An Introduction to Digital Methods in Remote Sensing of Forested Ecosystems: Focus on the Pacific Northwest, USA

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ABSTRACT / Aerial photography has been routinely used for several decades by natural resource scientists and managers to map and monitor the condition of forested landscapes. Recently, along with the emergence of concepts in managing forests as ecosystems, has come a significant shift in emphasis from smaller to larger spatial scales and the widespread use of geographic information systems. These developments have precipitated an increasing need for vegetation information derived from other remote sensing imagery. especially digital data acquired from high-elevation aircraft and satellite platforms. This paper Introduces fundamental concepts in digltal remote sensing and describes numerous applications of the technology. The intent is to provide a balanced, nontechnical view, discussing the shortcomings, successes, and future potential for digital remote sensing of forested ecosystems.

During the past decade, digital remote sensing has become an increasingly important tool for mapping and monitoring forest resources around the globe. This is due, in part. to an increasing visibility and understanding of remote sensing data, in general, and to the greatly expanded use of geographic information systems (GIS). Resource scientists and managers now require spatially explicit vegetation data over extensive geographic areas, which means that traditional field survey techniques, even when coupled with aerial photography, are of limited use. Another important factor is an increased understanding that large-scale monitoring of forest conditions is practical only if digital remote sensing is included in sampling and mapping schema.

In the past several years, the authors have had numerous conversations with forest managers and scientists concerning some fundamental issues associated with the use and understanding of digital remote sensing data. Although there are several texts on the subject (e.g., Jensen 1986, *Mather 1987, Richards 1993, Lillesand and Kiefer 1994), and a rich body of technical literature, there is need for a current summary of fundamental concepts in digital remote sensing from a nontechnical perspective. In addition to providing such a perspective. this paper reviews some important research and applications of digital remote sensing in both forest management and science. For this we focus on the Pacific Northwest region of the United States. a region of the globe where remote sensing has been widely used. Finally, we discuss several important current and emerging issues in remote sensing.

Aerial photographs lairphotos) have been commonly used for decades to assist in the mapping of forest resources (Barrett and Curtis 1992, p. 12). Thus, the focus here is on other remote sensing data, such as digital aircraft and satellite images. and nonimaging radiometer measurements. To ease the transition, we begin by comparing digital imagery to airphotos, with the intent of establishing a baseline for common understanding. Throughout. we strive to present a balanced perspective, one useful in understanding both the capabilities and limitations of t-emote sensing.

KEYWORDS: Remote senslng; Geographic information systems; Forest management: Ecosystem management; Forest inventory

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General Considerations

Like airphotos. digital images record energy properties at a point in time for a portion of the Earth's surface, Using different combinations of film sensitivity and fil-

Table 1. Regions of electromagnetic spectrum most commonly used in remote sensing and approximate wavelength boundaries and sensors used in detection of energy in each region

Region	Wavelength	Sensor
Visible	0.4-0.7 μm	Reflected solar energy detected by the human eye, black and white panchromatic film, color film, and electrooptical sensors.
Reflected infrared	0.7–3.0 μm	Reflected solar energy detected by infrared-sensitive film (up to 0.9 μm) and electro-optical sensors.
Thermal infrared	3-i and 8–14 μm	Emitted surface energy detected by electrooptical thermal sensors.
Microwave	0.1 mm-l m	Emitted surface energy and reflected energy from "active" microwave transmitters detected by microwave sensors.

ters. airphotos can selectively record certain wavelength ranges of the electromagnetic spectrum. Digital sensors also use filters, but in lieu of halide crystals in a a film emulsion. they use energy detectors that are similar in concept to voltmeters. Energy incident upon a detector is converted to a digital number, commonly 8-bit, but often 9-. lO-, 12-, or 16-bit. Normally, one detector is dedicated to a single wavelength range, and multiple ranges are sensed using multiple detectors. Whereas photographic film is limited in sensitivity to a narrow range of the electromagnetic spectrum, digital sensors can operate in a much wider range of the spectrum (Table 1).

Airphotos have an inherent spatial scale that is a function of camera focal length and aircraft flying height. Although photo scale can be thought of as related to the unit area of the Earth's surface that can be resolved, resolution of airphotos is also a function of the film's halide crystal grain size (or film speed). Digital sensors also have inherent spatial properties, but rather than referring to scale, the term spatial resolution or "pixel size" is most commonly used. Digital image spatial resolution refers to the size of the individual physical sample unit on the ground that is sensed by a given detector at any instant in time. For example, a resolution of 10 m means a single digital cell contains integrated spectral information from a nominal 10-m X 10-m unit of the Earth's surface. Likewise, a l-km resolution means that an integrated signal from a l-km X l-km area of the Earth's surface was detected and recorded in a single digital cell.

Atmospheric effects are an important problem in remote sensing. Clouds, haze, and the like contaminate energy signals from the Earth's surface. Sensing geometry is another important confounding factor. Sun angle, topographic variation, and the position of the sensor relative to these all have the potential to strongly influence the energy sensed. Although atmospheric effects and sensing geometry are important problems in airphoto interpretation. they are more important problems in digital imagery. The primary reason for this is that in the former case, as photointerpreters we can bring multiple corroborative sources of information to bear on our interpretations, such as size. shape, shadow, location, and convergence of evidence (Paine 1981). In the latter case. we are only now beginning to sufficiently understand the phenomena so that we can develop models and write computer codes that minimize their effects.

Image Processing Fundamentals

Basic processing considerations for digital images include geometric correction, radiometric correction, image enhancement. thematic classification and related procedures. and change detection. Not all of these procedures are applied for every project, hut an understanding of these fundamental principles is essential for intelligent use and interpretation of digital images and maps derived from them.

Geometric Correction

Geometric corrections include compensations for distortions that prevent images from being used directly as maps. Sources of these distortions include variations in sensor altitude, attitude, and velocity, Earth curvature, and relief displacement (Lillesand and Kiefer 1994). Some distortions are systematic and well understood. As such, corrections for these are relatively straightforward to apply (EOSAT 1994). Nonsystematic and uncompensated systematic distortions are corrected by a process that uses a set of ground control points (GCPs) that are located in the imagery (Heard and others 1992). Using the GCPs, a geometric transformation is derived that projects the image into a selected map projection. During this process, the image is "resampled" by one of several techniques, whereby data values from pixel locations in the original image are used to assign values to pixels in the output, "rectified" image (Chiesa and Tyler 1994). Distortions caused by topographic relief remain generally unaffected unless a digital elevation model (DEM) data set is used during rectification. Resampling requires that an output image pixel size be declared. Commonly, the pixel size chosen is near that of the original spatial resolution, but for some applications a much different pixel size might be declared.

Geometric rectification is inexact. Error tolerance for geometric rectification is commonly given in terms of a root mean square error, which describes how well the transformation fits the GCPs (Jensen (1986). Even under the most exacting of circumstances, one can expect to find that a given ground resolution cell (pixel) is displaced at least one cell from its “true” ground location, and it often can be displaced several cells. The importance of this error is amplified when attempting to register two or more images together or an image to other map data sets. For example. the greatest problem we have encountered has been the use of digitized polygons derived from airphotos and residing in a federal agency data base in conjunction with georeferenced satellite images in our data base. With few exceptions. the polygons are shifted and/or stretched so that two or more completely different cover types are included in a single polygon. Depending on the spectral differences among the cover types, the use of these polygons in training or testing of classification algorithms can he seriously compromised.

Radiometrlc Correction

Digital images are a set of twodimensional rasters of digital numbers (DN). The two dimensions. x and y, represent geographic space, and each member of the set consists of recorded electromagnetic energy in a given wavelength range or band (Figure 1). The corollary in airphotos is the three separate, superimposed layers of color or color-infrared film. Some digital data sets contain only one hand (e.g., panchromatic visible), whereas others may contain over 200 narrow wavelength bands over the full spectrum of reflected energy from visible to short-wave infrared. Energy recorded in a digital image is more than just a function of the cover types sensed. Factors such as topography, illumination conditions, atmospheric haze, and sensor characteristics influence the quality of the imagery. Radiometric corrections involve algorithms that attempt to remove these sources of “noise” from the image, such that the data best represent the Earth’s surface features of interest.

Radiometric corrections to digital image data include calibration to known energy sources, calibration among sensors, and conversions from radiance to reflectance and temperature. For satellite images, some radiometric corrections are routinely applied before they are delivered to the user. For some applications, such as linking remote sensing to energy balance models, calculations

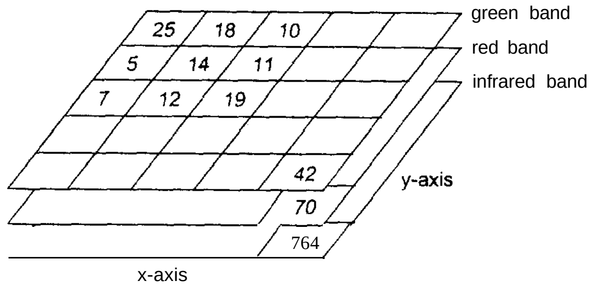

Figure 1. Structure of a digital image. The x and y axes represent geographic space and the different data lavers (bands) represent multispectral space. Each x-y cell consists of digital numbers (DN), one for each hand. When d-hit data are viewed on a computer monitor, a DN of zero appears black and a DN of 255 appears white. All other DN are linearly scaled between black and white. Three hands can be simultaneously viewed on the monitor, one through each of the three “guns,” red, green, and blue. This enables “true-color” and “false-color” viewing.

of albedo, or change detection, additional radiometric correction efforts are crucial. The most common radiometric corrections applied by users of digital remote sensing data involve algorithms for minimizing atmospheric and illumination angle effects (Teillet and others 1982 Ahern and others 1987. Hall and others 199la). The amount of literature on these two subjects is phenomenal, which is indicative of both our lack of a thorough understanding of the phenomena and of the intractability of the problems. The important thing to realize is that these corrections are only approximate. and the corrected image may still contain noise, some of which is new noise introduced by the correction algorithm.

Image Enhancement

Enhancement techniques are performed on the imagery to aid visual interpretation and to transform images into more meaningful data sets for specific digital analyses. The central purpose of image enhancement is to improve contrast among features of interest. These techniques include contrast stretches, spatial filtering, and derivation of spectral vegetation index (SVI) images.

Contrast stretching uses a transfer function to map original image intensities into a transformed image having improved contrast (Cracknell and Hayes 1991). With such stretches the pixel intensities are manipulated in a nonspatial context, i.e., irrespective of intensities of neighboring pixels. Examples include linear contrast stretching and histogram equalization, each of which alters the frequency distribution of pixel intensity values

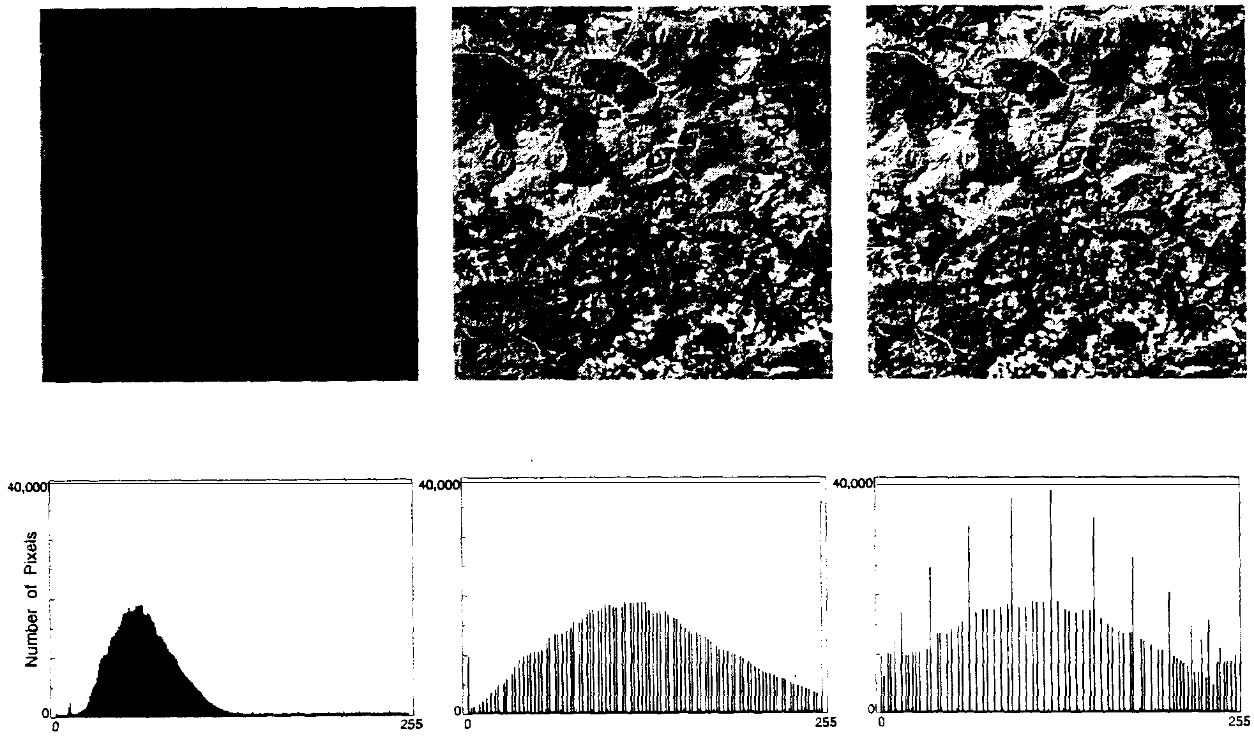

Figure 2. Different contrast stretches applied to 8-bit digital imagery left. no stretch: middle, linear stretch: and right. histogram equalization stretch. The associated frequency histograms for each stretch are shown under the images are shown under the images.

and thereby changes the appearance of the image (Figure 2).

Spatial filtering is used to enhance spatial features in images and thus relies on analyses in specified pixel neighborhoods (Richards 1993). Low-pass spatial filters suppress high spatial frequency detail, whereas high-pass filters enhance high-frequency detail. A technique that is used to sharpen an image is known as edge enhancement, which can have the effect of delineating objects in the scene (Jensen (1986). Texture algorithms provide a twodimensional statistical measure of an image, which relies on a moving window of some specified size (Hord 1986) and can he used to assist in segmenting a scene into different objects (Woodcock and Harward 1992).

Spectral vegetation indices (SVIs) are multispectral transformations of image data that generate new sets of image components, or bands, and thus represent alternative descriptions of the original data (Richards 1993). All SVIs ar nonspatial in nature, operating on the multispectral digital values of individual pixels. The simplest SVIs are ratios, in which one image band is divided by another or one band is subtracted from another and the result is divided by the sum of the values in the two bands (Figure 3). Excellent descriptions of many of the common SVIs are given by Tucker (1979) and Perry and Lautenschlager (1984). Principal components analysis (PCA) and the tasseled cap transformation are two widely used sets of SVIs that neither of the two references above discuss. PCA is a standard multivariate statistical procedure, described in any multivariate statistical text. The tasseled cap was specifically designed for Landsat data, having a multispectral scanner (MSS) variate (Kauth and Thomas 1976) and a thematic mapper (TM) variate (Crist and Cicone 1984). All of the SVIs are primarily designed to enhance vegetation components, generally by contrasting the vegetation against soil and background components in the scene.

Thematic Classification and Related Procedures

Thematic classification of multispectral images involves the assignment to pixels of labels containing real-world descriptions of ground features (Figure 3). Standard classification algorithms involve supervised and unsupervised methods (Mather 1987, Lillesand and Kiefer 1994). Unsupervised classification commonly relies on statistical clustering to separate pixels into groups

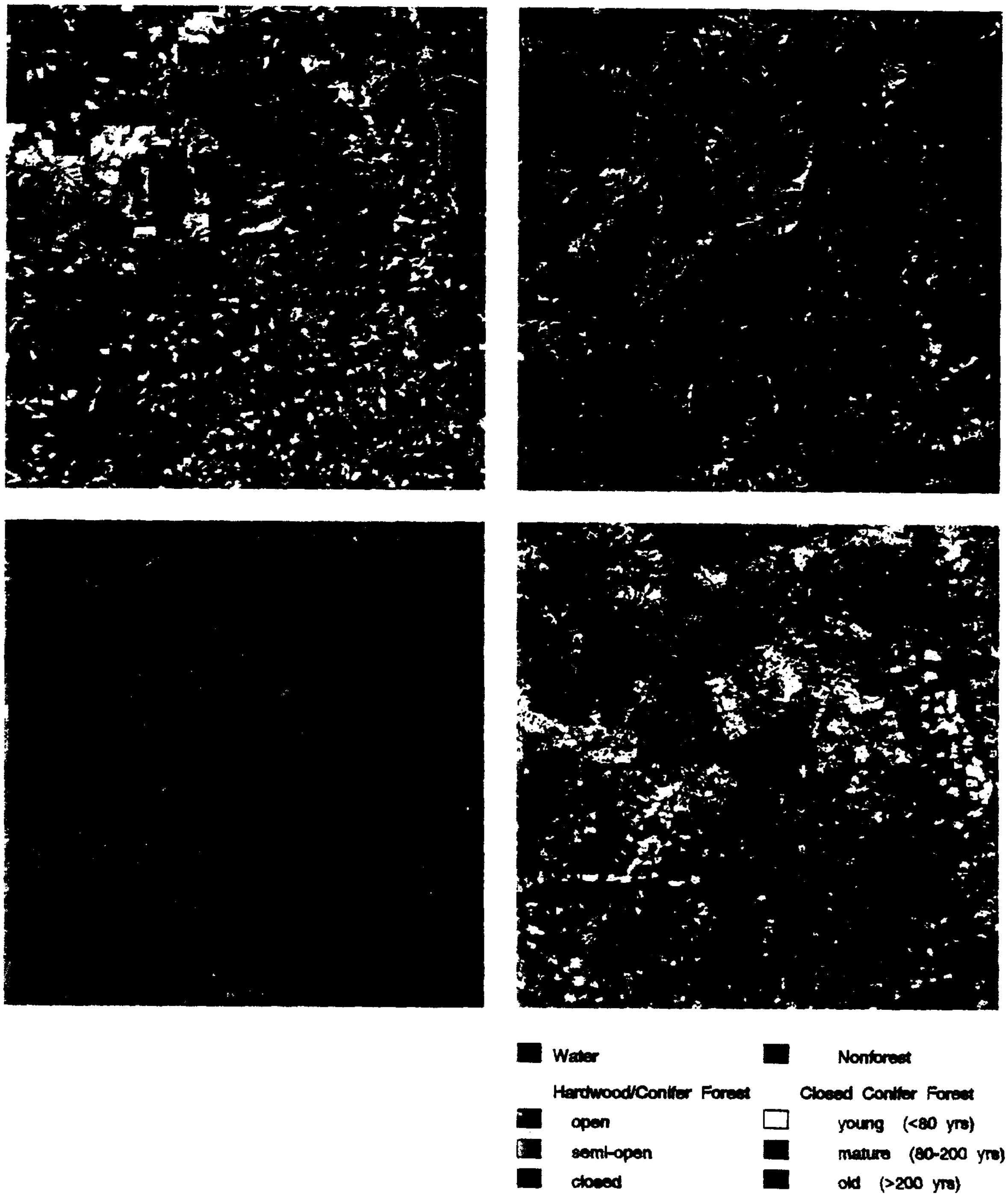

Figure 3. Raw digital imagery (upper left is the red hand, upper right is the near-infrared band), a spectral vegetation index created by dividing the near-infrared hand by the red hand of the imagery (lower left), and a thematic classification of the imagery.

Table 2. Typical error matrix used in remote sensing classification accuracy assessment (adapted from Congalton 1991)

	Reference data				
Classified data	Conifer forest	Hardwood forest	Water	Agriculture	Row total
Conifer forest	25	6	2	1	34
Hardwood forest	8	15	0	4	27
Water	1	1		0	7
Agriculture	2	3	0	13	18
Column total	36	25	7	18	86

'Producer's accuracy: Conifer forest = 25/36 = 69%; hardwood forest = 15/25 = 60%; water = 5/7 = 71%; agriculture = 13/18 = 72%. User's accuracy: Conifer forest = 25/34 = 74%; hardwood forest = 15/27 = 56%; water = 5/7 = 71%; agriculture = 13/18 = 72%. Overall accuracy: 58/86 = 67%.

based solely on the likeness of their multispectral values. Subsequent to definition of statistical clusters. labels can be applied to the clusters based on knowledge of the scene from ground data, field visits, or airphotos. Supervised classification requires the use of "training sets," which are groups of' pixels of a known type or label. The training sets are used to statistically define the known classes in spectral terms. Using some statistical decision rule, such as maximum likelihood, or nearest neighbor. the multispectral values of each pixel in the image to be classified are compared to the training data to determine which class the pixel is most like, and the pixel is labeled accordingly.

Many other options for classification exist. There are numerous examples where supervised and unsupervised classification methods were combined (e.g., Nelson 1981. Chuvieco and Congalton 1988). Texture images can he used for classification, with or without spectral bands (Peddle and Franklin 1991 I. Regression analysis is commonly used to derive relationships between ground data and spectral data for specific numerical attributes within a given class (Butera 1986, Peterson and others 1986). and predictions from regression equations may then be collapsed to classes (Cohen and others 1995). Ancillary data, such as digital elevation models (DEM), are often used to provide additional information during image classification (Strahler 1981, Franklin and Wilson 1992). Spectral mixture analysis has been used to map proportions of basic scene components (e.g., green vegetation, nonphotosynthetic vegetation, and shade), that were then collapsed into classes (Smith and others 1990a.b).

Thematic classification normally is followed by an assessment of classification accuracy. Reference data from field plots, aerial photography, and the like are used to array predicted versus observed observations in a table known as an error matrix (Table 2). Two types of' error are possible for any given thematic class X: commission, in which pixels from classes other than class X are classified as class X. and omission. in which pixels of class X are classified as another class. There are numerous problems associated with accuracy assesment (Congalton 1991), especially those concerning violation of underlying statistical assumptions, and the process is commonly subjective.

Change Detection

Change detection involves the comparison of images from a given location at two or more points in time. One can simply compare summaries of classifications for a given area at different points in rime or conduct a spatially explicit analysis involving direct comparisons on a pixel-by-pixel basis (Figure 1). In the latter, and more usual case. accurate spatial registration of' two or more images is required. Commonly used algorithms for conducting change detection include image differencing and image ratioing (Singh 1986. Muchoney and Haack 1994). In the former, digital numbers of' a single image band from one date are subtracted from digital numbers of a single band from a different date, and in the latter, a single image band from a given date is divided by a single image band from another date (Jensen 1986). Other methods involve calculation of principal components (PCA) of single hands of multi&ate imagery (Richards 1984, Fung and LeDrew 1987), use of fuzzy set theory (Gong 1993), color additive display of a single band from three different points in time (Sader and Winne 1992), Gramm-Schmidt orthogonalization (Collins and Woodcock 1994), and calculation of postclassification transition matrices (Hall and others 1991 b). Change vector analysis (Malila 1980) describes the vector and magnitude of change in multispectral, multidate imagery. This particular approach is currently becoming popular (Michalek and others 1993, Lambin and Strahler 1994) and is likely to see increased attention.

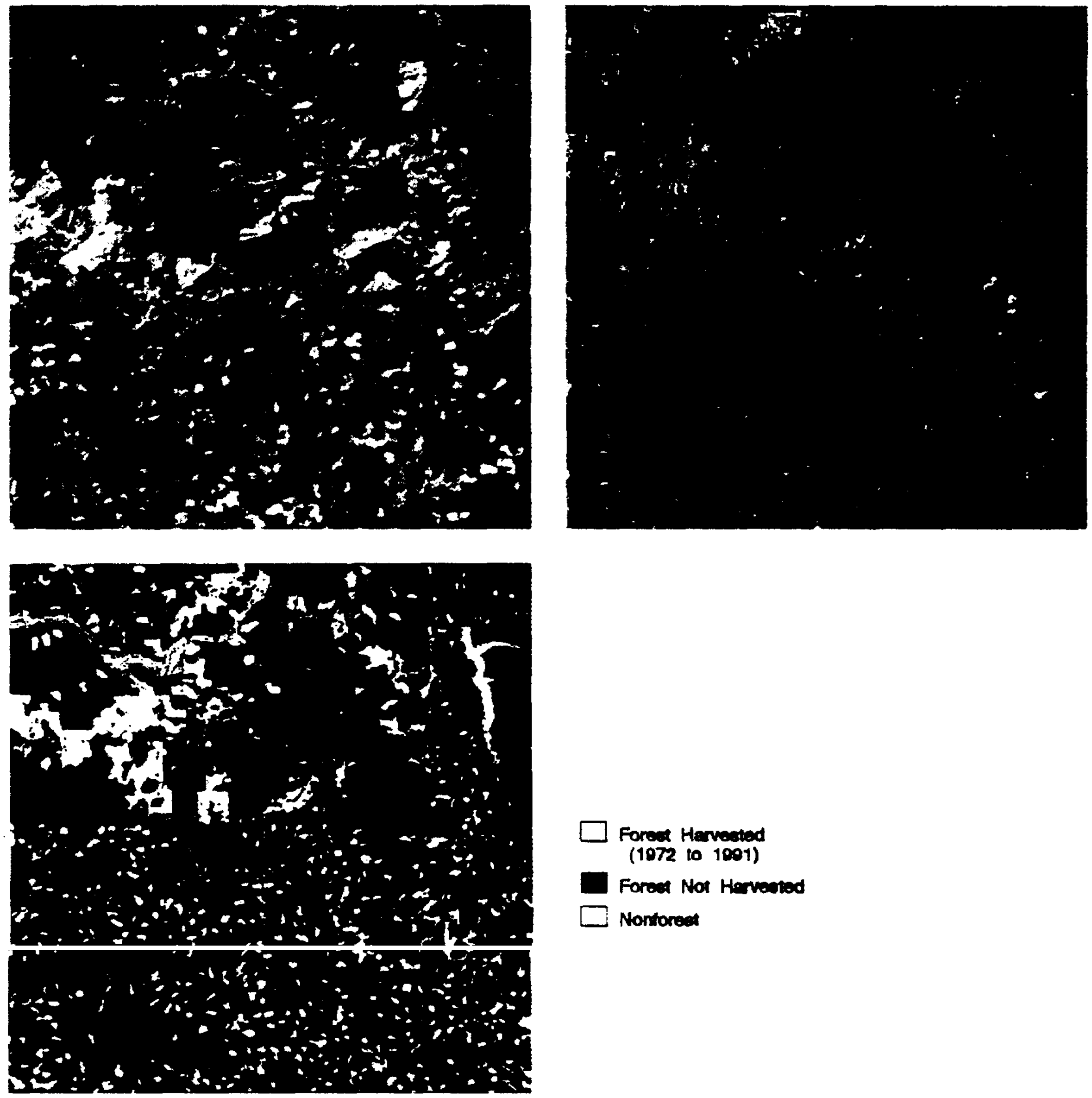

Figure 4. A three-band, false-color composite rendition of a 1972 image (upper left), the same for a 1991 image of the same area (upper right), and a change detection map created by subtracting one date of imagery from the other (lower left).

With ail change-detection algorithms, either raw or transformed images can be used. Determining the accuracy of change detection is a difficult problem unless good reference data exist for multiple dates. The greater the number of change features desired (e.g., clear-cut, insect damage, succession) and the higher the spatial frequency of these features in the imagery, the greater the chance for error. One of the greatest problems is associated with spatial misregistration of multidate images, which can cause high rates of error around edges of scene features (Townshend and others 1992).

Remote Sensing Research and Applications

This section illustrates the multifaceted utility of remote sensing data. The intent here is not to conduct a comprehensive review but to provide context to the previous sections by summarizing some varied application and research studies using remote sensing data. We concentrate on a region of the United States in which remote sensing has been widely used, the Pacific Northwest (PNW). Although limited in geographic scope, recent use of remote sensing among the land-management agencies, forest scientists, and other interested groups of this region has blossomed, and with it has come an array of very large-scale projects. Whereas production of vegetation cover and change maps is the most common goal in applications of digital remote sensing pertaining to forest ecosystems of the region, scientific aspects of remote sensing are more directed at understanding relationships between physical or ecological properties and spectral properties of these systerns and at developing algorithms to process digital imagery into accurate vegetation maps. Much of the remote sensing work in the PNW region has been a combination of research and application, driven by a few simple goals like mapping old-growth and general forest cover, understanding relationships between image data and stand structural, compositional, and functional attributes. and mapping changes in landscape patterns.

Mapping Forest Cover

Mapping with digital remote sensing data in the PNW region has involved general land cover mapping, the separation of structural and successional classes, and mapping of wildlife habitat. In one of the earliest studies. Walsh (1980) used Landsat MSS data to map 12 land cover types in Crater Lake National Park, Oregon. USA. with an 88.8% accuracy. In addition to cover type, topographic slope and aspect had strong effects on image spectral properties, with tree size and density having lesser effects. That study was later repeated (Walsh 1987), with a more in-depth analysis, but similar results. Isaacson and others (1982) mapped elk habitat in the Blue Mountains of northeastern Oregon using MSS data and large-scale aerial photography. Mapped attributes included vegetation type, crown cover, vertical structure, and disturbance. No accuracy statistics were reported. Cibula and Nyquist (1987) used MSS data to map vegetation cover in Olympic National Park. Washington, USA. Combining topographic data and climatological models with the MSS imagery, they achieved a 91.7% map accuracy for 21 land cover classes.

The largest set of mapping efforts in the PNW region involved locating remaining old-growth forests on the west side of the Cascade Range. This effort was undertaken independently by the USDA Forest Service, the Wilderness Society, and the Washington Department of Wildlife. The earliest work was by Eby (1987)) who modeled the relationship between near-infrared reflectance, stand age, and solar incidence angle at the time of acquisition of Landsat MSS imagery. This work was based on the fact that older forests exhibit lower near-infrared reflectance than younger forests and that illumination angle and near-infrared reflectance are highly correlated in older forests due to shadows associated with complex canopy structure. Using regression analysis, predicted ranges of values for different forest age classes at different incidence angles were calculated, and then these were used to develop a deterministic classification model. The experience from this research was extended by Eby and Snyder (1990) to map old-growth forests on 11.3 million acres of western Washington. They reported 80% accuracy for the Cascades of Washington and 85% accuracy for the Olympic peninsula.

Morrison and others (1991) used a variety of data sets and methods, from airphoto interpretation to relatively sophisticated digital techniques using multiple image sources [Landsat MSS, Landsat TM, and panchromatic SPOT high resolution visible (HRV)] and DEM data, to map old-growth forest on the national forests of the west side of the Oregon and Washington Cascade Range. Detailed documentation of actual methodology is not published, nor are map accuracies. Congalton and others (1993) mapped old-growth on much of the same terrain as Morrison and others (1991). The mapping was done with Landsat TM, airphotos, DEM, and field measurements. Although detailed methods are not published, the analysis appears to have involved extensive testing of relationships between ground and photo data and derived image variables, such as band ratios, band textures, and principal components. Accuracies between 80% and 91% were reported for nine national forests. An interesting and important observation can be made by comparing the results of Morrison and others (1991) and Congalton and others (1993). Although these independent estimates of forest conditions may have narrowed the uncertainty of the amount and location of old-growth forest on nine national forests in the PNW region, their acreage estimates for any given national forest differed as much as 100%.

Fiorella and Ripple (1993a) used unsupervised classification of TM imagery with an ERDAS (1993) topographic relief image calculated from a DEM to classify successional stages from clearcut to old growth in Douglas-fir forests with an overall accuracy of 78.3%. Use of the topographic relief image improved classification accuracy for younger stands, but not for later successional stages. They also found that the ratio TM 4/5 and the tasseled cap wetness were strongly correlated with each other and with stand age, except on poorly regenerated sites (Fiorella and Ripple 1993b). Ripple (1994) mapped percent conifer cover on 10.9 million ha of forest in Oregon using Advanced Very High Resolution Radiometer (AVHRR) imagery. The analysis was based on a regression relationship between Landsat MSS and coregistered AVHRR band values. The map depicted percent closed canopy conifer cover in l-km cells and was presented as an analysis of forest fragmentation in Oregon. Correlation (r) between the AVHRR conifer cover map and observations from U-2 airphotos was 0.90.

Cohen and others (1995) used TM data to map forest cover over a 1.24 million ha multiownership landscape in western Oregon. Unsupervised classification was used to separate four forest cover classes: open (<30%), semiopen (30-85%), closed canopy mixed conifer-hardwood (>85%), and closed canopy conifer (>85%). Of primary interest was distinguishing among successional stages within the closed canopy conifer class. Thus. for this class, regression analysis was used to explore relationships between the tasseled cap SVIs (brightness. greenness, and wetness), topography, and stand age. Topography strongly influenced the responses of brightness and greenness. but not ofwetness. A regression model for predicting forest age from wetness was developed and applied. Forest age predictions were collapsed to three classes: young (<8O years), mature (80-200 years), and old growth (>200 years) Accuracy of predictions for the three age classes was 75%. Overall. for the full land cover map, an accuracy of 82% was achieved.

Structure, Composition. and Function of Vegetation

Nonmappinq remote sensing studies focusing on biophysical and ecological properties of PNW forests are relatively numerous and have primarily been research-oriented. Relevant studies that have concentrated on vegetation structure. composition, and function are described below.

The Oregon Transect Ecological Research (OTTER) project was a major NASA-funded effort to evaluate the utility of a variety of sensors to provide input to ecosystem models for predicting forest growth and nutrient allocation (Peterson and Waring 1994). One major focus was on estimating leaf area index (LAI). In early studies across the transect, Spanner and others (1984) developed regression relationships between LAI of closed-canopy conifer stands and the simple ratio (SR). The SR is a spectral vegetation index (SVI) derived by dividing near-infrared reflectance by red reflectance. The SR was highly responsive up to an LAI of about 3, at which time it began to level off with increased LAI. Beyond an LAI of about 5, there appeared to be little sensitivity of the SR. Using the same data, Running and others (1986) found chat correcting the imagery for atmospheric effects enhanced the regression relationship and showed that the SR was not asymptotic until an LAI of about 10. With additional data, Peterson and others (1987) confirmed the value of the SR for estimating LAI across the OTTER transect and determined that it was better related to LAI than a number of other SVIs. Spanner and others (1990) showed that the SR was greatly influenced by canopy closure, understory vegetation, and background reflectance. In that study, the SR was asymptotic at an LAI of about 4 or 5. Using spectral reflectance data from a variety of scene components (e.g., crown foliage. understory vegetation, tree bark), Goward and others (1994) confirmed that SVIs are a function of not just LAI. but of canopy closure and background reflectance. as well as canopy optical properties. Using reflectance data of two understory vegetation species collected with a field spectrometer, Law and Waring (1994) demonstrated that SVIs leveled off at an LAI value of about 6.

Li and Strahler (198.5) developed a geometric-optical canopy reflectance model that can be inverted to provide estimates of tree size and density. The model has been used across the OTTER transect, with an observed versus predicted correlation coefficient of at least 0.90 for both crown radius and tree density (Strahler and others 1988). On a site-specific basis, however, or within a given forest cover type, the model provides less accurate predictions (Wu and Strahler 1994). Using a more advanced configuration of the model, Abuelgasim and Strahler (1994) demonstrated the potential for rstimating tree size. shape, and density using angular radiance measurements from newer experimental sensors. Moghaddam and others (1994) demonstrated that across the OTTER transect radar backscatter saturates at low levels of biomass and that at low levels of biomass the backscatter signal was only weakly related to biomass amount. Johnson and others (1994) and Matson and others (1994) used imaging spectrometer data (a sensor having over 200 narrow spectral wavebands) to estimate canopv biochemistry across the OTTER transect and found that the spectral region from red to near-infrared (the red-edge) was strongly related to canopy total nitrogen and canopy chlorophyll content.

Cohen and others (1990) used semivariograms to characterize the spatial domain of l-m-resolution aerial videography in relation to stand structural complexity of Douglas-fir forests. Image spatial patterns were strongly related to canopy size and vertical layering. In a subsequent study, Cohen and Spies (1992) found that texture of SPOT HRV 10 m was strongly correlated (>0.83) with several stand structural attributes (e.g., tree size, density, basal area). Cohen and others (1995) explored relationships between stand structure and TM tasseled cap SVIs. Models to predict structural attributes from brightness and greenness were significantly improved when the image data were stratified by topographic/solar incidence angle classes; however, these models were not as strong as nonstratified models based on wetness. As a part of this study, the effect of the defined number of classes on percent accuracy in mapping was evaluated. For two or three classes of any given structural attribute, acceptable accuracies (75% or greater) were observed, but for five or more classes accuracies declined to below 50%.

Ripple and others (1991) found that relatively strong relationships exist (correlation coefficients of -0.89 and -0.83, respectively) between near-infrared reflectance of SPOT HRV 20 m and TM 30 m data and forest volume in stands 25 years old and greater on the MacDonald-Dunn Forest along the Willamette Valley fringe of the Oregon Coast Range. Fiorella and Ripple (1993b) developed regression models to predict age of forest stands from 0 to 35 years old using a variety of SVIs and found that TM band ratio 4/5 gave the best results (r = 0.96). They also found that conifer regeneration success could be determined at approximately 12 years after planting.

Thermal imagery was used by Holbo and Luvall (1989) to detect cover types on the H.J. Andrews Experimental Forest (HJA) in the western Cascades of Oregon. They compared frequency distributions from two sets of diurnal multispectral thermal data to develop models for specific cover types. With additional analysis, Luvall and Holbo (1989, 1991) again used thermal data to model the radiation balance for specific cover types and develop models of short-term thermal responses to discriminate these different surfaces. They found that barren surfaces had the lowest response while forested surfaces had the highest, indicating that forest cover moderated incident radiation and was more efficient at dissipating heat. Sader (1986) found that slope and aspect had a greater effect on thermal emission of young regeneration than on older stands in the HJA. However, mean surface temperature decreased as age increased regardless of topographic position (Sader 1986).

Change Detection

Although several change detection projects using digital imagery are underway by various groups in the PNW region, few results are currently available. Thus far only coarse changes associated with harvesting and other major disturbances have been evaluated.

Spies and others (1994) evaluated the effects of forest havesting and regrowth between 1972 and 1988 on forest fragmentation over 258.000 ha of the west-central Oregon Cascades. They used raw MSS data from 1972, 1976, 1981, 1984, and 1988. After the images were coregistered, each was independently classified into three broad cover types: closed canopy conifer forest, water, and other forest and nonforest types. Using a GIS, the classified images were registered to an elevation class map derived from a DEM and a digitized land ownership data layer. Maps for multiple dates of forest edge and interior were then derived. From these, edge length and amount of interior habitat were quantified, and various landscape-level statistics calculated by ownership class.

Current and Emerging Issues

There is great potential for use of remote sensing to derive detailed information about forest conditions. .Much has already been done with long-standing data sets like MSS, TM. SPOT HRV. and AVHRR, and newer sensors having finer spatial, spectral. and radiometric resolution are becoming more readilv available. In this section, we summarize some of the most important current and emerging issues that must be addressed to better integrate developing remote sensing technologies with resource management needs and objectives.

Users of remote sensing data need a common frame of reference for efficient and effective communication. An excellent place to start is with the taxonomic structure for remote sensing models developed by Strahler and others (1986). This taxonomy distinguishes between a ground scene and an image of that scene. the continuous versus discrete nature of a scene, image spatial resolution and scene object resolution, and deterministic and empirical models of a scene. Concepts associated with scale and spatial resolution in relation to image-processing models are further developed by Woodcock and Strahler (1987) This paper is required reading for anyone faced with a choice of image data and processing schemes for a specific set of mapping objectives. What Woodcock and Strahler (1987) demonstrate is that the spatial structure of a scene in combination with the type of information desired from associated imagery tend to limit the choice of appropriate image processing models for classification (e.g., spectral classifiers. spatial classifiers, mixture models, and texture models). Together, these two seminal papers provide a foundation from which to build a solid understanding of remote sensing.

Forest scientists and resource managers routinely define forest stands visually by drawing polygons on airphotos. No two people will define stands in exactly the same way, and this problem is one that will be prevalent for the foreseeable future. When the focus shifts to stand/polygon definition in digital imagery using digital techniques, the problem is greatly exacerbated. Not only do we still have the interpreter-specific stand-definition problem, but we now have the additional difficulty of developing a computer algorithm with an appropriate set of rules. There are numerous examples of polygon definition algorithms (e.g., Kauth and others 1977, Hong and Rosenfeld 1984, Woodcock and Harward 1992). but additional research is needed to develop a rule-based system (Nazif and Levine 1984, Corr and others 1989) that is flexible for different purposes. For example, a wildlife biologist should be able to work with the same digital data set as a forest manager but should be able to have the computer program define a set of polygons that is different from those of the forest manager.

An area in need of substantial development is accuracy assessment. Widely applied techniques for accuracy assessment technology are relatively old (Congalton 1991). New mathematical and statistical techniques have been developed. and there have been some efforts to incorporate these into new ways of conducting assessments of accuracy (Craplewski and Catts 1992, Ma and Redmond 1995). Fuzzy set theory (or logic) is one particular approach that has the potential to revolutionize the field of accuracy assessment (Gopal and Woodcock 1994). The basic premise of fuzzy logic is that we may never be certain of a given label's correctness, but we are often quite confident. Fuzzy logic enables us to have relative degrees of certainty about the correctness of a label and what other possible labels may be correct.

The spectral resolution of most current operational remote sensing systems is quite limited. Landsat MSS has four spectral bands in the reflective portion of the electromagnetic spectrum. and TM has six there and one in the thermal-infrared region. SPOT HRV multispectral imagery consists of only three spectral bands. On the horizon is imaging spectrometer data (e.g., >200 narrow spectral bands), already available on an experimental basis (Vane and Goetz 1993). These data provide detailed spectral signatures that enable fine spectral absorption features to be evaluated. Much research has already been done using such data (e.g., Kruse and others 1993, Mustard 1993, Roberts and others 1993), but not for the extraction of detailed forest information.

One of the most difficult challenges in remote sensing of forests has been tree species identification. There are a multitude of factors influencing the spectral response of digital imagery, and species is only a minor influence relative to forest structure and topography (Colwell 1974). Life forms and functional groups, like hardwood, conifer. brush, etc., can be differentiated without too much difficulty based on spectral properties alone. By incorporating other factors such as climate, elevation, topographic aspect, soil properties, and the like, a more refined species differentiation is possible, as demonstrated by Woodcock and others (1994). However, few such models exist for the numerous forest regions around the globe. Imaging spectrometer data may also provide improved species identification, if narrow-band species-specific absorption features can be identified. Additionally, we need to explore temporal data sets to capture phenological events associated different tree species.

Detection of changes in forested environment-s is an increasing emphasis in the use of remote sensing. Progress has been made in detecting forest clear-cut activity (Skole and Tucker 1993) insect damage (Collins and Woodcock 1994), forest succession (Hail and others (199lb), pollution damage (Vogelmann and Rock 1986), and other important forest changes. However. the techniques used are not well developed or widely applied. Problems associated with spatial misregistration and radiometric differences among images in a temporal series are potentially large obstacles to detection of subtle forest changes. Algorithm development for change detection in forest environments are not well tested in a variety of forest types.

Remote sensing can play an important role in initializing, parameterizing, and testing landscape models of vegetative dynamics that are used to project successional changes under natural and anthropogenic disturbances. The types of modeling approaches used vary as a function of the intended objectives. Methods range from applying individual-based or stand-level simulators to polygonal units. each of which delineate similar vegetative conditions. to simplified cell-based state-transition models where predetermined states are advanced through time based on deterministic or multiple pathways of transition. Regardless of the modeling approach used, it is essential to define initial vegetative conditions of the landscape at a grain size and at a level of detail commensurate with the vegetative model. For detailed modeling applications, remote sensing is essential for characterizing the structural and compositional distribution of the overstory. State-transition models require representation of general seral stage, which is easily detectable with remote sensing, and sometimes an explicit estimate of age. Broader consideration of the dynamics of understory species and dead wood is an integral part of the ecosystem management emphasis. Simulation methods for handling these features are beginning to come on-line. Delineating understory and coarse woody debris levels are problematic, however, with remote sensing. Nevertheless. given general overstory characteristics, observed data for nonoverstory features from similar areas can be extrapolated to those delineated only by remote sensing. Parameterization of models relies on a host of procedures and data sources. Analysis of historical changes in structural and compositional changes or general development of seral stages with remote sensing offers an efficient means to aid in calibrating the dynamic attributes of vegetative models. Dividing the time series into model calibration and corroboration data sets additionally provides the abilitv to independently test model behavior, at least over the temporal span represented by available data.

Sustainable forest management requires consistent vegetation data for large geographic areas. While there is a definite role for remote sensing in providing these data, current remote sensing technology cannot provide the level of detail required for all purposes. Furthermore, a great amount of research is required to keep ahead of applications needs. As new data sets become available, time is required to explore those data and to develop algorithms for processing them into useful vegetation maps. There is ample reason to expect that :-emote sensing, when properly understood and applied. will be of increasing utility for the foreseeable future. This future will need to include adoption of remote sensing technology by agencies willing to make an operational commitment to applications. It will be important to use remote sensing in concert with GIS. as part of an ongoing decision support system to set policy based on both historical trends and future simulations of landscapes with spatial data. Specific future applications include topics in landscape ecology, forest fire analysis, biodiversity, habitat models for rare and endangered species, ecosystem management based on natural disturbance regimes, analysis of riparian zones, forest health. forest inventory, and harvest scheduling. With remote sensing and GIS, we will have more functional and integrated systems for spatial analysis. The repetitive and synoptic coverage provided by these technologies will help give us a better understanding of forest systems. how they function, and how to manage them with a holistic view.

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