetically active radiance (f_{APAR}) (e.g., Pinter, 1993). The basic theory of this approach is well understood (Jackson and Huete, 1991) and the field validation studies for a variety of crops, locations, and meteorological conditions are endless. Recent improvements to this approach include developing VIs are that insensi-

tive to soil/atmosphere/sensor noise (e.g., Huete, 1988; Malthus et al., 1993) and developing empirical relations that are robust for application to a variety of crops, locations, and conditions (Richardson et al., 1992; 1993; Wiegand et al., 1992). Because of the inherent advantages of SAR data acquisition (cloud penetration and night acquisition), there have been some suggestions that SAR backscatter in short wavelengths could be used to monitor crop cover and relative growth (Bouman and Hoekman, 1993; Moran et al., 1997a). Other approaches are based on the premise that remote sensing alone is not sufficient for producing accurate vegetation information. Such approaches are generally based on crop growth models or canopy radiative transfer models (RTM). An example of the former was presented by Clevers et al. (1994) using optical reflectance measurements to calibrate the SUCROS crop growth model and improve estimates of crop yield. An example of the latter was presented by Kimes et al. (1991) in the development of a knowledge-based system (VEG) to infer reflectances of a vegetation target, or inversely, to derive vegetation characteristics from multiband or multiview reflectance measurements. The use of canopy RTMs has been particularly successful with off-nadir reflectance measurements since they can use the multidirectional measurements as an additional source of information about the canopy structure (Qi et al., 1995a). The conclusion of a review by Myneni et al. (1995) was a good summation of the state-of-the-art in remote sensing of vegetation:

> In spite of obvious limitations, spectral vegetation indices are still preferable in the analysis of large spatial data sets. The promise of remote sensing, however, lies in those methods that utilize physical models and advances in computer science and technology.

Crop Evapotranspiration Rate

Crop stress, due to crop disease, water deficiency, some insect infestations, and other problems, is often manifested by a decrease in the transpiration rate of the crop. As such, much work has been conducted to use remote sensing for monitoring crop evapotranspiration rates. One of the more promising approaches for operational application is the use of remotely sensed crop coefficients (the ratio of actual crop evapotranspiration and that of a reference crop) for estimation of actual, site-specific crop evapotranspiration rate from readily available meteorological information (e.g., Bausch, 1993). This approach requires only a measure of spectral vegetation index (e.g., NDVI) and is simply an improvement of an approach already accepted and in use by farmers to manage crops, where such improvements include increases in accuracy of the evaporation estimates and, with use of images, the ability to map within-field and between-field variations. Another approach that has obtained commercial success is the crop water stress index (CWSI), which provides a measure of crop stress from

0 to 1 based on the difference between surface and air temperature with reference to the vapor pressure deficit and a crop-specific baseline (Jackson et al., 1981). The commercial applicability of CWSI is evidenced by the commercial production of a handheld instrument designed to measure CWSI, several commercial imaging companies that are providing CWSI to farmers, and the multitude of examples of application of this theory with airborne and satellite-based thermal sensors combined with ground-based meteorological information [see reviews by Moran and Jackson (1991) and Norman et al. (1995)]. Other approaches are being explored to use near-linear relations between spectral vegetation indices and canopy stomatal conductance and photosynthesis with respect to photosynthetically active radiation (PAR) (Sellers, 1987; Verma et al., 1993). The location of the red edge determined with hyperspectral measurements also shows promise for early detection of water stress (Shibayama et al., 1993).

Crop Nutrient Deficiency

Plant nitrogen content and canopy nitrogen deficits have been related to reflectance measurements in the green (0.545 μm), red (0.66 μm), and NIR (0.80 μm) spectrum (Fernández et al., 1994; Buschmann and Nagel, 1993). However, most such relations are sensitive to variations in soil reflectance, and the best bandwidths are narrow and unavailable with satellite-based wide-band sensors. Blackmer et al. (1995) proposed the images of canopy reflectance centered at 0.55 μm acquired late in the growing season could be used to detect portions of the field that were nitrogen deficient. Such information could be obtained earlier in the season by ratioing crop reflectance spectra with a reference spectrum from the same crop to define absorption maxima and minima that were related to nitrogen levels (Chappelle et al., 1992).

Crop Disease

Remote sensing has some potential for detecting and identifying crop diseases. Toler et al. (1981) used false color IR photography to detect Phymatotrichum root rot of cotton and wheat stem rust. In fungal and mildew infected leaves, changes in remotely sensed reflectance have been detected before symptoms were visible to the human eye (Malthus and Madeira, 1993; Lorenzen and Jensen, 1989). Though wide visible and near-infrared bands may be helpful for discriminating healthy and diseased crops (due to changes in foliage density, leaf area, leaf angles, or canopy structure), the best results for *identifying* diseases were obtained with hyperspectral information in the visible and near-infrared spectrum. Discrimination of diseases may be possible with knowledge of the physiological effect of the disease on leaf and canopy elements. For example, necrotic diseases can cause a darkening of leaves in the visible spectrum and a cell collapse that would decrease near-infrared reflectance. Chlorosis inducing diseases (mildews and some virus) cause marked

changes in the visible reflectance (similar to N deficiency) and other diseases may be detected by their effects on canopy geometry (wilting or decreases in LAI).

Weed Infestation

Herbicides are generally applied both prior to planting and post-emergence. For precision management of preplant applications, the information requirement is simply determination of presence or absence of plants, and the remote sensors should be comparably simple, such as the tractor-based sensors previously described in the previous main section or interpretation of digital images based on VI or supervised classification (e.g., Richardson et al., 1985). In fact, since perennial weeds tend to remain in the same location each year, there is even the possibility of using the previous year's weed map for preplant control decisions (Brown and Steckler, 1995). Management of postemergence herbicide applications poses more difficulty because it requires discrimination between weeds and crops. This is generally accomplished based on the differences in the visible/NIR spectral signatures of crops and specific weeds (Brown et al., 1994) or by acquiring images at specific times during the season when weed coloring is particularly distinctive (i.e., during flowering). An example of an integrated system for management of weeds with remote sensing input was presented by Brown and Steckler (1995). Their system combined image-derived weed maps with a GIS-based decision model to determine optimum herbicide mix and application rates for no-till corn and resulted in reductions of herbicide use by more than 40%.

Insect Infestation

Few studies have been reported on the use of remote sensing for directly assessing insect infestation. Indirectly, insect damage to plants has been detected through remote sensing of insect habitat (Hugh-Jones et al., 1992), growth and yield of plants (Vogelmann and Rock, 1989), or changes in plant chemistry. Peñuelas et al. (1995) found that increasing infestations of mites in apple trees caused a decrease in the leaf chlorophyll concentration and an increase in the carotenoid/chlorophyll *a* ratio. These chemical changes were detected with reflectance measurements made in narrow bandwidths in the visible and NIR spectrum.

There is considerable evidence that multispectral images can be used for identifying and monitoring the following seasonally variable soil and crop conditions:

4a. Soil moisture content,
4b. Crop phenologic stage,
4c. Crop biomass and yield production,
4d. Crop evapotranspiration rate,
4e. Crop nutrient deficiencies,
4f. Crop disease,
4g. Weed infestation, and
4h. Insect infestation.

Determining the *Cause* of the Variability in Crop Production

Remote sensing has a variety of roles in determining the cause of spatial and temporal crop and soil variability. The most obvious role, which has been advanced throughout this review, is the use of remote sensing information to improve the capacity and accuracy of DSS and agronomic models by providing accurate input information or as a means of model calibration or validation. Another role is the use of hyperspectral imagers for direct crop diagnosis. Issues related to these two independent functions of remote sensing in PCM will be the topic of this subsection.

The link between remote sensing and simulation modeling has been illustrated through examples of the use of remote sensing for parameterization of models (Wiegand et al., 1986b), within-season model calibration (Maas, 1993), and model validation (Fischer, 1994). Another option, which is receiving less attention, was articulated by Bouma (1995). His option is based on the premise that the most useful models will be those in which the degree of complexity is in equilibrium with the available data. Bouma laments the examples of complicated deterministic models being used without adequate basic data, yielding irrelevant results. In terms of the synergy between remote sensing and models, this premise could be interpreted in two ways. Either emphasis must be put on the relation of remote sensing measurements with common model inputs or models must be refined to relate existing remote sensing information to the unavailable data needed for the model. The latter option holds the most promise.

In this review we have cited examples where hyperspectral data in the visible and NIR wavelengths have been used successfully for discrimination of crop stress caused by N deficiency, crop disease, water stress, chlorosis, and more. Carter (1994) reported that narrow wavebands derived from hyperspectral data could be used to discriminate the cause of plant stress in six plant species due to eight stress agents: competition, herbicide, pathogen, ozone, mychorrhizae, island, senescence, and dehydration. At this time, there are no hyperspectral instruments available on satellite platforms and few available on aircraft; furthermore, processing, analysis, and interpretation of hyperspectral images is time-consuming for both the computer and computer-user. The vision of remote sensing for analysis of yield variability in PCM may include the use of airborne sensors with wide-bands to map crop stress variability and the subsequent deployment of hyperspectral sensors for determination of the cause of the stress for making application management decisions.

Thus, we suggest the following:

5a. Remote observations could provide accurate input information for agricultural DSS.

5b. Remote sensing information could be combined with agro-meteorologic models to determine the cause of soil and crop variability.

5c. Hyperspectral sensors could be used to determine the cause of soil and crop variability.

Mapping Spatially Distributed Information on Meteorological/Climate Conditions

In nearly every application of PCM and in every agro-meteorological model, knowledge of spatial variations in meteorological conditions is crucial. Yet, most applications are based on output from a single meteorological station that may be many kilometers distant from the field, and the instruments are generally located over a grassy plot that is not indicative of field conditions. There are numerous examples of the use of satellite spectral images for estimation of insolation (e.g., Pinker and Ewing, 1985), PAR (e.g., Frouin and Pinker, 1995), net long-wave radiation (Ellingson, 1995), rainfall (Petty, 1995), and other meteorological variables. Further work has focused on combining remote sensing with mesoscale meteorological models to make regional estimates of such variables as air temperature, wind speed, and vapor pressure deficit (Toth et al., 1996). These studies are possible because of geostationary satellite sensors that can provide coarse-resolution multispectral data with twice/day coverage and near-instantaneous turnaround times. These sensor characteristics are suitable for PCM applications.

Thus, we suggest the following:

6. Multispectral images of coarse spatial resolution and fine temporal resolution should be used to produce local or regional maps of meteorological parameters such as insolation, PAR, rainfall, and others.

Producing Fine-Resolution Digital Elevation Data

Today, it is possible to generate DEMs from stereopairs of aerial or satellite images using software available for personal computers (Gagnon et al., 1990). Automated stereo correlation procedures are available to derive DEM information from stereo images without the need of the user to view the images and/or conduct measurements (Chagarlamudi and Plunkett, 1993). Thus, we suggest the following:

7. DEMs could be produced from stereopairs of aerial or satellite images with the spatial resolution and accuracy required for PCM applications.

Addressing Time-Critical Crop Management (TCCM) Applications

In a previous subsection (Monitoring Seasonally Variable Soil and Crop Characteristics) we recognized that crop damage can be caused by many agents, such as insects,

disease, insufficient or excess water and nutrients, mechanical, and chemical damage. In many cases, crop damage is manifested in changes in above-ground foliage, such as tone or color of leaves, leaf condition (wilting or distortion), leaf area (including defoliation), and leaf or stem orientation (such as lodging). Airborne imaging sensors can record these effects and provide an accurate, timely means of assessing the extent of the damage and identifying management units for time-critical material applications. This approach has been used extensively and successfully with aerial photographs (Toler et al., 1981; Blakeman, 1990) for determining the spread of crop disease and insect infestation, and the efficacy of applications of herbicide, defoliant, and water. Nutter (1989) found that he could track disease gradients in peanuts by quantifying leaflet defoliation with measurements of NIR crop canopy reflectance. Currently available airborne sensors have the capacity to provide digital images within a few hours of acquisition to allow proper management of these time-critical problems.

Thus, we suggest the following:

8. For TCCM, multispectral images from aircraft-sensors could be used as a quick means of assessing the extent of the damage and identifying management units for damage control.

TECHNICAL LIMITATIONS OF REMOTE SENSING

Aircraft and Satellite Image Processing

Most of the remote sensing applications recommended for PCM in this review are "quantitative"; that is, they are based on measurements of surface physical properties such as reflectance, temperature, or SAR backscatter, not on an uncalibrated, uncorrected digital number (DN). Thus, a significant barrier to implementation of most remote sensing techniques is the conversion of digital images to information on surface properties that is temporally comparable and geometrically correct. This conversion generally involves instrument calibration, atmospheric correction, normalization for off-nadir viewing effects, cloud screening (for satellite-base images), and such procedures as vignetting correction, line-shift correction, band-to-band registration, and frame mosaicing (for video- or digital-camera multispectral images). For use in a GIS, the images must subsequently be registered to map coordinates (e.g., UTM). For most applications of RS in PCM, these procedures must be automated for quick turnaround, yet accurate for minimizing management-related risk. Some promising options for processing images for PCM applications are discussed in this section.

Instrument Calibration
Instrument calibration is no longer a serious impediment to the use of satellite-based sensors because most or-

biting sensors have on-board calibration instrumentation and some are regularly calibrated with in-flight procedures (e.g., Slater et al., 1987). This is not the case for video and digital cameras aboard small aircraft. For such sensors, calibration has been attempted in preflight, laboratory settings (Crowther, 1992), but this approach is often not appropriate since the conditions aboard the aircraft differ significantly from those in the laboratory and some sensors cannot be calibrated due to automatic gain compensation. On the other hand, there are viable options for in-flight calibration based on intercalibration of side-by-side mounted uncalibrated video systems and calibrated radiometers (Neale et al., 1995) and (for reflected data) conversion of digital number to apparent reflectance based on side-by-side mounted up-looking and down-looking sensors (Piekotowski et al., 1996). The latter approach has additional merit since it provides a partial atmospheric correction by accounting for within-flight variations in insolation; however, the output is *apparent* reflectance, not surface reflectance. Commercially available thermal video systems generally provide a digital number to apparent temperature (i.e., at-sensor temperature without atmospheric correction) conversion for each frame.

Atmospheric Correction

Great strides have been made in simplification and speed of atmospheric correction of optical images through development and refinement of radiative transfer models (RTM). For most satellite-based sensors, existing RTMs have been used to develop simple lookup tables (LUT) that compute relations between at-satellite radiance and surface reflectance and/or temperature based on a minimum number of atmospheric inputs (Rahman and Dedieu, 1994) or on input from the image itself (Teillet, 1992; Gonima, 1993). With these tools, digital images from calibrated satellite-based sensors can be converted quickly to images of surface reflectance or temperature with considerable accuracy. Again, these tools are not suitable for aircraft-based sensors that are flown at variable altitudes within the atmosphere, that have spectral response functions different from those of orbiting sensors, and that are generally not calibrated. Thus, alternative approaches that circumvent the need for RTM have been used for airborne sensors in the optical region. Some based on simple linear regression with such ground-based targets as pseudo-invariant objects (Muller and James, 1994), reflectance tarps of a constant reflectance over a spectral region (Moran et al., 1996a), and painted plywood (Richardson et al., 1993). Such methods have two disadvantages: 1) They require that a pseudoinvariant object be available within the image or that a reference target be deployed during flight, and 2) they do not account for spatially or temporally variable atmospheric conditions (such as variable cirrus clouds) during flight. *Relative* correction procedures have been proposed based on image processing techniques such as histogram equalization and dark object subtraction (Chavez, 1988). Though these methods are useful for temporal comparison of images, they do not provide absolute reflectance and temperature information, and, in some cases, the result is greater error than no correction at all (Moran et al., 1992). In-flight SAR calibrations are generally based on corner reflectors deployed on the ground at strategic locations during the flight.

Atmospheric correction of single-band thermal images is generally accomplished through the use of RTMs based on estimates or measurements of atmospheric water vapor (Kaufman, 1989). However, there is repeated evidence that, for clear sky conditions (high visibility and low water vapor content), the correction of thermal images over land surfaces may not be necessary because the atmospheric absorption is approximately compensated by the path radiance emitted by the atmospheric constituents (Sugita and Brutsaert, 1993; Bartolucci et al., 1988). Another concern in the use of thermal data is the conversion from radiometric temperature (measured by the sensor) to kinetic temperature (true surface temperature corrected for emissivity). A recent issue of *Remote Sensing Environment* (Vol. 42, 1992) was dedicated to measurement and separation of kinetic temperature and spectral emissivity. An approach that has promise for operational mapping of thermal emissivity, and thus retrieval of kinetic temperature from radiometric temperature, was based on the relation between emissivity and NDVI (Van de Griend and Owe, 1993).

Normalization of Off-Nadir Effects on Optical Data

Off-nadir viewing, due to either pointable sensors (e.g., SPOT HRV) or the wide-angle field-of-view of the sensors (e.g., NOAA AVHRR or airborne video systems) has two major effects on optical images: 1) the influence of the atmosphere is increased due to a longer path from sensor to ground (relative to a nadir view at the same altitude) and 2) the measured surface reflectance or temperature varies with the nonlambertian characteristics of the surface. The first effect can be adequately corrected with appropriate atmospheric correction procedures, as discussed by Martonchik (1994). The second effect requires some knowledge of surface conditions for normalization, where normalization consists of converted off-nadir measurements to those that would be measured with a nadir-looking sensor or to a hemispherical spectral albedo. Attempts to normalize bidirectional effects through band ratioing, such as NDVI, have been unsuccessful since the bidirectional response varies in the visible and NIR spectrum (Qi et al., 1993); in fact, band ratioing could worsen the problem (Cihlar et al., 1994). In a simple approach, Moran et al. (1990) proposed that the bidirectional reflectance distribution function (BRDF) along a single azimuthal plane was similar for several rough agricultural surfaces and a correction based

on a single algorithm could be applied. For greater accuracy, canopy BRDF models have been proposed based on either information about the canopy geometry or measurements of multiple off-nadir views from which information about the canopy can be derived. The use of BRDF models to normalize off-nadir viewing effects has been successfully applied with either multiple acquisitions from pointable sensors or with the overlapping multidirectional views provided by airborne video or digital cameras (Qi et al., 1995b; Pickup et al., 1995) and represents a viable option for correction of surface-related bidirectional effects on reflectance measurements. Another approach, as mentioned earlier, is to circumvent the normalization process and, instead, use the additional information provided by bidirectional measurements to compute biophysical parameters such as LAI and percent vegetation cover (Qi et al., 1995a; Myneni et al., 1995). This approach has great promise for application with pointable sensors or overlapping video frames. There is also evidence that view angle has a significant effect on temperature measurements; Lagouarde and Kerr (1993) stressed the need for directional thermal infrared models.

Cloud Screening
One characteristic of SAR data that makes it desirable for agricultural applications is the ability to penetrate clouds and obtain imagery regardless of cloudy conditions. Unfortunately, optical wavelengths are absorbed or reflected by clouds, resulting in either degraded images that must be screened for clouds or no image at all. Generally, cloud screening is accomplished using statistical methods with histogram analysis (Phulpin et al., 1983), threshold tests applied to different combinations of channels (Saunders and Kreibel, 1988), or pattern recognition based on spatial (Ebert, 1987) or temporal (Gutman et al., 1987) analysis. The most successful methods are generally based on the combined analysis of both visible and thermal infrared data (Derrien et al., 1993; Gutman et al., 1994), though adequate screening can be obtained based on either wavelength region separately (França and Cracknell, 1995). The other concern related to clouds is the ability to obtain an image at a given time of year or a time series of high-quality images. Marshall et al. (1994) concluded that for study of relatively stable features, the 16-day repeat cycle of Landsat would suffice; but for monitoring short-term events or obtaining time-critical acquisitions, it may be necessary to combine images obtained with both optical and SAR sensors. They found that frequency of imagery "with little cloud cover" within the European Arctic sector was between 7 and 54% of the total possible acquisitions, depending upon region.

Processing Images from Airborne Video and Digital Cameras
There is no question about the usefulness of airborne cameras for agricultural applications. The desirable char-

acteristics include low cost, real-time imagery, flexible spectral bands and band widths, and data redundancy due to overlapping frames (Mausel et al., 1992). The disadvantages are also well documented, including line-shifting in video frames, vignetting effects, bidirectional reflectance variations due to wide fields-of-view, band-to-band misregistration, and difficulties in frame registration and mosaicing. However, as the popularity of such systems increases, advancements in automated image processing have been proposed. Vignetting effects are generally corrected with a sensor-specific filtering function (Neale et al., 1995). There are several procedures that show promise for automated correction of video line-shifting and band-to-band registration (Pickup et al., 1995; Mitchell et al., 1995) and correction of bidirectional effects based on the overlap of video frames (Pickup et al., 1995; Qi et al., 1995b). However, there has been little progress in automated frame registration and mosaicing to produce seamless regional images. Unlike images obtained with satellite-based sensors for which a single geometric registration procedure can be used for a large region, aircraft-based systems generally result in a multitude of frames that must be registered separately and mosaiced for local or regional coverage. Current manual procedures produce high-accuracy registration but are based on time-consuming, tedious registration of ground control points with individual frames; automated mosaicing can be achieved with in-flight tagging of individual frames with information on yaw, pitch, and roll of the aircraft and GPS location coordinates, but the accuracy of the mosaiced images is on the order of 20 pixels. Methods for obtaining timely, geometrically accurate maps from video or digital frames obtained with airborne cameras are not yet available. This is a serious limitation for operational use of such imagery for PCM applications where the 20 pixel accuracy provided by automated methods is not sufficient.

Instrument Design
One of the greatest obstacles to incorporation of RS images in PCM will be the inherent limitations of currently available sensors. Satellite-based sensors have the advantages of good geometric and radiometric integrity; the disadvantages include fixed spectral bands that may be inappropriate for a given application, spatial resolutions too coarse for within-field analysis, inadequate repeat coverage for intensive agricultural management, and long time periods between image acquisition and delivery to user. A variety of image processing techniques have been proposed to remedy these shortcomings, including techniques to merge images of differing spatial and spectral resolutions to improve the spatial resolution of the coarser image (Moran, 1989), attempts to "unmix" coarse spectral- and spatial-resolution reflectance and thermal data (Caselles et al., 1992), proposals to use

modeling to supplement intermittent image acquisitions (Moran et al., 1995), and attempts to combine images of differing sensors and different spectral and spatial resolutions to increase the number of acquisitions during a specific time period (Moran, 1994). Delivery times for most satellite-based sensors has recently improved, and images are now available (at a significant additional cost to the buyer) within 48 h of acquisition. Though sensors aboard airplanes, helicopters, and zeppelins will be able to meet the requirements for fine spatial resolution, flexible and narrow spectral bands, frequent repeat coverage, and quick turnaround times, the previously discussed difficulties in calibration and geometric correction may preclude such data from many applications. The new digital cameras will allow larger area coverage in each frame (up to 1024×1024 pixels) and there is hope that the upcoming launch of commercial satellites (described in the next section) will meet some of the stringent time, space, and spectral needs of PCM applications [see review by Fritz (1996)].

SYNTHESIS

In this section, we propose an approach for evaluation of the usefulness of current and proposed aircraft- and satellite-based sensors for PCM applications (tractor-based sensors are not considered here). This approach is based on the concept that each PCM application has requirements for management unit size, turnaround time from image acquisition to map product, image coverage and repeat acquisitions, and optimal spectral regions. Correspondingly, each sensor has defined pixel resolution, image delivery and processing times, repeat cycle, and spectral wavelengths. These application requirements and sensor attributes need only be matched to see if a certain application can be implemented with a given sensor. We applied this concept to the applications identified in two sections before and some current aircraft- and satellite-based sensors.

Synthesis Approach
The first step was to evaluate the attributes of current aircraft- and satellite-based sensors (Table 1) relative to requirements for PCM applications listed two sections before. Such evaluation was based on the following criteria developed to determine appropriate pixel resolution, image turnaround time, and sensor repeat cycle.

Pixel Resolution
The relation between the size of the management units for each application and the appropriate sensor pixel resolution must account for sensor optics, atmospheric interference, image registration accuracy, and detector signal/noise ratio. That is, the sensor pixel resolution (PR,

m) needed for the PCM management unit (MU, *m*) is a function of the sensor signal-to-noise ratio ($f_{S/N}$) and the geometric registration accuracy (f_{RA}), where

$$PR = MU/(f_{S/N} + f_{RA}),\qquad(1)$$

where the functions $f_{S/N}$ and f_{RA} are factors that must be considered when determining the PR that can best discern information about the MU (note the dimension of *m* for PR and MU in the equation refer to the side of a square area). $f_{S/N}$ is a function of the sensor signal-to-noise ratio related to sensor optics and atmospheric interference. For optical sensors, a number of pixels are contaminated by edge effects of the MU due to atmospheric scattering (often termed "adjacency effect") and sensor modulation transfer function (MTF) (Slater, 1980). For SAR data, low sensor S/N results in "speckle" which must be filtered, resulting in a degradation of PR. For aircraft-based video cameras flown at 2300 m, Moran et al. (1996a) found that $f_{S/N} = 10$ (e.g., PR must be 1 m to manage an MU of 10 m) based on analysis of uniform targets. f_{RA} is a function of the image registration accuracy (RA); thus, assuming the accuracy of registration is to within 1 pixel, $f_{RA} = 1$; otherwise, $f_{RA} > 1$.

There are other considerations in determination of PR for PCM applications. In some cases, the objective of using RS is not to characterize an MU, but rather to determine the edge of an anomaly, such as a weed infestation. In that case, Eq. (1) could still be used to determine PR but the left side of the equation would be the "edge width" and $f_{S/N}$ would be smaller than the value needed to characterize an entire MU. One must also consider the unique case in which the objective is *early detection* of a seasonally variable anomaly (e.g., insect infestation) to avoid extreme economic damage. In such cases, PR must be fine enough to detect a very small MU.

Turnaround Time
The turnaround time (T_T) is the total time the user can afford to postpone treatment while waiting for the desired, processed information. Thus, T_T includes both the delivery time from acquisition to user and the processing time for conversion of raw data to information. The relation between T_T, image delivery time (T_D) and processing time (T_P) is

$$T_T > T_D + T_P.\qquad(2)$$

The estimates of image T_D from acquisition to user for the sensors listed in Table 1 are the best times quoted by the companies responsible for delivery. Expedition comes at a cost. For example, 3-day delivery of Landsat TM scenes from EOSAT Corp. will result in image costs of three times the normal price. Regarding processing time, estimates had to be made of the time it would take to process the aircraft- or satellite-based data. For aircraft-based data, we assumed that all preprocessing

Table 1. Some Current Satellite-Based Sensors along with Their Spectral Regions, Pixel Resolution, and Orbital and Delivery Characteristics

Satellite	Sensor	Spectral Region			Pixel Resolution (PR)	Orbital Characteristics	Repeat Cycle	Time of Data Acquisition	Delivery Time from Acquisition to User (T_D)
		Reflective (μm)	Thermal (μm)	Microwave (GHz)					
GOES-1 to GOES-5	Visible and Infrared Spin Scan Radiometer (VISSR)	0.55–0.70	10.5–12.6		Acquired at 1 km, archived at 8 km	Geostationary	Stationary	Every 30 min	Instantaneous at ground station
METEOSAT	VISSR	0.4–1.1, 5.7–7.1	10.5–12.5		Acquired at 1 km, archived at 8 km	Geostationary	Stationary	Every 30 min	Instantaneous at ground station
NOAA-12, 14	Advanced Very High-Resolution Radiometer (AVHRR-2)	0.58–0.68, 0.725–1.1	3.55–3.93, 10.5–11.5, 11.5–12.5		1.1 km (Local Area Coverage), 4 km (Global Area Coverage)	Near-polar, sun-synchronous	12 h, every 9.2 days	19.30 (ascending) and 07.30 (descending)	Instantaneous at ground station
Landsat-5	Thematic Mapper (TM)	0.45–0.52, 0.52–0.60, 0.63–0.69, 0.76–0.90, 1.55–1.75, 2.08–2.35	10.4–12.5		30 m (Vis-IR), 120 m (thermal IR)	Near-polar, sun-synchronous	16 days	Late morning	72 hours at best, generally 2 weeks to 1 month
SPOT-1 to SPOT-3	High Resolution Visible (HRV)	0.50–0.75, 0.50–0.59, 0.62–0.66, 0.77–0.87			10 m (panchromatic), 20 m (multispectral)	Near-polar, sun-synchronous	26 days, and pointing capability provide shorter cycles	Late morning	48 hours at best, generally 2 weeks to 1 month
IRS-1C	Panchromatic Linear Imaging Self-Scanning III (LISS-III)	0.50–0.75, 0.52–0.59, 0.62–0.68, 0.77–0.86, 1.55–1.70			5.8 m, 23 m (70 m for 1.44–1.70 band)	Near polar, sun-synchronous	24 days, and pointing coverage for shorter cycle with panchromatic sensor	Late morning	72 hours at best, generally 2 weeks to 1 month
ERS-1 to ERS-2	Active Microwave (AM-I), Along-Track Scanning Radiometer (ATSR)	1.6, 3.7	11, 12	5.3 VV (C-Band)	1 km (Optical) 30 m (3 looks, SAR) 100 m (@ radiometric resolution of 1 dB)	Near-polar, sun-synchronous	3 days	Mid-morning and late-evening	48 hours at best, generally 2 weeks to 1 month
JERS-1	Optical Sensor (OPS), Visible and Near IR (VNIR) Radiometer, Short Wavelength, InfraRed (SWIR), Radiometer Synthetic Aperture Radar (SAR)	0.52–0.60, 0.63–0.69, 0.76–0.86, 1.60–1.71, 2.01–2.12, 2.13–2.25, 2.27–2.40		1.275 HH (L-band)	20 m (OPSVNIR and SWIR) 18 m (3 looks, SAR)	Near-polar, sun-synchronous	44 days	Mid-morning and late-evening	48 hours at best, generally 2 weeks to 1 month
RADARSAT	Synthetic Aperture Radar (SAR)			5.3 HH (C-band)	28 m (4 looks, standard product)	Near-polar, sun-[synchronous]	24 days	Mid-morning and late-evening	48 hours at best, generally 2 weeks to 1 month

Figure 1. Estimated requirements for management unit size and image turn-around time for PCM applications identified in the third section (summarized in Table 2). Also included are the sensor specifications [according to Eqs. (1)–(3)] for the Landsat5 Thematic Mapper sensor for measurements of surface reflectance and temperature (L5R and L5T, respectively) and the SPOT High Resolution Visible (HRV) sensor for multispectral and panchromatic bandwidths (SMS and SP, respectively). The black dashed lines delineate nonexclusive regions that might be best for tractor-based, handheld, small-aircraft-based, or current satellite-based sensors. Note that both axes are based on a logarithmic scale (also in Figs. 2 and 3).
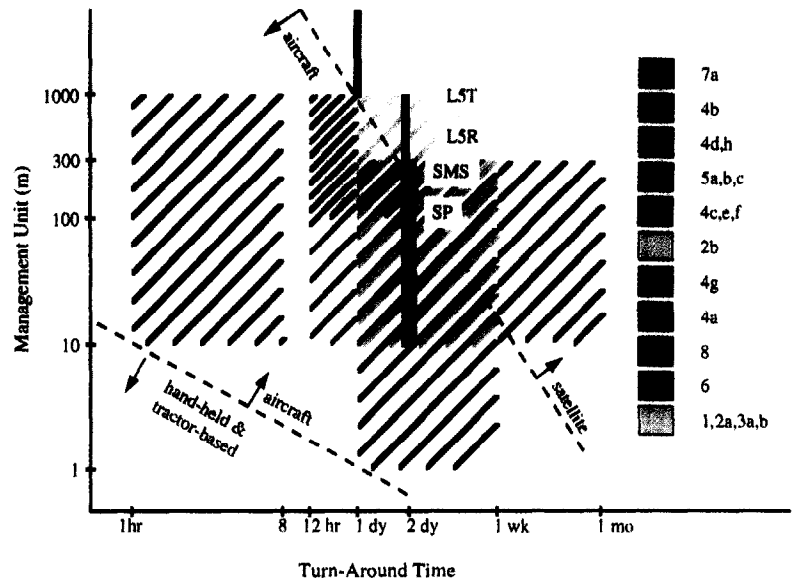
(frame grabbing, correcting for vignetting, line-shifting, and band-to-band registration) would be automated and would take 4 h. We took into account two types of geometric registration and mosaicing. Manual registration, based on ground control points, would take 30 min per frame and we limited the time to 8 h, allowing only 16 frames to be registered to an accuracy of 1 pixel ($f_{RA}=1$). Automated registration, based on a GPS and information about pitch, yaw and roll, would take 4 h for up to 100 frames and would result in registration accuracy of 20 pixels ($f_{RA}=20$). For satellite images, we estimated that cloud screening and manual geometric registration ($f_{RA}=1$) would take 8 h total. For all optical images, atmospheric correction would be accomplished in 4 h; it would be accomplished using an LUT-based RTM for satellite-based data, and deployment of reference targets during flight for aircraft-based data. Correction for bidirectional effects would be accomplished with a modeling approach and would take another 4 h. Thus, the following are estimates of processing time (under best conditions) for aircraft- and satellite-based images:

- Processing aircraft-based frames with manual registration: 24 h, $f_{RA}=1$, 16 frames
- Processing aircraft-based frames with automatic registration: 20 h, $f_{RA}=20$, 100 frames
- Processing optical satellite-based images: 16 h, $f_{RA}=1$

Repeat Cycle

The revisit period (RP) is the user's requirement for repeat image acquisitions for the specific farm management application. To meet PCM revisit requirements, one must account for cloud interference in optical image acquisition and scheduling conflicts with pointable sensors. There is evidence that in many locations three out of every four possible satellite acquisitions will have ex-

cessive cloud interference (Marshall et al., 1994). Though the flexibility of pointable satellite-based sensors allows a greater chance of acquiring cloud-free images, Moran (1994) found that up to three fourths of the requested images were usurped by the requests of other users. Thus, RP for sensors on a fixed repeat cycle (RC) should be a function of the probability (0 to 1) of cloud interference (f_C) and of scheduling conflicts with other users (f_S), where

$$RC=RP[1-(f_C+f_S-f_Cf_S)], \qquad (3)$$

and both f_C and f_S can be as large as 0.75 for satellite-based sensors. Aircraft-based systems will have more flexibility.

In some cases, the RP required by the application is coarse (e.g., requests every 6 months) but the timing of the request is crucial and inflexible (e.g., linked to crop phenology or the time of other sampling). In such cases, the use of orbiting, pointable sensors may be cost prohibitive. For example, SPOT Image Corp. charges an extra $2000 (nearly twice the normal cost) for requests of image acquisitions guaranteed on a certain date or in a narrow time interval.

Synthesis Demonstration

For each PCM application, we made estimates of the logical size of the management unit (ranging from 1 m to 1 km), the turnaround time from image acquisition to map product, the requirements for image coverage and repeat acquisitions, and the potential spectral region. Based on Eqs. (1)–(3) and these estimates of MU, T_T, and RP, it was possible to make a tentative synthesis of opportunities and limitations for each PCM application with existing sensors. As an example, the specified application requirements were plotted by attributes of the Landsat5 TM and SPOT3 HRV sensors. In each case,
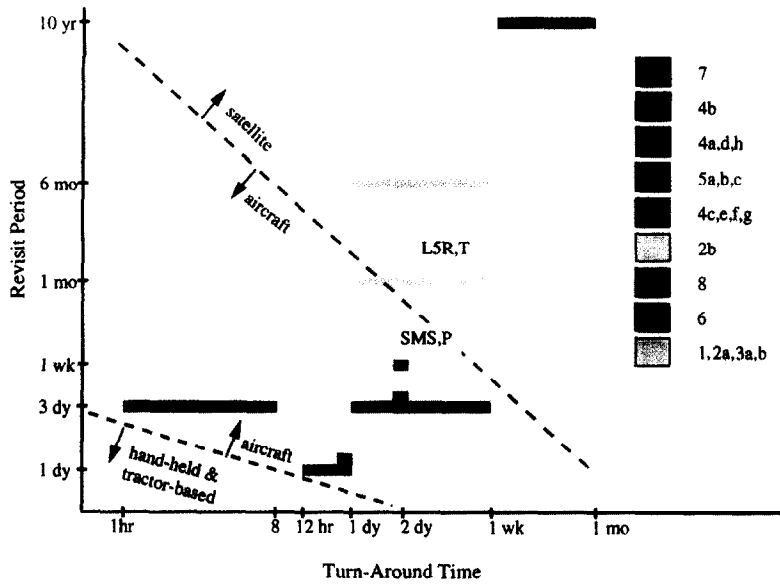
Figure 2. Estimated requirements for sensor revisit period and image turn-around time for PCM applications identified in the third section (with same internal labeling as Fig. 1).

we assumed $f_{S/N}=10$, $f_{RA}=1$, $T_D=48$ h, $T_P=16$ h, and RC=16 days for TM and 3 days for HRV. It is apparent from the results presented in Figures 1–3 that such satellite-based sensors have limited application for seasonally variable conditions in PCM, mainly because they are constrained by infrequent repeat cycles and coarse pixel resolution.

Dashed lines were drawn on Figures 1–3 to delineate the PCM applications that might have greatest potential for current satellite-based sensors or sensors mounted on small aircraft. These delineations are not exclusive since many applications could be accomplished with both aircraft- and satellite-based sensors or ground- and aircraft-based sensors. Potential for use of upcoming satellite sensors and sensors aboard large aircraft are discussed in the next section.

RECOMMENDATIONS

The following general recommendations for the use of RS in PCM are based on our estimates of PCM application requirements and an assessment of current RS technology (Figs. 1–3). Considering that both RS and PCM technology and methodology are rapidly improving, these recommendations may quickly be obsolete. Nonetheless, recommendations for feasibility were made in Table 2 and organized into four groups for discussion: images from current satellite-based sensors, raw and calibrated images from aircraft-based sensors, and images from future satellite-based sensors.

Though currently orbiting pointable sensors can provide the pixel resolution and frequent revisit required for many applications, it is still difficult to obtain images for
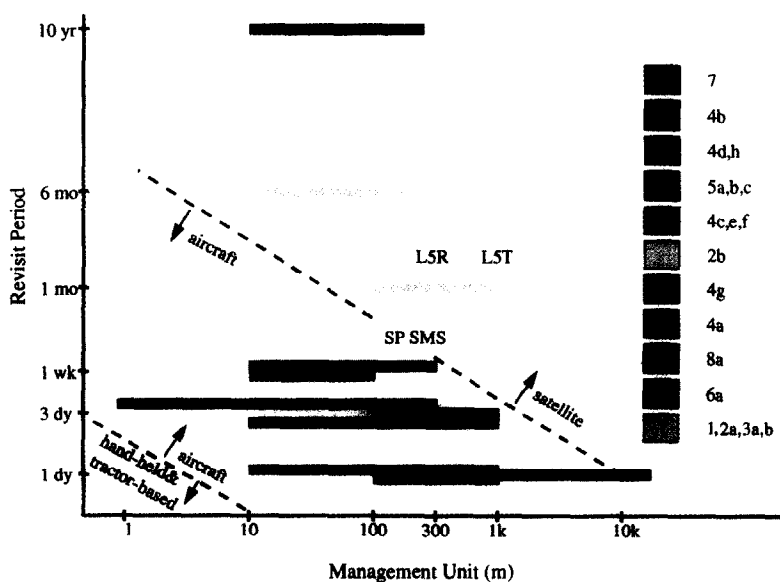

Figure 3. Estimated requirements for sensor revisit period and management unit size for PCM applications identified in the third section (with same internal labeling as Fig. 1).

Table 2. Evaluation of RS as a Source of Information for PCM Applications Using Sensors Aboard Small Aircrafts, Sensors Aboard Currently Orbiting Satellites, and Sensors Planned for Future Commercial Satellites.[a]

	Ar	Ac	CS	FS
Converting Point Samples to Field Maps				
1. On-site measurements of soil and crop properties could be combined with multispectral imagery to produce accurate, timely maps of soil and crop characteristics for defining precision management units	✓	✓	✓L	✓
Mapping Crop Yield				
2a. Multispectral images obtained late in the crop growing season could be used to map crop yields with approaches as simple as regression or in combination with agro-meteorological models	✓	✓	✓L	✓
2b. Remote sensing information could be combined with crop growth models to predict final yield		✓	✓L	✓
Mapping Soil Variability				
3a. Multispectral images obtained when soils are bare could be used to map soil types relevant to PCM with approaches based on models and/or on analysis of single or multiple image acquisitions	✓	✓	✓L	✓
3b. Maps of spectral variability (obtained under conditions of either bare soil or full crop cover) may prove useful for revision of maps of management units	✓	✓	✓L	✓
Monitoring Seasonally Variable Soil and Crop Characteristics				
4a. Soil moisture content		✓		
4b. Crop phenologic stage		✓		✓
4c. Crop biomass and yield production		✓		✓
4d. Crop evaporation rate		✓		
4e. Crop nutrient deficiencies	✓W	✓		✓
4f. Crop disease	✓W	✓		
4g. Weed infestation		✓		✓
4h. Insect infestation	✓W	✓		✓
Determining the *Cause* of the Soil/Crop Variability				
5a. RS could providing accurate input information for agricultural decision support systems (DSS)		✓		✓
5b. RS information could be combined with agro-meteorologic models to determine cause of soil/crop variability		✓		✓
5c. Hyperspectral sensors could be used to determine cause of soil and crop variability		✓		✓
Mapping Spatially Distributed Information on Meteorological/Climate Conditions				
6. Multispectral images of coarse spatial resolution and fine temporal resolution should be used to produce local or regional maps of meteorological parameters such as insolation, PAR, rainfall, and others			✓	
Producing Fine-Resolution Digital Elevation Data				
7. Accurate, fine-resolution DEMs could be produced from stereopairs of aerial or satellite images	✓	✓	✓	
Addressing Time-Critical Crop Management (TCCM) Applications				
8. For TCCM, multispectral images from aircraft-sensors could be used as a quick means of assessing the extent of the damage and identifying management units for damage control	✓			

[a] A: data from sensors aboard small aircrafts, where Ar: raw image data and Ac: calibrated data converted to values of reflectance, temperature or SAR backscatter; CS: data from sensors aboard currently orbiting satellites; FS: data from sensors planned for future commercial satellites. The check mark (✓) indicates that the application is appropriate for the designated sensor; ✓L indicates that the application is appropriate, however the fields must be large; and ✓W indicates applications which are only appropriate "within fields" because the data are not calibrated and cannot be reliably compared over time or space.

specific dates (due to conflict with other users and excessive costs). Thus, many applications may not be feasible with currently orbiting, pointable sensors. There is more flexibility in applications that require an image during bare soil conditions than in those requiring images during specific crop phenologic stages. Another big limitation of currently orbiting satellite sensors for PCM is revisit time. If you can only expect to obtain one of four acquisitions, then even coverage with a pointable sensor may be available only every 12 days (Moran, 1994). The most promising approaches to overcome this limitation may be synergy of data from multiple sources and use of physical models to supplement intermittent RS information.

On the whole, current satellite-based sensors have little potential for most PCM applications due to coarse spatial resolution and long repeat cycles. However, they may be useful for mapping local or regional meteorological parameters and producing high-resolution, accurate DEMs. For very large fields, current satellite-based sensors could have limited utility in converting point samples to field maps of soil and crop properties, mapping seasonally stable crop or soil variability, and predicting final field-scale yield.

Regarding aircraft-based images, difficulties in calibration and geometric correction may preclude data from small aircraft for use in many applications. Only those applications that require single field coverage are suitable for single frame video applications. Whole-farm applications will require some frame mosaicing but may be feasible with manual registration. Applications covering the local area will likely require an automated registration procedure.

The options best suited for raw data from aircraft-based sensors (uncalibrated and not atmospherically corrected) include converting point samples to field maps of soil/crop properties, mapping crop/soil conditions with regression equations, revising maps of management units within season, and mapping damage based on on-site

Table 3. Some Upcoming Satellite-Based Sensors along with Their Spectral Region, Pixel Resolution, and Orbital Characteristics

Satellite	Sensor	Spectral Region			Pixel Resolution (PR)	Orbital Characteristics	Off-Nadir Repeat Cycle	Time of Data Acquisition (h:min)	Delivery time from acquisition to user (T_D)
		Reflective (μm)	Thermal (μm)	SAR (GHz)					
EOS-AM (launch in 1998)	Moderate Resolution Imaging Spectrometer (MODIS-N)	MODIS 0.66–0.87 (2 bands), 0.47–2.13 (4 bands), 0.42–0.94 (12 bands)	3.8–14.2 (17 bands)		MODIS 0.25 km (visible, NIR), 0.5 km (Vis, NIR, SWIR), 1 km (Vis, NIR, TIR)	Polar orbiting, sun-synchronous	MODIS 1–2 days	10:30	48 h
	Advanced Space Born Thermal Emission and Reflectance Radiometer (ASTER)	ASTER 0.52–0.86 (3 bands), 1.60–2.43 (6 bands)	8.3–11.3 (5 bands)		ASTER 15 m (visible, NIR), 30 m (SWIR), 90 m (thermal)		ASTER VNIR 5 days SWIR&T 16 days		
	Multi-angle Imaging Spectro Radiometer (MISR)	MISR 0.40–0.88 (4 bands)			MISR 240 m, 192 km		MISR 9 days		
ADEOS (launch in 1996)	Advanced Visible and Near InfraRed (AVNIR) Radiometer	AVNIR 0.52–0.72 0.40–0.50 0.52–0.62 0.62–0.72 0.82–0.92			AVNIR 8 m (panchromatic), 16 m (visible, NIR)	Polar orbiting, sun-synchronous	41 days. global coverage every 3 days. AVNIR daily	10:30 equitorial cross time	48 h
	NASA Scatterometer (NSCAT)			NSCAT 13.99	NSCAT 25 km				
	Polarization and Directionality of the Earth's Reflectance (POLDER)	POLDER 0.43–0.96 (8 bands)			POLDER 5 km				

Earth Watch	Early Bird (launch 1997)	Early Bird 0.45–0.80 0.50–0.59 0.61–0.68 0.79–0.89	Early Bird 3 m (panchromatic), 15 m (multispectral)	Inclination 97.3°, sun-synchronous	3 days	Late morning	15 min to 48 h
	QuickBird (launch 1998)	QuickBird 0.45–0.90 0.45–0.52 0.53–0.59 0.63–0.69 0.77–0.90	QuickBird 1 m, 2 m (panchromatic), 4 m (multispectral)				
Space Imaging	Space Imaging System (SIS) (Launch 1997)	0.45–0.90 0.45–0.52 0.52–0.60 0.63–0.69 0.72–0.90	1 m (panchromatic), 4 m (multispectral)	Inclination 98.1°, sun-synchronous	1–3 days	Late morning	24–48 h
Orbital Sciences	OrbView-1 (launch 1997)	0.45–0.90 0.45–0.52 0.52–0.60 0.63–0.69 0.76–0.90	1 m, 2 m (panchromatic), 8 m (multispectral)	Inclination 97.3°, sun-synchronous	<3 days	Late morning	15 min to 48 h
Resource 21	Resource 21 (launch 1999)	0.45–0.52 0.53–0.59 0.63–0.69 0.76–0.90 1.55–1.65 1.23–1.53	10 m (visible/NIR), 10 m (SWIR 1.55–1.65), 100 m (SWIR 1.23–1.53)	Inclination 98.4°, sun-synchronous	Twice in 25 min (with 4 satellites)	Late morning	Unknown

Table 4. Some Sensors aboard Large Aircraft

Sensor	Number of Channels	Spectral Bandwidth (μm)	Spectral Sampling Interval	Sensor Resolution	Reference
Advanced Solid-State Array Spectrometer (ASAS)	30	0.45–0.88	14 nm	0.85 mrad	Irons et al., 1991
Airborne Visible-Infrared Imaging Spectrometer (AVIRIS)	220	0.41–2.45	9.4–9.7 nm	20 m	Vane, 1987
Thermal Infrared Multispectral Scanner (TIMS)	8	8.2–12.2	0.4–1.4 μm	2.5 mrad	Aircraft Data Facility, NASA-Ames Research Center, Moffet Field, CA
Thematic Mapper Simulator (TMS-NS001)	8	0.45–12.3	0.06–1.4 μm	2.5 mrad	Aircraft Data Facility, NASA-Ames Research Center, Moffet Field, CA
Thematic Mapper Simulator (TMS) Daedalus	10	0.38–14.0	0.02–5.5 μm	2.5 mrad, FOV 86°	EG&G Energy Measurements Remote Sensing Laboratory (RSL), Las Vegas, NV
Airborne MultiPod System (Daedalus, CASI, SAR)	Multisensor	Daedalus: CASI: SAR:	See TMS 0.4–0.9 μm (2 nm) Ku (15 GHz)	2.5 mrad, FOV 15–60°, 1–3 m	DOE Office of Arms Control and nonproliferation, Washington, DC

knowledge of crop conditions. The options increase for aircraft-based data that has been converted to values of surface reflectance, temperature or SAR backscatter. These include predicting final yield with models and ancillary data, monitoring seasonally variable crop and soil conditions, and determining the cause of crop/soil spatial variations (with ancillary data).

Another sensor system that is currently not being used to its potential for PCM is the fleet of large aircraft-based systems flown by NASA and some defense contractors (Table 4). These systems can provide high quality, calibrated data at fine resolutions (depending upon flight altitude) at wavelengths including hyperspectral, wide-band multispectral, and SAR. These systems are not suited for general crop monitoring purposes because of the excessive cost of deployment and the lengthy turn-around time for raw data delivery (generally 1 month to 6 months); however, they should be considered for research related to PCM, and for PCM applications with long turn-around times and infrequent revisit requirements, such as determining management units based on soil or yield variability.

Since many of the applications identified here require information at pixel resolutions from 1 m to 100 m and revisit times of 1 day to 1 week (Fig. 3), the upcoming launches of the EOS-AM and ADEOS satellites will not hold much potential for use in many PCM applications (see specifications in Table 3). However, the upcoming launches of commercial earth observation satellites (Table 3) will meet many of the PCM requirements. Data will potentially be available in panchromatic and multispectral visible and NIR wavelengths at 1–15 m pixel resolutions, respectively. The sensor repeat cycle will be every 3 days and the raw data turnaround time could be as quick as 15 min. With these sensor specifications, the biggest deterrents to use in PCM will be data management (Allan, 1990) and the effects of bidi-

rectional sensor viewing. However, since none of the planned commercial satellites will support thermal or SAR sensors, many promising RS applications for PCM discussed in previous sections will still not be possible.

CONCLUDING REMARKS

Image-based RS can provide information for many PCM applications for which information is now lacking. Some opportunities are possible for currently orbiting satellites, and many more opportunities are possible with currently available sensors aboard small aircrafts. Image-based remote sensing has a unique role for monitoring seasonally variable crop and soil conditions, and providing crop development stage information for time-specific crop management (TSCM) and near-real-time information for time-critical crop management (TCCM).

The limitations for image-based applications are mainly due to instrument design. Current satellite-based sensors have fixed spectral bands that may be inappropriate for a given application, spatial resolutions too coarse for within-field analysis, inadequate repeat coverage for intensive agricultural management, and long time periods between image acquisition and delivery to user. Aircraft-based sensors avoid these limitations, but are difficult to calibrate and the frame-based output is hard to register to map coordinates for large area coverage. There is hope that such limitations will be overcome by the upcoming launches of commercial satellite-based sensors, rapid advancements in digital camera technology, and the cooperative deployment of defense-related aircraft-based sensors for agricultural applications.

The potential market for RS products in PCM is good. Holt and Sonka (1995) envision that PCM will succeed with the collective knowledge and experience of specialists, assembled and integrated through team efforts. They foresee a long sequence of intermediate
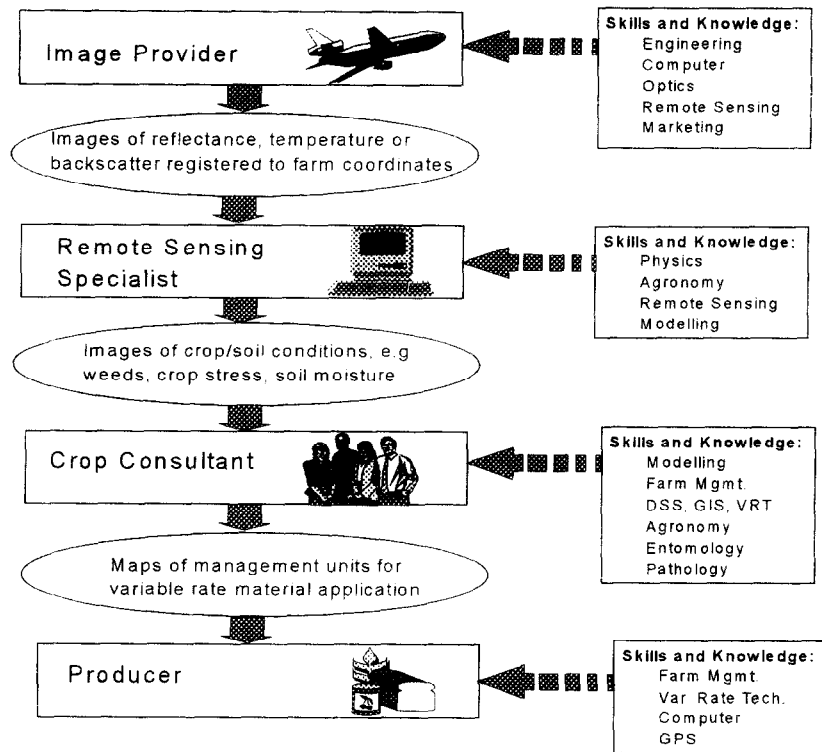
Image Provider

Skills and Knowledge:
Engineering
Computer
Optics
Remote Sensing
Marketing

Images of reflectance, temperature or backscatter registered to farm coordinates

Remote Sensing Specialist

Skills and Knowledge:
Physics
Agronomy
Remote Sensing
Modelling

Images of crop/soil conditions, e.g weeds, crop stress, soil moisture

Crop Consultant

Skills and Knowledge:
Modelling
Farm Mgmt
DSS, GIS, VRT
Agronomy
Entomology
Pathology

Maps of management units for variable rate material application

Producer

Skills and Knowledge:
Farm Mgmt
Var Rate Tech.
Computer
GPS

Figure 4. An infrastructure that may lead to widespread adoption of image-based remote sensing for precision crop management.

products, where each item of information and technology will fit in the PCM system and each "value-added" product will have a market. Some team members will simply purchase components and services from specialized suppliers and merely assemble the final product. Searcy (1995) predicted that much of the collection of spatial data for PCM will be done by contract, on a fee-for-service basis. This scenario bodes well for use of RS in PCM since the acquisition and processing of spectral data is a specialized science with a defined product.

An infrastructure that may have promise for incorporating aircraft- or satellite-based RS technology into PCM is illustrated in Figure 4. There appear to be three stages of image processing that could lead to a useful product for farm managers. In stage one, the images are acquired and processed to values of surface reflectance, temperature or SAR backscatter and registered to farm coordinates. This requires engineering skills for instrument development, knowledge of optics (possibly atmospheric science), understanding of remote sensing, and expertise with computers. In the next stage, these images are converted to physical crop and soil information, such as images of weed infestations, insect infestations, crop water stress, etc. This requires a background in agronomy, knowledge of physics and remote sensing, and experience in computer modeling. In the third stage, this distributed information about crop and soil conditions is interpreted with the assistance of a DSS to produce maps of management units for variable rate material application. This requires experience with DSS and GIS, understanding of modeling and farm management and a

background in agronomy. These maps are provided to the farm manager for support in farm management decisions. The farm manager should have variable rate applicators and a tractor-mounted GPS system and should be able to determine the proper management strategy for the farm. The four "entities" portrayed in Figure 4 illustrate the four requirements for skills and knowledge necessary to produce the three intermediate products; actually, a single company could encompass the skills of the first three entities and provide the final product to the farmer. However, until such an infrastructure is in place, there is little hope for widespread adoption of image-based remote sensing for PCM.

Future work should be focused on determining which RS applications listed in Table 2 are most economically beneficial and technically feasible. Season-long pilot projects with aircraft-based or satellite-based sensors designed specifically to investigate the economic and scientific viability of RS products for PCM applications should be given high priority (e.g., Moran et al., 1996b; Hough, 1993). These projects should be designed with input from the end user (farmers and consultants), and the potential commercial provider. Such validation will provide the confidence in RS that is required for technology transfer and eventual commercial development.

their thoughts on this topic, and sent us their published and draft manuscripts.

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Appendix. Acronym List

ADEOS	ADvanced Earth Observing System	LUT	Lookup Table
AM-I	Active Microwave	METEOSAT	Meterological Satellite
ASAS	Advanced Solid-State Array Spectrometer	MISR	Multi-angle Imaging Spectro Radiometer
ASTER	Advanced Spaceborne Thermal Emission and Reflectance Radiometer	MODIS-N	MOderate Resolution Imaging Spectrometer
		MTF	Modulation Transfer Function
ATSR	Along-Track Scanning Radiometer	MU	Management Unit
AVHRR	Advanced Very High-Resolution Radiometer	NDVI	Normalized Difference Vegetation Index
AVIRIS	Airborne Visible-Infrared Imaging Spectrometer	NIR	Near-Infrared
AVNIR	Advanced Visible and Near Infrared Radiometer	NSCAT	NASA Scatterometer
BRDF	Bidirectional Reflectance Distribution Function	OPS	OPtical Sensor
CASI	Compact Airborne Spectrographic Imager	OPSVNIR	OPS Visible and Near IR (VNIR) Radiometer
CCD	Charge Coupled Device	P	Panchromatic
CERES	Cereal growth model	PAR	Photosynthetically-Active Radiation
CWSI	Crop Water Stress Index	PCM	Precision Crop Management
DEM	Digital Elevation Model	POLDER	Polarization and Directionality of the Earth's Reflectance
DGPS	Differential GPS	PR	Pixel Resolution
DN	Digital Number	RA	Registration Accuracy
DSS	Decision Support System	RADARSAT	Canadian RADAR SATellite
DSSAT	Decision Support System for Agrotechnology Transfer	RC	Repeat Cycle
EOS	Earth Observing System	RP	Revisit Period
EOSAT	Earth Observation Satellite Company	RS	Remote Sensing
ERS	European Remote-sensing Satellite	RTM	Radiative Transfer Model
ET	Evapotranspiration	SAR	Synthetic Aperature Radar
f_{APAR}	Fraction Absorbed PAR	SORKAM	Sorghum growth model
f_c	Function of cloud interference	SPOT	Systeme Pour l'Observation de la Terre
f_{RA}	Function of registration accuracy	SUCROS	Crop growth model
f_s	Function of scheduling conflicts	SWIR	Shortwave Infrared
$f_{S/N}$	Function of signal/noise ratio	T_T	Turn-around time
FOV	Field of View	T_D	Delivery time
GIS	Geographic Information Systems	T_P	Processing time
GOES	Geostationary Operational Environmental Satellite	TCCM	Time-Critical Crop Management
GPS	Global Positioning System	TIMS	Thermal Infrared Multispectral TIR
HRV	High Resolution Visible	TM	Thematic Mapper
HS	Hyperspectral	TMS	Thematic Mapper Simulator
IPM	Integrated Pest Management	TSCM	Time-Specific Crop Management
IR	Infrared	UTM	Universal Transverse Mercator
IRS	Indian Remote-sensing Satellite	VEG	Knowledge-based canopy reflectance model
JERS	Japanese Earth Remote-sensing Satellite	VI	Vegetation Index
LAI	Leaf Area Index	VISSR	Visible and Infrared Spin Scan Radiometer
LISS	Linear Imaging Self Scanning Sensor	VRT	Variable Rate Technology