GIS Applications Perspective: Current Research on Remote Sensing of Forest Structure

Warren B. Cohen

Introduction

The Pacific Northwest (PNW) region of the United States has received much attention in the past several years concerning the amount and distribution of late-successional forest conditions. This concern has prompted a number of studies to define, characterize, and map forest cover and structural attributes in the region. The mapping efforts have had at their core the use of satellite and other remotely sensed data (e.g., The Wilderness Society 1991, Congalton et al. 1993) and have proceeded with little or no scientific research component. Rather, the emphasis has been on map creation, using primarily established image analysis and GIS techniques. Although such techniques are useful and *can* provide reasonable and often acceptable results, research can help bring about a better understanding of the relationships between image characteristics and forest attributes. In turn, improved methods and models, and therefore more accurate map representations, can result. Equally important, research can help us better recognize the limitations of current remotely sensed data and of algorithms designed to extract the needed forest information. The latter is extremely important because, increasingly, maps derived from remotely sensed data are being commissioned by policymakers and others who have little knowledge of the technology.

Cohen and Spies (1990) are addressing the need for remote sensing research in the PNW region, and this chapter is a summary of two specific and focused research projects to that end. For further details on this research, see Cohen et al. (1990) and Cohen and Spies (1992).

Our first project involved the use of a geostatistical technique known as the semivariogram (Cohen et al. 1990). Semivariograms enabled exploration of the image spatial domain, which, depending on image spatial resolution, may contain substantial amounts of information with respect to forest structure. This is because forest structure is largely a spatial phenomenon. For the second research effort, the spatial domain was further explored by evaluating relationships between image texture and structural attributes (Cohen and Spies 1992). Most of the research in remote sensing of forested ecosystems has focused on the image spectral domain; that is. the analysis of multispectral images using statistics-based decision rules for determining the identity, with respect to forest stand characteristics of interest, of each pixel in the images. This holds significant promise; therefore, we incorporated analyses of image spectral properties as a part of this second study.

The primary emphasis in these research projects, thus far, has been on Douglas-fir *(Pseudotsuga menziesii* forests of the western hemlock ***(Tsuga*** heterophylla) zone described by Franklin and Dymess (1988), which dominates the PNW region. As a result of past fires, steeply dissected terrain, and intensive forest-management practices, the western hemlock zone has a complex pattern of stand structural conditions. Initially, the focus was on stands having a closed canopy (those in which at least 85 percent of horizontal space is occupied by trees), a condition that commonly occurs within the first 25 years or so after a major disturbance. In closed-canopy conifer forests of the region, structural conditions can be characterized on a continuum from simple in young, even-aged stands to complex in old-growth stands. Structural differences among these successional stages are described by Spies and Franklin (1988). Generally, simply structured stands have a single canopy layer of similar-sized small trees with few canopy gaps, high tree density, and low basal area. Complex structured stands commonly have multiple canopy layers with numerous gaps and a variety of tree sizes, and relatively low tree density and high basal area in the upper canopy layers.

Image Spatial Domain

Implicit in an analysis of image spatial properties is a recognition that image pixels exist within a neighborhood of other pixels, and that the spatial variability of the spectral properties of images contains information about the spatial characteristics of the ground scene. As forest structure is largely a set of spatial characteristics, we hypothesized that the spatial domain of images should contain valuable information about forest structure. Two major questions were: (1) "What structural attributes can be reliably estimated by spatial algorithms?" and (2) "What is the effect of image spatial resolution on attribute estimation?"

Image Semivariograms

A semivariogram is a graphical representation of the spatial variability in a given set of data. The semivariogram, or $\gamma(h)$, is calculated as

$$\gamma(h) = \frac{1}{2(n-h)} \sum_{i=1}^{n-h} [Z(x_i) - Z(x_i + h)]^2 \qquad [1]$$

where h is the lag (or distance) over which γ (semivariance) is measured, n is the number of observations used in the estimate of $\gamma(h)$, and Z is the value of the variable of interest at spatial position x_i (Webster 1985, Joumel and Huijbregts 1978). The quantity $Z(x_i + h)$ is the variable value at distance h from x_i. Thus for spectral data, $\gamma(h)$ estimates the variability of radiance Z as a function of spatial separation.

Typically, the shape of a semivariogram is such that γ increases with h until it reaches a maximum, or sill (Figure 7.1). The lag at which the sill is reached is called the range. The range and the sill are the two most important parameters of the semivariogram used to describe the data. The range can be used as a measure of spatial dependency, or homogeneity,. whereas the sill reflects the amount of spatial variability. For a more in-depth discussion of semivariograms and related theory see Matheron (1971), Clark (1979), Journel (1989), Oliver et al. (1989a and 1989b), and Webster and Oliver (1990). For examples of semivariogram usage in remote sensing other than that presented here see Yoder et al. (1987), Atkinson and Danson (1988), Curran (1988), Jupp et al. (1988a,b), Woodcock et al. (1988a,b), Curran and Dungan (1989), Ramstein and Raffy (1989), Wald (1989), Webster et al. (1989), de Miranda and MacDonald (1990), Rubin (1990), Atkinson et al. (1990), and Townshend et al. (1992).

The primary objective for our use of semivariograms was to evaluate their potential utility for distinguishing among forest stands having different canopy structures (Cohen et al. 1990). Digitized aerial true-color videography, at a nominal 1-meter pixel size, was used. As we also wanted to examine the potential utility of semivariograms for use with SPOT HRV panchromatic and Landsat TM data, analyses were repeated after the video data were spatially degraded to 10 and 30 meters.

Images of five forest stands were selected for study. The only quantified forest stand attribute was tree crown size. The stands were selected primarily on a qualitative basis so that they had different canopy structures, labeled as young, mature, old-growth, young-mix, and mature-mix. The

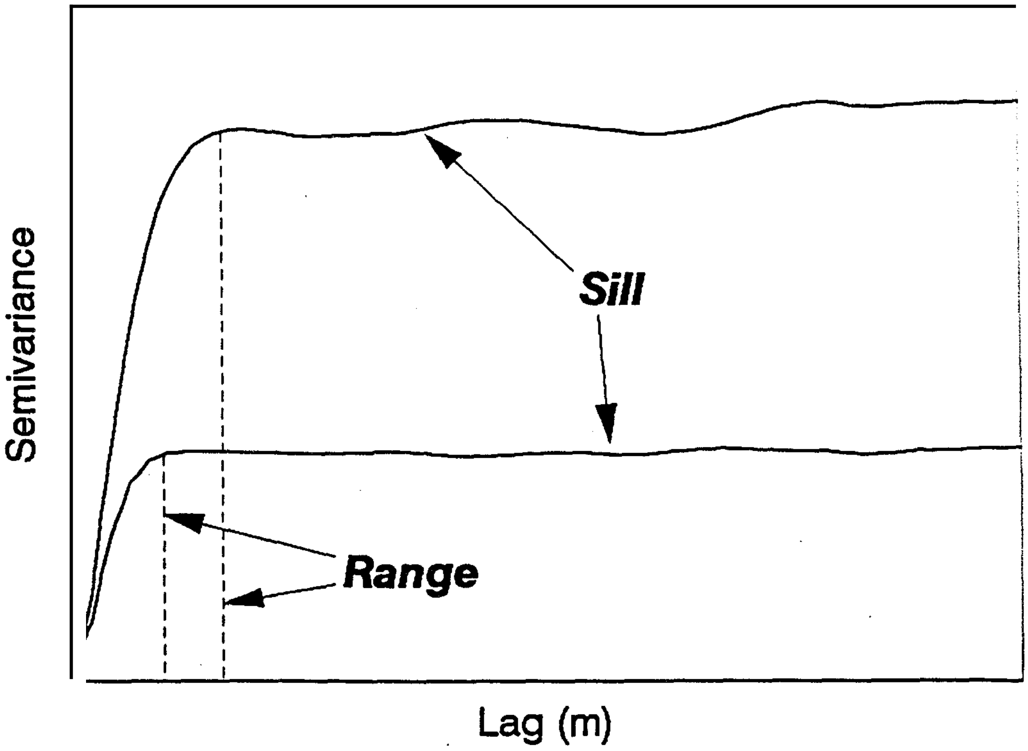

Figure 7.1 Typical shape of semivariograms with ranges and sills shown

young and mature stands had relatively simple canopy structures and the old-growth and mixed stands had complex structures. Semivariograms were calculated for each stand using the digital numbers (DN) in the red band of the images. The analysis was undertaken in two separate ways: (1) using a transect method that evaluates single transects of pixel DN, and (2) a matrix method that uses DN of the full two-dimensional pixel matrices in the images.

We concluded from this study that semivariograms of image data should be a useful means of evaluating canopy structure in the Douglas-fir forests of the PNM region. The matrix semivariogram should provide fairly accurate estimates of stand structure parameters, but will not readily permit the evaluation of patterns in stand structure. Because transect semivariograms exhibit periodicity, they may permit the detection of patterns in forest stands. However, as transects represent only a sample of data values, transect semivariograms will not depict stand structure parameters as accurately as matrix semivariograms.

It was clear from this study that the utility of semivariograms for evaluating within-stand conifer canopy structure from remotely sensed images is greatly influenced by image spatial resolution. At a spatial resolution of 1 meter, radiant energy sensed from all tree crowns, excluding those of saplings, will be expressed in the DN of several pixels. Because of this, the range of the 1-meter matrix semivariogram is a valuable measure of tree crown size in a conifer forest stand. At a 10-meter pixel size (e.g., SPOT HRV panchromatic data) the range of the matrix semivariogram is less useful, yielding only a coarse estimate of crown size. As few trees have crowns that are 30 meters in diameter or greater, the range of the semivariograms using Landsat TM data should not be useful for estimating tree crown sizes.

Sills of the 1-meter matrix semivariograms depict the presence of canopy layering and gaps in forest stands. Because the sill responds to both percent canopy cover and canopy layering, however, their use may not always facilitate distinguishing mixed-stand structures from old-growth structures. Likewise, these categories of forest structure are not always clearly distinguishable on the ground. Because the sills are reduced with increasing units of regularization, like the range, the sills are less informative as image pixel size increases. For the 30-meter data the sills were very similar in magnitude, again indicating a limitation for the potential usefulness of semivariograms of Landsat TM data for stand structure analysis.

To apply the semivariogram technique to image data for within-stand structure analysis, separate semivariograms must be calculated for each stand. This requires either the use of image segmentation algorithms (e.g., Woodcock and Harward 1992) or digitization of photointerpreted polygons. Image segmentation is a critical yet largely underdeveloped area of remote sensing research. Until a number of reliable image segmentation algorithms are developed, the use of semivariograms may be impractical on a full HRV scene that may contain hundreds, or perhaps thousands, of individual stands. If this procedure were to be executed, however, the sills could be used as an index of stand structural complexity. An alternative and maybe more practical approach would be to create a new data layer from the existing image data (e.g., HRV or merged HRV and TM) that largely distinguishes each stand's structural complexity from that of the other stands. This data layer could be used in the multispectral image processing context. Some measure of local variance for an image containing numerous stands would be helpful. Several measures of local variance, or texture, are possible (e.g., Woodcock and Strahler, 1987; Rubin, 1990; Wang and He, 1990), and adapting or developing one that performs well was a focus of our second research project.

Image Texture

A wide variety of texture algorithms have been used to process digital imagery (Irons and Petersen 1981, Gool et al. 1985, and Mather 1987). From these we chose the standard deviation and absolute difference algorithms described by Rubin (1990). Using these algorithms, texture images were created from an unenhanced HRV 10-meter image, and from 30-meter TM data (Cohen and Spies 1992). Initial evaluation indicated that the absolute difference algorithm provided a greater dynamic range of texture information and therefore had potentially more discriminating power.

From the absolute difference images, the boundaries of more than 40 forest stands representing a variety of conifer closed-canopy conditions were digitized. Then, those pixels corresponding to the ground location of each stand were extracted from the images. Ground data were collected by Spies and Franklin (1991) and used to calculate a number of attribute values for those stands relating to mean tree size, tree size variability, tree density and basal area, two newly developed canopy structural indices, and stand age. One new structure index was the Canopy Height Diversity index (CHD), which is based on theoretical concepts that describe the relative volume of "ecological space" occupied by trees in a stand. Development of the other index, the Structural Complexity Index (SCI), was inspired by the fact that most of the stand attributes evaluated are highly correlated in a given forest stand. Thus, the SCI is a means with which to capture in a single stand atmbute the variability found in several stand attributes.

Results of this effort indicated that many of the stand attributes evaluated were strongly correlated with the mean texture number of a forest stand, as calculated from HRV data (Table 7.1). Texture numbers of TM data'were not well correlated with stand attributes. An important finding was that for the mean tree size attributes and tree density relationships with texture were strong when only the dominant and codominant trees were considered. This is because trees in the understory layers are highly variable in size and number and, coincidentally, are not visible to the sensor. The tree size variability attributes, stand age, the CHD, and the SCI also were well correlated with HRV texture.

These results supported our hypothesis that spatial algorithms using 10-meter data are useful, and that 30-meter data are not, for analysis of conifer canopy structure of forests in the region. We found further support for this from Woodcock and Strahler (1987), who state that the value of

TABLE 7.1 Value of correlation coefficients for the relationships of stand structural attributes and variables derived from the satellite data (texture of SPOT 10-m HRV imagery, and the TM Tasseled Cap brightness, greenness, and wetness axes)

Stand attribute	HRV texture	Brightness	Greenness	Wetness
DBH (mn, all)	0.55	0.44	0.44	-0.60
DBH (sd, all)	0.88	0.53	0.55	-0.87
DBH (mn, upper)	0.88	0.43	0.47	-0.87
CD (mn, all)	0.67	0.33	0.35	-0.69
CD (sd, all)	0.72	0.27	0.25	-0.67
CD (mn, upper)	0.88'	0.42	0.27	-0.88
HGT (mn, all)	0.45	0.37	0.37	-0.5 1
HGT (sd, all)	0.88	0.30	0.42	-0.81
HGT (mn, upper)	0.86	0.35	0.43	-0.85
DNY (all)	-0.62	0.49	0.5 1	-0.69
DNY (upper)	-0.84	0.39	0.5 1	0.87
BA (all)	0.73	0.53	0.52	-0.69
BA (upper)	0.73	0.47	0.53	-0.71
AGE	0.87	0.55	0.63	-0.90
SCI	0.88	0.55	0.65	-0.86
CHD	0.75	0.53	0.54	-0.69

Source: Adapted from Cohen and Spies 1992.

DBH is tree diameter at breast height, CD is crown diameter, HGT is total tree height, DNY is tree density, BA is basal area, AGE is stand age, SCI is the Structural Complexity Index, CHD is the Canopy Height Diversity Index, mn is mean, sd is standard deviation, all is all trees in the forest stand, and upper is only trees in the dominant and codominant canopy positions.

texture measures in image processing depends on whether image resolution cells are smaller than the elements of interest in the scene. The basic element of interest in our study is the individual tree or, as viewed from above, the tree crown. In the young, simply structured Douglas-fir stands evaluated by us the dominant tree crown is approximately 5 meters in width, whereas in mature (moderately complex) and old-growth (complex) stands it is roughly 10 and 15–20 meters, respectively (Cohen et al. 1990, Spies et al. 1990). Even though young closed-canopy stands have tree crowns that are subpixel size, the fact that more complex stands have numerous tree crowns that are at least as large as the pixels helps to discriminate simply structured stands from more complex stands. Likewise, because stands with moderately complex structures have tree crowns roughly equivalent in size to the image pixels and complex structured stands have crowns larger than one pixel, these two conditions also are distinguishable using textural measures of 10-meter data. With the 30-meter data at least two or three large trees generally appear in many pixels, severely diminishing the ability of TM texture to discriminate.

Image Spectral Domain

Remotely sensed images consist of pixels that contain data, in any number of bands, on the electromagnetic spectral properties of a ground scene. Analyses of image data that evaluate pixels irrespective of their neighbors operate solely in the spectral domain. Excluding radiometric and geometric preprocessing considerations, the common choices for such analyses are to work either with the unprocessed band data or to first create one or more vegetation indices (Perry and Lautenschlager 1984, Cohen 1991a). The normalized difference vegetation index (NDVI) is by far the most commonly used. However, the NDVI does not take full advantage of the TM data, as it uses only two spectral bands. Nonetheless, a strong tendency exists by users of remotely sensed data to compute only the NDVI and then use it in further analyses. Why this has happened is not clear from the literature, but the reasons seem to be rooted in the fact that NDVI is simple to compute and exhibits a strong relationship with a number of vegetation characteristics (e.g., Tucker 1979, Ajai et al. 1983).

Other indices that received a significant amount of attention in the early days of digital image analysis still continue to experience some, albeit relatively little, application. The Tasseled Cap brightness and greenness indices are perhaps the most important of these (Kauth and Thomas 1976). The Tasseled Cap was adapted to TM data by Crist and Cicone (1984) and an additional index, or axis, was defined. That axis has been called wetness (Crist et al. 1986). The TM Tasseled Cap indices were designed to take optimal advantage of the original six TM bands, and together these first three axes account for as much as 85 percent or more of the spectral information of a vegetated TM scene.

Brightness is a weighted sum of the six reflectance bands of the TM imagery, and greenness is a contrast between the near-infrared band (TM4) and the three visible bands (TM1, TM2, and TM3). Use of the terms brightness and greenness is well accepted within the remote sensing community, and there is a substantial body of literature suggesting that the names of these spectral features of TM data are consistent with the information they represent. Wetness is a contrast of the mid-infrared bands (TM5 and TM7) with the other four bands, and has been shown to correlate with the amount of moisture in a scene (Crist et al. 1986, Musick and Pelletier 1988, Cohen 1991a). Wetness has received little attention in an image processing framework.

We turned to the Tasseled Cap set of spectral indices for evaluations of the TM spectral domain. This was done in concert with our analysis of the HRV texture data; thus, the same general methodology as described .earlier applies here as well. Results indicated that of the three Tasseled Cap indices, only wetness was strongly correlated with the stand attributes (Table 7.1, shown earlier). This was because brightness and greenness responded more to topographic variation than to stand condition, whereas wemess did not. The attributes most strongly correlated to wetness were generally the same as those for HRV texture. In fact, the relative strengths of the attribute relationships with HRV texture and TM wemess were generally consistent. This was somewhat surprising, as two apparently fundamentally different phenomena drive these image algorithms.

As described earlier, our understanding of the relationships between HRV texture and stand structure was fairly sound; but we did not understand what structural phenomena were influencing wetness. Thus, we consulted the literature and collected ground radiometer data of individual scene components (Cohen and Spies 1992). The radiometer we used was a Barnes Modular Multispectra: Radiometer (MMR) equipped with filters that replicate the six TM reflectance bands. In-situ reflectance measurements were obtained from canopies of the most prevalent tree species, for foliage of herbaceous and hardwood plant species commonly found in the western hemlock zone, and for deadwood, tree bark, soil, and epiphytic canopy lichens. Spectra of the same components were also collected in completely shaded conditions.

The scant literature on the subject revealed that both theory and empirical evidence are in support of each other. In essence, wemess responds to both the amount of water and shadows in the ground scene, with these relationships being positive. After giving this topic additional thought we discovered an apparent incongruency with respect to how we would expect the wemess index to respond to different types of canopy structures. In forest canopies the amount of "water-filled" foliage viewed by the sensor is closely linked to the degree of canopy shadowing. In general, the older and more complex the stand, the greater the proportion of shadow present. Because the amount of shadow is greater in more complex stands, we can safely assume that the amount of foliage per unit area visible to the TM sensor is less in these stands than in closed-canopy stands with more simple structures. This is in fact true. Therefore, with increasing structural complexity, wetness should increase due to greater proportions of canopy shading; however, wetness should decrease due to less foliage being viewed by the sensor. It might appear that the effect of less water is dominant, since wetness clearly decreases with increasing structural complexity. In reality however, wemess values for young, simply structured sunlit Douglas-fir and western hemlock foliage and for shaded components are very similar (Cohen and Spies 1992), depriving this whole argument of practical significance.

In Cohen and Spies (1992) we hypothesized that the controlling factor may be in part the amount of age-related canopy die-back, tree death, and increase in epiphytic lichen. This is based on the fact that with increasing age, individual tree crowns in the upper layers begin to die, thereby losing foliage and exposing bark and deadwood. At the same time, canopy lichens begin to grow in increasingly greater amounts. The tops of many of the trees break, as others become snags. Cohen (1991b) demonstrated that woody and other nongreen plant materials have wemess values considerably lower than does green foliage. The same result can be inferred from Guyot et al. (1989) and Elvidge (1990). Our radiometer data from this study indicate that canopy lichen, bark, and deadwood have significantly lower wemess values than sunlit Douglas-fir and western hemlock foliage and all shaded components. Our hypothesis is further supported by evidence that the inner half-radius of an old Douglas-fir tree crown can be covered by as much as 75 percent canopy lichen, as viewed from above (Bruce McCune, pers. comm.).

If our hypothesis for the response of wemess to vegetation senescence holds true, the question must be asked, "Is use of the term wemess appropriate?" Viewing a wemess image of a landscape containing distinct water bodies reveals that water is not the wettest feature. This alone is cause for dropping use of the term wemess and searching for an alternative, more appropriate name for this important spectral feature of TM data — one that is robust enough to describe a general vegetation condition, or process, across numerous ecosystem types. In Cohen and Spies (1992) we made the case for a term such as maturity index. Recently, we have noticed that stands not particularly aged in years but which exhibit structural characteristics similar to old-growth forest stands have wetness values like those of old stands. Such stands tend to grow on rocky, steep slopes that are drier and therefore prematurely age the forests growing on them.

Topographic Effects

Effects of topography on image data are well documented, and several means exist with which to try to ameliorate their effects (e.g., Holben and Justice 1980, Justice et al. 1981, Ahern et al. 1987, Civco 1989, Colby 1991). Most methods are designed to correct the image data by a cosine function to force an incident energy level that would exist if the sun's position were normal to the surface (Smith et al. 1980). Although this methodology may be sufficient for some relatively simple vegetation structures like a field of corn or wheat, it is generally inappropriate for forest canopies. This is because the interaction of solar angle, topographic position, and vegetation structure is completely ignored, and it can be this interaction that is most important. Alternative means for minimizing effects of topography are needed. One method is to capitalize on this interactive relationship by its explicit incorporation into a classification scheme (Eby 1987), or to use something like a geometric-optical reflectance model (Li and Strahler 1985). Another method is to use algorithms that create new indices or images that do not exhibit strong topographic effects. Texture algorithms produce images that are generally insensitive to topography because local variability is evaluated rather than local means. Wetness images are not very sensitive to topography for at. least two probable reasons.

First, the Tasseled Cap transformation is similar to a principal component analysis (PCA). As such, brighmess, the first axis, accounts for most of the spectral variability in the data. Likewise, the greenness, or second axis accounts for the next largest proportion of spectral variability. Together brighmess and greenness account for about 75 percent of the spectral variation in a TM image. As a topographic effect is so prominent in digital imagery, it tends to dominate the first two PC, or Tasseled Cap, axes. The third axis is therefore "free" to reflect a different source of spectral variability. We believe this source is largely related to maturity of vegetation.

The second probable reason we observed wemess to be insensitive to topography is likely that maturity in forested systems commonly causes changes visible in the upper canopy layers. As such, unless the topography is extremely steep so that the upper canopy layers are in almost total shadow, the tree crowns remain visible. Where there are topographic shadows wetness values should be high regardless of vegetation cover.

Current Research

We now are faced with the opportunity to map forest attributes over large geographic areas in the PNW region, and to quantify change in the forest over the more than 20-year Landsat data record. This brings with it some additional challenges.

For one, it would be best if we could have maximum flexibility for defining strata in the imagery. That is, we prefer to use an ecoregion (Omerlink and Gallant 1988) or some other concept to identify strata for image processing purposes; rather than having the strata be defined by image boundaries. For this, a method of radiometric rectification is needed. Radiometric rectification is used here to refer to some sort of normalization applied to image data to make multiple data sets more radiometrically compatible. Several options are available, but we are first testing a method developed by Hall et al. (1991a). This method "matches" digital numbers of each band of a subject image to those of a reference image. First, dark and bright radiometric control sets are selected from the reference and subject images in brightness-greenness space. The control sets are selected interactively by viewing images and highlighting potential control-set pixels in the images. Then, raw band-to-band linear transformations are developed from relationships between control sets of the subject and reference images, and the resultant linear transformations are applied to rectify each band of the subject image.

When we attempted to apply the Hall et al. (1991a) methodology, we were immediately confronted with an unexpected challenge. Our brightness-greenness histograms had a considerably different shape than those illustrated in Hall et al. (1991a). Whereas their histograms had a distinctly triangular shape, our histograms had several "tails" making up the brightness axis or "leg" of an otherwise triangular shape. The dark end of the brightness axis was close to what we expected, but the bright end of this axis contained several bifurcations. This raised the issue of where to select control sets.

After experimenting with control-set selection we found that the bifurcation that most closely resembled the Hall et al. (1991a) brightness axis did not provide good results for our images. Rather we found that one or more bifurcations below the brightness axis (i.e., into negative greenness) gave better results. Because the bifurcation that worked best was variable, we could not consistently get the desired result simply by picking what appeared to be the best brightness control set. Thus, we found it necessary to select three to five candidate bright control sets and evaluate which worked best. Furthermore, we found that the control set that worked best was band-dependent. In the final analysis, we decided to use the control set that worked best for a given band to rectify that band. This was determined from a combination of visual assessment and comparison of digital numbers from test sites of ground areas that overlapped in the subject and reference images.

The correction is imperfect, but does provide significantly improved radiometric matching among images. This should permit us to make spatial mosaics of images and to do temporal analyses on spatially coincident images, without having to overly concern ourselves about differing radiometric properties.

Another challenge is associated with change detection, which when done in a spatially explicit manner involves spatial overlay of two or more images from different dates (Hall et al. 1991b, Sader and Winne 1992). Three types of change detection algorithms are commonly used: (1) difference, (2) ratio, and *(3)* PCA. The difference and ratio algorithms require simply subtracting one image from another, or dividing one image by the other, respectively. These two algorithms are generally limited to comparison of two images, and should give similar results except for how the resultant image is scaled. The PCA algorithm can be applied to any number of images, with each PC axis generally representing change between two distinct time periods. Other algorithms have been applied but,' to date, only in isolated situations.

We have just begun to experiment with change detection, and thus we have nothing to report here. We are aware, however, that spatial misregistration will cause erroneous results around "sharp" edges such as clearcut and forest boundaries. Initial experimentation reveals that we can filter these narrow boundaries out of the change image.

References

Ahem, EJ., R.J. Brown, J. Cihlar, R. Gauthier, J. Murphy, R.A. Neville, and P.M. Teillet. 1987. Radiometric correction of visible and infrared remote sensing data at the Canada Centre for Remote Sensing. Int. J. Remote Sens. 8:1349-1376.

Ajai, D.S., G.S. Kamat, A.K. Chaturvedi, A.K. Singh, and S.K. Sinha. 1983. Spectral assessment of leaf area index, chlorophyll content, and biomass of chickpea. Photogram. Eng. Remote Sens. 49:1721-1727.

Atkinson, P.M., and EM. Danson. 1988. Spatial resolution for remote sensing of. forest plantations. In: Proceedings, IGARSS '88 Symposium, Edinburgh, Scotland, 13–16 September 1988, ESA Publ. Division, pp. 221-223.

Atkinson, P.M., P.J. Curran, and R. Webster. 1990. Sampling remotely sense imagery for storage, retrieval and reconstruction. Prof. Geographer 42:345 353.

Civco, D.L. 1989. Topographic normalization of Landsat Thematic Mapper dig tal imagery. Photogram. Eng. Remote Sens. 55:1303-1309.

Clark, I. 1979. Practical geostatistics. Elsevier, London.

Cohen, W.B. 1991a. Response of vegetation indices to changes in three measure of leaf water stress. Photogram. Eng. Remote Sens. 57:195-202.

Cohen, W.B. 1991b. Chaparral vegetation reflectance and its potential utility fc assessment of fire hazard. Photogram. Eng. Remote Sens. 57:203-207.

Cohen, W.B., and T.A. Spies. 1990. Remote sensing of canopy structure in th Pacific Northwest. Northwest Environ. J. 6:415-418.

Cohen, W.B., T.A. Spies, and G.A. Bradshaw. 1990. Semivariograms of digit: imagery for analysis of conifer canopy structure. Remote Sens. Enviror 34:167–178.

Cohen, W.B., and T.A. Spies. 1992. Estimating structural attributes of Douglas fir/western hemlock forest stands from Landsat and SPOT imagery. Remot Sens. Environ. 41:l-17.

Colby,.J.D. 1991. Topographic normalization in rugged terrain. Photogramm Eng. Remote Sens. 57:531-537.

Congalton, R.G., K. Green, and J. Teply. 1993. Mapping old-growth forests or National Forest and Park Lands in the Pacific Northwest from remotel sensed data. Photogram. Eng. Remote Sens. 59:529-535.

Crist, E.P., and R.C. Cicone. 1984. **A** physically based transformation of The matic Mapper data—the TM Tasseled Cap. IEEE Trans. Geosci. & Remot Sens. 22:256-263.

Crist, E.P., R. Laurin, and R.C. Cicone. 1986. Vegetation and soils informatio: contained in transformed Thematic Mapper data. In: Proceedings, IGARSS '86 Symposium, Zurich, Switzerland, 8–11 September 1986, ESA Puhl. Divi sion, SP-254:1465–1470.

Curran, P.J. 1988. The semivariogram in remote sensing. Remote Sens. Environ 24:493-507.

Curran, P.J., and J.L. Dungan. 1989. Estimation of signal-to-noise: a new pro cedure applied to AVIRIS data. IEEE Trans. Geosci. Remote Sens. 27:620-628.

de Miranda, EP., and J.A. MacDonald. 1990. A variogram study of SIR-B data in the Guyana Shield, Brazil. In: Proceedings, Image Processing '89, 23 Ma 1989, Sparks, Nevada, pp. 66–77, ASPRS, Falls Church, VA.

Eby, J.R. 1987. The use of sun incidence angle and infrared reflectance levels in mapping old-growth coniferous forests. In: Technical Papers, 1987 ASPRS ASCM Fall Convention, Reno, Nevada, pp. 36–44, ASPRS, Falls Church VA.

Elvidge, C.D. 1990. Visible and near-infrared reflectance characteristics of dry plant materials. Int. J. Remote Sens. 11:1775-1796.

Franklin, J.F., and C.T. Dymess. 1988. Natural vegetation of Oregon and Washington. Oregon State University Press, Corvallis, OR, 452 pp.

Gool L.V., P. Dewaele, and A. Oosterlinck. 1985. Texture analysis anno 1983. Comput. Vision, Graph., and Image Process. 29:336-357.

Guyot, G., D. Guyon, and J. Riom. 1989. Factors affecting the spectral response of forest canopies: a review. Geocarto Int. 4(3):3-18.

Hall, EG., D.E. Strebel, J.E. Nickeson, and S.J. Goetz. 1991a. Radiometric rectification: toward a common radiometric response among multidate, multisensor images. Remote Sens. Environ. 35:11–27.

Hall, EG., D. Botkin, D.E. Strebel, K. Woods, and S.J. Goetz. 1991b. Large-scale patterns of forest succession as determined by remote sensing. Ecology 72:628-640.

Holben, B., and C. Justice. 1980. The topographic effect on the spectral response of nadir-pointing sensors. Photogramm. Eng. Remote Sens. 46:1911.

Irons, J.R., and G.W. Petersen. 1981. Textural transforms of remotely sensed data. Remote Sens. Environ. 11:359-370.

Journel, A.G. 1989. Fundamentals of geostatistics in five lessons. Short Course in Geology: Volume 8, American Geophysical Union, Washington.

Journel, A.G., and Ch.J. Huijbregts. 1978. Mining geostatistics. Academic Press, New York.

Jupp, D.L.B., A.H. Strahler, and C.E. Woodcock. 1988a. Autocorrelation and regularization in digital images: I. Basic theory. IEEE Trans. Geosci. Remote Sens. 26:463-473.

Jupp, D.L.B., A.H. Strahler, and C.E. Woodcock. 1988b. Autocorrelation and regularization in digital images: II Simple image models. IEEE Trans. Geosci. Remote Sens. 27:247-258.

Justice, C.O., S.W. Wharton, and B.N. Holben. 1981. Application of digital terrain data to quantify and reduce the topographic effect on Landsat Data. Int. J. Remote Sens. 2:213-230.

Kauth, R.J., and G.S. Thomas. 1976. The tasseled cap—a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. In: Proc. Symp. on Machine Processing of Remotely Sensed Data, 4b:41-51, 6 June–2 July, 1976, LARS Purdue Univ., West Lafayette, IN.

Li, X., and A.H. Strahler. 1985. Geometric-optical modeling of a conifer forest canopy. IEEE Trans. Geosci. Remote Sens. 23:705-721.

Mather, P.M. 1987. Computer processing of remotely-sensed images. John Wiley, New York.

Matheron, G. 1971. The theory of regionalized variables and its application. Les Cahiers du Centre de Morphologie Mathematique de Fontainbleau, No. 5, Published by Ecole Nationale Superieure des Mines de Paris.

Musick, H.B., and R.E. Pelletier. 1988. Response to soil moisture of spectral indices derived from bidirectional reflectance in Thematic Mapper wavebands. Remote Sens. Environ.

Oliver, M., R. Webster, and J. Gerrard. 1989a. Geostatistics in physical geography. Part I: Theory. Trans. Inst. Br. Geogr. N.S. 14:259-269.

Oliver, M., R. Webster, and J. Gerrard. 1989b. Geostatistics in physical geography. Part I: Applications. Trans. Inst. Br. Geogr. N.S. 14:270-286.

Omerlink, J.M., and A.L. Gallant. 1986. Ecoregions of the Pacific Northwest USEPA, ERL, Corvallis, OR. 39 pp.

Perry, C.R., and L.F Lautenschlager. 1984. Functional equivalence of spect; vegetation indices. Remote Sens: Environ. 14:169–182.

Ramstein, G., and M. Raffy. 1989. Analysis of the structure of radiometric motely sensed images. Int. J. Remote Sens. 10:1049-1073.

Rubin, T. 1990. Analysis of radar texture with variograms and other simplified descriptors. In: Proceedings, Image Processing '89, Sparks, NV, 23 May 198 ASPRS, Falls Church, VA, pp. 185–195.

Sader, S.A., and J.C. Winne. 1992. RGB-NDVI color composites for visualizir forest change dynamics. Int. J. Remote Sens. 13:3055-3067.

Smith, J.A., T.L. Lin, and K.J. Ranson. 1980. The Lambertian assumption ae Landsat data. Photogramm. Eng. Remote Sens. 46:1183-1189.

Spies, T.A., and J.F Franklin. 1988. Old growth and forest dynamics in tl Douglas-fir region of western Oregon and Washington. Natural Areas 8:190-201.

Spies, T.A., J.F Franklin, and M. Klopsch.1990. Canopy gaps in Douglas-forests of the Cascade Mountains. Can. J. For. Res. 20:649-658.

Spies, T.A., and J.F Franklin. 1991. The structure of natural young, mature, ar old-growth forests in Washington and Oregon. In: Wildlife and vegetation unmanaged Douglas-fir forests. L.F Ruggiero et al. (eds.). USDA Fore Service Gen. Tech. Rep. PNW-GTR-285, Portland, OR, pp. 90–109.

Townshend, J.R.G., C.O. Justice, C. Gurney, and J. McManus. 1992. The impa' of misregistration on change detection. IEEE Trans. Geosci. Remote Sen 30:1054–1060.

Tucker, C.J. 1979. Red and photographic infrared linear combinations for mon toring vegetation. Remote Sens. Environ. 8:127-150.

Wald, L. 1989. Some examples of the use of structure functions in the analysis satellite images of the ocean. Photogram. Eng. Remote Sens. 55:1487-149(

Wang, L., and D.C. He. 1990. A new statistical approach for texture analysi Photogram. Eng. Remote Sens. 56:61-66.

Webster, R. 1985. Quantitative spatial analysis of soil in the field. Advances i Soil Science 3:l-70.

Webster, R., P.J. Curran, and J.W. Munden. 1989. Spatial correlation in reflecte radiation from the ground and its implications for sampling and mapping b ground-based radiometry. Remote Sens. Environ. 29:67-78.

Webster, R., and M. Oliver, M. 1990. Statistical merhods in land and resourc survey, Oxford University Press, Oxford.

Wilderness Society. 1991. Ancient Forests in the Pacific Northwest. The Wilde ness Society, Washington, D.C.

woodcock, C.E., and A.H. Strahler. 1987. The factor of scale in remote sensing. Remote Sens. Environ. 21:311-332.

Woodcock, C.E, A.H. Strahler, and D.L.B. Jupp. 1988a. The use of variograms in remote sensing: I. Scene models and simulated images. Remote Sens Environ. 25:323-348.

Woodcock, C.E, A.H. Strahler, and D.L.B. Jupp. 1988b. The use of variograms in remote sensing: II. Real digital images. Remote Sens. Environ. 25:349-379.

Woodcock, C., and V.J. Harward. 1992. Nested-hierarchichal scene models and image segmentation. Int. J. Remote Sensing 13:3167-3187.

Yoder, J.A., C.R. McClain, J.O. Blanton, and L. Oey. 1987. Spatial scales in CZCS-chlorophyll imagery of the southeastern U.S. continental shelf. Limnol. Oceanogr. 32:929-941.