IMAGE SPECTRAL AND SPATIAL INFORMATION IN THE ASSESSMENT OF FOREST STRUCTURAL AND BIOPHYSICAL DATA

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ABSTRACT

Remote sensing instruments generally regularize a continuous ground surface into a grid of similarly sized and shaped pixels. This regularization results in similarity of neighboring pixels which represent the same objects on the ground. The above ground organization of vegetation in a forest is considered the forest structure. At a high spatial resolution, at approximately 1m, the spatial information that is created though this discretization represents the forest structure. This image spatial information may be applied to improve the accuracy of estimates of forest biophysical and structural parameters from remotely sensed data. In this paper the relationship between image spatial structure and forest structural information is presented. To demonstrate this relationship, examples of the estimation of forest structural parameters from the spatial and spectral information collected with an airborne imaging spectrometer (CASI) at a spatial resolution of 1m are presented.

Keywords: forest structure, forest inventory, leaf area index, image spatial structure, autocorrelation, semivariance, texture, Getis statistic, clustering, digital image processing.

RÉSUMÉ

INFORMATIONS SPECTRALES ET SPATIALES D'IMAGERIE AUX FINS DE L'ÉVALUATION DES DONNÉES SUR LA STRUCTURE ET LA BIOPHYSIQUE DES FORÊTS

Les données de télédétection se rapportant à une surface continue au sol sont généralement structurées en une matrice de pixels de dimension et de forme homogènes. Cette structuration matricielle se traduit par l'obtention d'une similarité entre pixels adjacents associés aux mêmes objets au sol. L'organisation au sol de la végétation forestière constitue ce qu'on appelle la structure de cette forêt. Avec une résolution spatiale élevée, soit jusqu'à environ un mètre, l'information spatiale résultant de cette discrétisation représente la structure de la forêt et peut être utilisée pour améliorer le degré de précision des évaluations des paramètres biophysiques et structurels forestiers à partir de données de télédétection. Ce rapport fait état du lien qui existe entre la structure spatiale des images et l'information sur la structure des forêts. Pour illustrer ce lien, l'auteur présente des exemples d'évaluations des paramètres structurels réalisées à l'aide d'informations spatiales et spectrales recueillies par un spectromètre imageur aéroporté compact (CASI) à une résolution spatiale de un mètre.

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INTRODUCTION

INCLUSIVE FOREST MANAGEMENT PRACTICES

Canada contains approximately 10%, or 417.6 million hectares, of the global forest cover (Westoby, 1989). Canadian forest products account for 18% of the world's forest products exports, which in 1993 were valued at $27 billion (NRC, 1995). Canada's forests have been estimated to contain 2.6 X 10^{10} tonnes of biomass and 2.4 X 10^{10} m^3 of gross merchantable timber (Brand, 1990). The importance of forests, both environmentally and economically, has necessitated a change in Canadian forestry policy. The implementation of ecosystem management shifted the emphasis from maintaining the ability to harvest a known quantity yearly, based on annual allowable cut, to the maintenance of healthy, diverse ecosystems. This change in forest management policy in Canada illustrates the shift in global forest management priorities from stand management to ecosystem management (NRC, 1995). A key change resulting from this change in priorities is the monitoring of complete natural ecosystem areas, not only the artificial boundaries of a forest management area. Inventories under traditional forest stand management generally consisted of measures of age, species, and timber volume; yet within an ecosystem management framework, the level of detail of measures is increased, requiring information on soils, productivity, and habitat requirements (Wagner, 1994). Within an ecosystem management framework, the future management goals for a forest are considered in terms of age, composition, structure, distribution, and aesthetics (Gillis and Leckie, 1993), as well as non-timber values, such as potential for employment and recreation (CCFM, 1995). The techniques utilized by forest managers and forest scientists are continuing to overlap as the need for sustainable forest management increases (Toman and Ashton, 1996).

FOREST STRUCTURE FOR ECOSYSTEM MONITORING AND MANAGEMENT

Forest structure is the above ground organization of plant materials (Spurr and Barnes, 1980) with the structure of a given forest being the result of competition for light, water, and nutrients at a particular location (Kozlowski et al. 1991). Forest structure may vary from homogeneous even aged stands to heterogeneous mixed stands with multiple age classes. The greater complexity of mixed forests compared to pure forests is a reflection of the variations among species in crown form, phenology, growth rate, longevity, and size. Accordingly, the ability to assess the structure of a forest permits insight into environmental factors such as hydrology, albedo, productivity, and soils. An understanding of forest structure enables the monitoring, modeling, and prediction of important biophysical processes, such as the interaction between the forest and the atmosphere, based upon the input of a forest structural measure to a forest productivity model (Running et al. 1994). Changes in forest structure may also provide for forest inventory information related to forest vigor, harvests, burns, stocking level, disease, and insect infestations (Gillis and Leckie, 1996). As suggested, forests may be characterized in terms of inventory measures or biophysical parameters. Inventory parameters provide detailed data on the location and extent of forest resources, such as species composition, age, height, tolerance level, density, and crown closure (Gillis and Leckie, 1993).

Forest biophysical parameters provide data on the productivity, structure, and amount of forest resources. Table 1 presents and defines the most common forest biophysical parameters. These measures are most commonly used as they are often correlated to other measures, can be applied to any plant canopy and may be integrated into regional scale models (Running and Hunt, 1994). Forest biophysical parameters are often an attempt to simplify the measurement of forest structure into a single measure, such as leaf area index. LAI is an important structural attribute of forest ecosystems because of its potential to be a measure of energy, gas, and water exchanges. Maximum canopy leaf area is correlated to mean annual temperature, length of growing season, mean annual minimum air temperature, and water availability (Gholz, 1982). Further, physiological processes such as photosynthesis, transpiration, and evapotranspiration are related to LAI (Pierce and Running, 1988).

Parameter	Detail
LAI	leaf area index - is a measure of area of foliage per unit area of ground
Biomass	biomass - is the total of absolute amount of vegetation present (often considered in terms of above ground biomass)
NPP	net primary productivity - is similar to biomass, but has a temporal component as it is related to the amount of biomass accumulated over a given time period

Table 1. Typical forest biophysical parameters (definitions after Bonham, 1989).

The collection of the detailed measures that characterize a forest inventory has previously been limited by the technical capabilities of remote sensing instruments. Current technological developments are enabling greater spectral and spatial resolution on a variety of platforms enabling the remote measurement of inventory parameters (Leckie, 1990; Leckie et al. 1995). Forest assessment approaches which incorporate data from a variety of spectral and spatial resolutions are necessary to address the complexity of sustainable forest management with remotely sensed data (Wulder, 1998a).

REMOTE SENSING OF FOREST STRUCTURE

Assessment of forests within an ecosystem management framework implies both geographic and economic advantages in applying remote sensing methods to generate data on forest extent and location. Yet, often remote sensing methods fail to capture the diversity of forests necessary for management decisions (Peterson and Running, 1989). Traditional methods for the estimation of forest structural parameters from remotely sensed data are commonly limited by low spatial resolution (Nemani et al. 1993) and a reliance on spectral information (Wulder et al. 1996a) resulting in an inability to capture the complexity of the forest cover. Further, complex multi-age and multi-species forests which are prevalent in Canada are especially difficult to assess with traditional remote sensing tools and techniques. High spatial resolution remotely sensed imagery has demonstrated potential for increased accuracy in the estimation of forest structural parameters through a combination of image spatial and spectral data. Image spectral information represents the vegetative characteristics of a stand while the structural characteristics are related through spatial information. The vegetative characteristics are commonly related through vegetation indices, while the spatial information may be represented by image texture. The spatial information present in variance rich high spatial resolution imagery is related to the forest structural variability. At a high spatial resolution, the local variance indicates the organization of forest vegetation.

Figure 1 demonstrates the succession of a forest stand, initially occupied by grasses, giving way to shrubs, then trees. The tree species will grow towards a climax forest of species that are best suited for the conditions at that location. Also demonstrated in Figure 1 is the increasing complexity of both vertical and horizontal structure of the forest. The vertical structure refers to tree height distribution and the horizontal distribution pertains to stand density and spatial distribution (St-Onge and Cavayas, 1995). The grasses have minimum vertical stratification and are well represented from above, in contrast to the mature forests which all appear similar from the nadir view (Wulder et al. 1996a).

The relationship between image resolution and size of the objects of interest to the analyst is a key consideration in the analysis of remotely sensed data of forests. If a number of pixels comprise an image object of interest, the imagery is considered H-resolution (Strahler et al. 1986). Yet, within an H-resolution environment there are differences in what type of information may be extracted. If the resolution/object relationship is close, where few pixels compose an object, less forest structural information will be discernible than if 100 pixels were making up the same object. This is the approximate difference between 1m and 10cm resolution imagery. At the 1m level of resolution, when considering complex multi-age and multi-species forests, a limited number of forests structural parameters may be considered for potential estimation. Inventory parameters, such as, crown closure, stand destiny, and the biophysical parameter LAI, from a combination of image spatial and spectral information will be considered in this paper.

REMOTE MEASUREMENT OF FOREST STRUCTURAL AND BIOPHYSICAL PARAMETERS

High spatial resolution (1m) image data, collected with a 2-dimensional imaging spectrometer (CASI), will be utilized to demonstrate the estimation of forest structural and biophysical parameters. After a description of the study area, and field and image data, two examples which incorporate spatial information into the estimation of forest structural parameters are presented. The first study involves the estimation of LAI from image spectral response and texture. The second example requires an initial discussion of image spatial dependence characteristics prior to presentation of how this information is related to forest structure.

STUDY AREA DESCRIPTION

The Fundy Model Forest (FMF) is a 420,000 hectare working forest in southeast New Brunswick, Canada. The model forest is located in the Acadian forest region and is composed of a variety of broadleaf deciduous and coniferous species and includes a wide range of forest conditions (Rowe, 1972) with stand ages ranging from regeneration to old growth. The Acadian forest region is characterized by a wide variety of forest species. Coniferous tree species are predominantly jack pine (*Pinus banksiana*), white spruce (*Picea glauca*), and balsam fir (*Abies balsamea*), and red spruce (*Picea rubens*). The predominant deciduous species are red maple (*Acer rubrum*) and white birch (*Betula papyrifira*), with stands also including beech (*Fagus grandifolia*), striped maple (*Acer pensylvanicum*), trembling aspen (*Populus tremuloides*), long tooth aspen (*Populus grandidentata*), and sugar maple (*Acer saccharum*) (Wulder, 1996). The study area was centered near Sussex at 45° 43’ North and 65° 31’ West, with data collected immediately north and south of the town site. Stands were selected for inclusion in the study to represent a range of forest types, crown closures, stand densities, tree species, and LAI values.

Ground Survey Data

The ground reference data is the result of a combination of a summary survey, which collected a minimum of parameters of every tree in the sample plot, with an intensive survey that measured a selection of trees in detail (Table 2). A random sampling technique was utilized to select trees for the intensive survey within the 20 X 20m plot. For each tree in the summary survey, the diameter at breast height (DBH, 1.37m) was measured, the species noted, an identification number given, and location within the plot were recorded. Bivariate regression relationships are generated between DBH and the intensively surveyed parameters which allowed for extrapolation of all characteristics of interest to all trees in the summary sample.

plot number
slope
aspect
stand type
date
tree number
species
diameter at breast height (DBH)
location 1 (X)
location 2 (Y)
crown class (C.C.) (C = co-dominant, I = intermediate, S = suppressed, D = dominant)
sapwood width
bark width
total height
base to live crown
crown width one (with flight line)
crown width two (perpendicular to flight line)

Table 2. Ground reference data included in the intensive sample of each plot.

Based upon the plot information generated from the field data, plot maps were created. The plot maps have been degraded to a 1m grid to allow for comparison to the 1m spatial resolution remotely sensed data. The plot maps are created from the field data held in a GIS. To generate the field plot maps, information relating to tree height, canopy size, and canopy layer are included. To enable consistent integration of the plot information a C program was written.

Remotely Sensed Image Data

On July 31, 1995, at 13:00 local time, compact airborne spectrographic imager (CASI) imagery was acquired from a Cessna 310 aircraft at an elevation of 700 m and at a speed of approximately 55 knots utilizing the standard CASI 12.5 mm focal length (Anger et al. 1996). This configuration was selected to scan 1 X 1m resolution imagery with five user selected spectral bands (Table 3), to characterize significant locations on a vegetation spectral response curve. The azimuth of the data acquisition flight lines were approximately towards the sun to reduce changing illumination conditions and view angle effects. The sky was clear and the relative humidity was low, reducing the effects of the atmosphere on the imagery (Wulder et al. 1996b).

Channel and Spectral Location	Bandwidth(nm)	Centre (nm)	Width (nm)
channel 1 (green)	560.5 to 569.4	565.0	8.9
channel 2 (red)	640.9 to 649.8	645.4	8.9
channel 3 (red well)	660.6 to 669.6	665.1	9.0
channel 4 (red edge)	707.4 to 714.6	711.0	7.2
channel 5 (infrared)	748.8 to 752.4	750.6	3.6

Table 3. Fundy Model Forest CASI imagery spectral wavelength channel summary.

An atmospheric correction of the image data was undertaken utilizing the pseudo-invariant feature (PIF) calibration method outlined by Freemantle *et al*. (1992). Spectral information was recorded in the field concurrent with the CASI overflight to enable atmospheric correction of the CASI data. Paved roads, which intersect the flight lines at a number of known locations, were used as PIF targets. Image preprocessing of the CASI data is performed to radiometrically correct the data for the effects of scattered light, to remove instrument offsets, and to convert the digital numbers to standard radiometric units. An initial bundle adjustment was undertaken to correct for the non-systematic airborne imaging effects of roll, pitch, and yaw . Collection of global positioning system (GPS) ground data and flight locational data enabled differential correction and geometric adjustment of the airborne imagery. The aircraft position and angular orientation was recorded for each scanline using the onboard GPS receiver and a two-axis vertical gyro. The geometric correction process utilized this aircraft attitude information and placed each pixel of the image on a georeferenced UTM grid (Cosandier et al. 1992). The base station GPS receiver unit, located at a known geographic point, was used to correct the imagery acquired by the airborne GPS unit. For this study locational data were collected with a L1 Carrier Phase Novatel GPS receiver units at a 5 second epoch rate.

INTEGRATION OF TEXTURE AND VEGETATION INDICES FOR THE ESTIMATION OF LAI

The ability to estimate LAI from spectral response is strong up to an LAI of approximately 3 (Gong et al. 1992), after which an asymptote is normally encountered (Wulder et al. 1996a). The flattening of the relationship is due to the inability of NDVI, generated from a nadir remote sensing instrument, to sense increases in foliage overlap (Baret and Guyot, 1991) as forest complexity increases. As a result, additional information is required which still undergoes change as the forest increases in complexity. Forest spatial structure varies through levels of forest development (Waring and Schlesinger, 1985). Image spatial information may capture some of the variability in forest structure (St-Onge and Cavayas, 1997). Digital image processing provides spatial measures which characterize the spatial neighborhood of a pixel, such as, digital image texture (Wulder et al. 1998) and image semivariance (Cohen et al. 1990; Franklin and McDermid, 1993) capture information relating to the variability around a pixel related to the forest structure.

Example Estimation of LAI from NDVI and Texture

Texture has been demonstrated to be valuable in the statistical estimation of LAI (Wulder et al. 1996a). Yet, many texture measures are limited by subjective user based decisions, such as the texture measure to apply and the size of window. In this example, digital image semivariance is computed to assess the mean spatial dependence within image sample plots to dictate customized window sizes (Franklin et al. 1996) for the derivation of first and second order texture measures. First-order texture is a representative statistical value for the central cell of a fixed moving window which is passed over the image (Jensen, 1986). Second order texture measures are not computed directly from the image values but rather from the statistical distribution of local properties in the spatial domain. An example is the calculation of second order statistics from pixel relationships stored in a grey level co-occurrence matrix (Haralick et al. 1973). A hybrid spatial measure is also presented in this example, semivariance moment texture, or SMT (Wulder et al. 1998). SMT is derived from the semivariance response found at each pixel. At each pixel semivariance response is computed and significant locations of the semivariance response are utilized as spatial descriptors. The nugget, sill, range, mean semivariance between nugget and sill, and the slope of the semivariance response between nugget and sill, are the values which may be derived for each pixel with SMT.

The work of Wulder *et al*. (1996, 1998) is an exploration of the relationship between LAI, NDVI, and texture. A summary of the findings of Wulder *et al*. (1998) demonstrates the potential of a variety of texture measures in the estimation of LAI from airborne spectrometer data. The relationship between LAI and NDVI is important to provide the vegetative characteristics of a stand. The relationship between LAI and NDVI is weak when considered over a variety of stands simultaneously, due to spectral variation between stands. Within stands, the species heterogeneity will also diminish the relationship with LAI and decrease the strength of the relationships. The spectral and structural variability between stand types dictates the need for stratification between stand types for analysis. For hardwood stands, a strong initial relationship between LAI and NDVI may be found based upon broad canopy elements and species spectral similarity. In hardwood stands, primary texture measures and SMT values are found to be best related to LAI. Primary texture measures are most successful for the estimation of homogeneous cover types. SMT measures are sensitive to the spatial characteristics of the stand such as crown closure and density and as a result are useful in the estimation of a variety of cover types. Multivariate estimation of LAI from NDVI and two texture measures resulted in an increase of coefficient of variation to 0.61 from an initial 0.42 between LAI and NDVI. An assessment of softwood plots demonstrated the need for stratification between regeneration regimes. In plantations the tree planting pattern results in a strong textural component to the softwood stands. Mixed wood plots, containing both deciduous and coniferous species, consequently contain spectral variability based upon both species and vegetation distribution. As a result, texture proved significant in increasing the ability to estimate mixed forest LAI.

Based upon these encouraging results, further investigation of image spatial information in the estimation of forest structure will be pursued. Some conclusion which may be drawn from these previous studies are:

- first- and second-order texture are capturing different information based upon factors such as species spectral response and density,
- SMT is generating data related to the distribution of vegetative elements of a stand and the spectral response of these elements, and
- the performance of the texture measures in the predictive equations of LAI is found to be dependent upon forest cover type. Accordingly, in the spectral estimation of LAI, a specific texture measure may be required as input on a species specific basis.

OBJECT CLUSTERING FROM SPATIAL INFORMATION

The previous section related the increase in model variance which may be explained when estimating the forest biophysical structure variable LAI with the incorporation of image spatial information. The SMT values demonstrated the ability of semivariance to generate unique spatial information from the image spectral values. The image spatial dependence, as measured with semivariance, is a mean difference between pixels computed over a distance (Jupp et al. 1988). Semivariance computation results may provide an image analyst with an indication of the distance in which pixels are found to be similar from the semivariance range value (Bowers et al. 1994). Knowledge of the strength of spatial dependency and the magnitude of the values within the range of the semivariogram may provide unique local spatial information relating to forest structure.

Getis Statistic

Remotely sensed imagery of forest landcover is a discretization of a continuous natural surface into a grid of regularly sized and shaped pixels. Low resolution imagery when regularized is a variance reduced representation of the surface due to the inclusion of a variety of surface cover types within each pixel. Airborne remote sensing, and the proposed high resolution satellite instruments, partition the surface into smaller pixels and, as a result, enable a representation of the surface that is capturing a greater amount of the original variance. The high resolution environment enables elements of the surface cover to be composed of more than one pixel, an H-resolution environment (Strahler et al. 1986). For example, high resolution imagery of a forest will be composed of contiguous pixel regions which represent individual trees or groups of trees. Tree objects may be understood as regions of marked spatial autocorrelation. The ability to extract information from the spatial relationships found between pixels is an appropriate complement to the more commonly extracted spectral information, such as image texture and semivariance.

Traditional methods of spatial autocorrelation are global in nature and generate values which indicate the degree of spatial association of the entire image (Goodchild, 1986). However, such approaches yield a single summary measure which may be unrepresentative if the nature and extent of spatial autocorrelation varies significantly over the image. To overcome these limitations, local indicators of spatial association (LISA) have been developed (Anselin, 1995). In contrast to existing methods, LISA measures focus on local variations *within* patterns of spatial dependence. Thus, they have the potential to uncover discrete spatial regimes which might be overlooked by existing techniques. Measures of spatial dependence, such as semivariograms, have proven valuable in digital image processing of remotely sensed imagery. Local indicators of spatial association are complementary to semivariograms while also providing some information not detectable in semivariogram analysis which allows for an improved understanding of image spatial structure. Knowledge of the magnitude of autocorrelated values is additional information available through the digital image processing of remotely sensed imagery. LISA statistics, specifically the Getis statistic, provide information based on the spatial structure of digital images. The ability to assess the strength of interpixel relationships, as well as the magnitude of the autocorrelated data, may prove valuable when the values computed from semivariance, as a positive valued function, prove inadequate for a particular objective. Measures of spatial dependence, such as the Getis statistic (G_i^*), may be modified to relate the degree of association found between pixels in remotely sensed imagery (Wulder and Boots, 1998a). Getis statistic results relate the strength of the inter-pixel relationships and the magnitude of the values found to be clustered. The intent of this section is to provide for a brief introduction of the Getis statistic and to demonstrate how it may be applied to aid in the interpretation of high spatial resolution imagery of forests.

The suite of G statistics were initially developed by Getis and Ord (Getis and Ord, 1992; Ord and Getis, 1995). Although these statistics were initially developed for the analysis of point data, Getis (1994) has demonstrated their potential to identify significant spatial dependency in remotely sensed imagery. One Getis statistic, G_i^*, yields a standardized value which indicates both the degree of autocorrelation in the values of the digital numbers centered on a given pixel and the magnitude of these values in relation to those of the entire image. Wulder and Boots (1998b) have applied G_i^* in the assessment of a Landsat Thematic Mapper (TM) image of a managed forest region. Study results indicate a strong Landsat TM channel and cover type dependence to local spatial autocorrelation measured by the G_i^*.

In general, LISA measures evaluate the extent and nature of concentration in the values of a variable x in a local region within the study area. The Getis statistics achieve this by expressing the sum of the weighted variate values within a specified distance of a particular observation i as a proportion of the sum of the variate values for the entire study area. This value can be compared with the statistic's expected value under an hypothesis of no local spatial autocorrelation to indicate if the degree of clustering of x values in the vicinity of i is greater or less than chance would dictate (Getis, 1994). Ord and Getis (1995) provide steps to derive a standardized version of G_i^*. A complete description of the derivation of G_i^* for applications in remote sensing may be found in Wulder and Boots (1998a). First global mean and variance values are computed for the entire image allowing for computation of a standardized version of G_i^* for processing at each pixel with the following equation,

$$G_i^*(d) = \frac{\Sigma_j w_{ij}(d)x_j - W_i^* \bar{x}}{s[W_i^*(n - W_i^*) / (n - 1)]^{1/2}} \tag{1}$$

where $W_i^* = \Sigma_j w_{ij}(d)$, which generates results in a Z-score standardized form. Significant positive values indicate clustering of high variate values while significant negative values indicate clustering of low variate values. In consideration of remotely sensed imagery, the G_i^* values measure the extent to which a pixel is surrounded by a cluster of high or low values of a particular variable, such as image digital number (DN) values. Large positive G_i^* values denote a cluster of high DN values; large negative G_i^* values denote a cluster of low DN values. In addition, computing G_i^* within a series of increasing windows and noting the distance at which the largest G_i^* value occurs allows for an assessment of the size of the region of association around an individual pixel. A small window size (distance) indicates that spatial dependency is confined to a very localized region while a large distance value indicates more spatially extensive spatial dependence. A weakness of the G_i^* statistic, which it shares with other LISA measures (Tiefelsdorf and Boots, 1997), is that it cannot be used to identify clustering of medium values since mid-range values of G_i^* (i.e., values around zero) can result from either this situation or an absence of clustering of similar variate values.

The spatial dependency information computed with remotely sensed imagery is based upon the synthesis of image spatial resolution with the size of the objects of interest. In the case of forest inventory trees are the objects of interest. The size of the tree crown in relation to the image resolution dictates the type of spatial dependency information which will be generated. At a high spatial resolution (>≈10cm), the spatial dependency information computed with G_i^* may relate the within crown spectral variability. As image resolution decreases (≈1m), the pixel spatial dependency will be sensitive to the spectral differences between tree crowns, understory, and shadow spectral components. Tree crowns are complex spectrally due to forest architectural and structural considerations, such as within crown variation in reflectance, irregular shading patterns, and tree overlap. This results in an effective resolution less than what the instrument collects, which relates the need for image data collected at a resolution finer than the objects of interest (Hyppanen, 1997). The following examples will utilize image data of 1m spatial resolution in a simulated panchromatic wavelength to simulate the specifications of proposed satellite sensors (Aplin et al. 1997) to estimate the stand density and crown closure. To illustrate the potential of image spatial dependence data in the estimation of LAI, 1m spatial resolution multispectral data is used.

Spatial Dependency within Semivariance Range

A variogram describes the magnitude, spatial scale, and general form of the variation in a given set of data (Matheron, 1963). Semivariograms are a graphical representation of spatial variability and provide a means of measuring the spatial dependency of continuously-varying phenomenon (Curran, 1988). The semivariogram also displays the average change of a property with increasing lag, although the true variogram is continuous (Oliver et al. 1989). Semivariance is the variance per site when sites are considered as profiles or areas of pixels and is developed from the theory of regionalized variables (Curran, 1988). Image semivariance has been used extensively in the assessment of L-resolution forest structure (see Bowers et al. 1994; Cohen et al. 1990 for examples; Ramstein and Raffy, 1989 for the theory). In analysis of H-resolution data, image semivariance has been demonstrated to capture image structural information (Franklin and McDermid, 1993). St-Onge and Cavayas have utilized the information inherent in the directional variogram as a method to estimate the stocking and height of forest stands (1995) and in the automated delineation of forest stands (1997).

In the near future, ≈1m spatial resolution panchromatic (450-900nm) data may be available from the proposed high spatial resolution satellite sensor QuickBird (Aplin et al. 1997). To explore the forestry potential of such imagery, 1m panchromatic data collected with the CASI is assessed in this study. The panchromatic image data was processed to generate an image of semivariance range values. Semivariance was computed in Rook's case, 4 directions, for each pixel with the results averaged to represent the pixel (Woodcock et al. 1988).

Figures 2a-d numerically illustrate the spatial dependence characteristics of a subset of CASI panchromatic image data. The central number outlined is the pixel of reference for this example. The initial panchromatic digital numbers (Figure 2a) represent a cluster of four deciduous trees, two of which have canopy radii in excess of 3m. The semivariance range values, denoted in bold in the four computation directions, illustrate the pixels which resulted in a range value of 4 to result for the pixel of interest (Figure 2b). The strength of the relationship between neighboring pixels, within the range of 4 computed with semivariance, is illustrated in Figure 2c. As noted in Figure 2d, this G_i^* value was found to be at a maximum at a distance of one. The 3X3 window in which the G_i^* was found to be at maximum is also noted in bold type. The local spatial dependency is found to be at a maximum at the central point of the cluster. The high level of autocorrelation between the pixels within the tree cluster is demonstrated by the low distance values in which the G_i^* value is maximized. The complementary nature between the semivariance generated range and G_i^* allows for the extraction of image information that increases the utility of semivariance measures. Elsewhere in the illustration high distance values are seen to relate to regions of transition. The relationship between spectral transitions and the nature of the pattern of distances at which G_i^* is maximized relates well to stand density. To enable comparison, Figure 3a-d graphically illustrates the spatial dependence characteristics of the same image subset used for demonstration in Figure 2a-d. With 1m spatial resolution, as stand density increases, the amount of change of distance values within an area also increases. Segmentation of Getis statistic values is relatively straightforward as each pixel is a value which relates its association to its neighbors. From local minimum and maximum seed points, clusters are grown based upon group inclusion through minimum difference between pixels.

SPATIALLY CLUSTERED OBJECTS IN THE ESTIMATION OF INVENTORY PARAMETERS

In Wulder (1998b), the spatial dependence information of 1m panchromatic and multispectral CASI imagery are investigated for properties which may allow for estimation of forest structural parameters. The following is a summary of that work utilizing 1m spatial resolution panchromatic data to estimate the forest inventory parameters of crown closure and stand density. Estimation of the forest biophysical parameter of LAI is enhanced through the incorporation of image clusters representing large individual trees or groups of smaller trees.

The sample plots for this study are within complex stands of variable density, closure, species, and productivity. When considering the spatial dependence characteristics of remotely sensed imagery the relationship between the objects of interest and resolution is of prime importance. Very high spatial resolution data, when processed for spatial dependency clusters, generate data relating to characteristics such as branch level clustering and distribution of foliage at the individual tree crown level. While at a spatial resolution of ≈1m, spatial dependency data is generated which relates the presence of tree objects. Further decreases in spatial resolution result in the generation of clusters which relate the variability between stands of trees.

Measurement of the forest inventory parameter of crown closure with spatial dependency information shows promise, with image estimates of crown closure normally within 10% of field estimates. The field estimates of crown closure are based upon the areal contribution of clusters generated from clusters of high panchromatic values compared to field collected data.

Estimation of stand density may be made from multiple sources generated from the Getis statistic spatial dependency data. The actual Getis statistic values may be utilized to isolate stems, the maximum positive Getis statistic value normally relates a cluster centroid. If the tree is large, the stem may be isolated, yet if the cluster has been generated from the spectral response related to a group of trees, the cluster centroid will represent a group of trees. Density is not a measure that is well characterized by cluster information, as a variable number of trees may compose a cluster in a given instance. Relative indications of density may be discerned from the local rates of transitions between Getis distance values, while absolute measurement is problematic. In contrast to the complex image data used in this study, a simulation study with image elements of known size and distribution would be a means to decipher the effective resolution at which trees, or other objects, may be discerned.

ENHANCED LAI ESTIMATION WITH GETIS CLUSTERS

As described above, in the summary of the work by Wulder *et al*. (1996, 1998), spatial information was incorporated into empirical models for the estimation of LAI with promising results. One problem with the empirical estimation of LAI from image spectral and spatial values is the selection of pixels from which to extract the reflectance information. In Wulder (1998b), image spatial information is utilized to generate clusters (from NIR image data) which represent regions of foliage presence in a forest stand. Generation of these clusters allows for an increase in the likelihood that the pixels selected for incorporation in the empirical estimation of LAI are indeed the foliage unit suspected. Image spectral response in the clusters is compared to field collected spectral information which allows for a broad image object classification into general cover classes, such as deciduous, coniferous, and mixed, for inclusion in the computation of LAI. The image spatial information dictates the regions from which pixels are selected for spectral data, while the textural information is collected to represent the region around the pixel, not merely within the object. This allows for the characteristics of the local region to be incorporated in the empirical estimation of LAI. Utilizing spatial information to assist in the selection of pixels for analysis has improved the accuracy of estimates of LAI over previous spectral and spatial data incorporation techniques.

CONCLUSION

Image spatial information has been demonstrated to capture forest structural information. Empirical estimates of LAI from high spatial resolution imagery are enhanced by the inclusion of texture to the estimation model. Spatial clustering, based upon image autocorrelation, has also illustrated that forest structural information may be captured in image spatial data. At the 1m spatial resolution of this present study limitations on what may be estimated are imposed. Individual trees with a small crown radius are difficult to discern, yet may be grouped into clusters generated from the image spatial information. As a result, currently with this technique crown closure may be estimated with greater accuracy than stem density.

Tree clusters generated with the Getis statistic also show promise in the estimation of LAI. The ability to use image spatial information to assist in the selection of pixels appropriate for the extraction of spectral information improved the consistency of the empirical models through the input of systematically derived data. The inverse of this approach may be applied to estimate the extent and spectral characteristics of stand shadow fractions.

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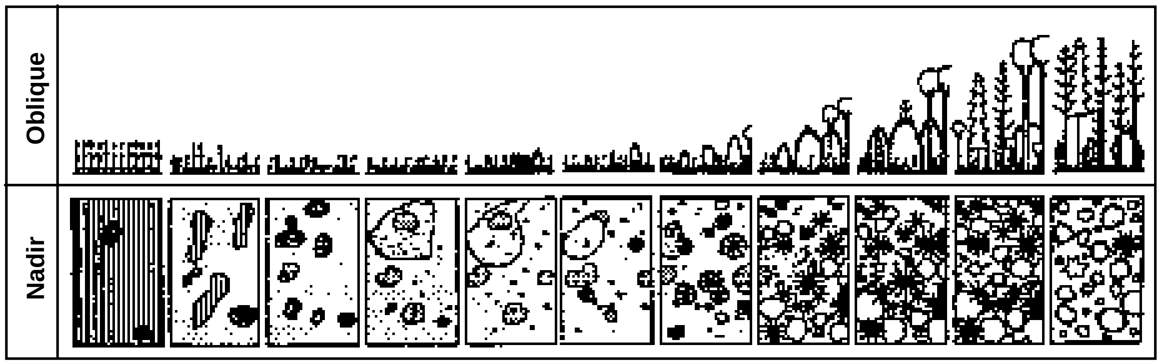

Figure 1. Demonstration of vegetation succession with increasing horizontal and vertical vegetation complexity (modified from Falinski, 1989).

38	32	29	28	28	24	26	26	25	25	25
29	27	26	29	32	**27**	26	28	27	26	25
27	31	32	29	30	**32**	29	27	26	26	24
30	34	34	30	30	**34**	27	24	25	27	28
26	33	34	35	**33**	**36**	**34**	34	33	32	36
24	**28**	**34**	**35**	**37**	37	**37**	**36**	**37**	**32**	32
26	28	29	31	**36**	**35**	**33**	34	36	28	33
32	25	23	21	29	**32**	31	30	34	31	29
28	24	20	20	26	**28**	26	29	32	30	27
21	20	19	15	19	**26**	27	28	31	30	29
15	11	9	6	9	18	26	29	28	24	22

Figure 2a. Sub-set of image panchromatic CASI data.

3	4	4	4	5	4	4	3	4	4	4
3	3	4	4	4	**3**	3	3	4	4	4
3	4	4	4	4	**4**	3	4	4	4	4
3	3	3	4	4	**4**	3	3	4	4	4
4	5	4	4	**4**	**4**	**4**	4	4	5	5
4	**4**	**3**	**4**	**4**	4	**4**	**3**	**4**	**4**	5
3	4	4	5	**4**	**4**	**4**	3	4	4	4
5	4	4	4	4	**4**	5	4	5	4	5
4	3	3	4	4	**3**	3	4	5	5	5
3	4	3	4	3	**3**	4	3	5	5	5
4	4	4	5	4	5	3	3	4	4	5

Figure 2b. Semivariance range values computed for each pixel using Rooks case.

1.38	1.16	1.11	0.94	0.84	0.76	0.65	0.50	0.37	0.33	0.09
0.91	0.98	1.01	0.99	0.92	**0.69**	0.56	0.49	0.43	0.33	0.34
0.91	0.91	1.00	1.01	0.96	**0.87**	0.86	0.80	0.72	0.66	0.63
0.86	1.07	1.23	1.17	1.18	**1.13**	1.06	0.96	0.89	0.86	0.92
0.76	1.01	1.30	1.37	**1.44**	**1.41**	**1.33**	1.16	1.06	1.09	1.24
0.78	**0.81**	**1.16**	**1.40**	**1.56**	1.60	**1.57**	**1.54**	**1.37**	**1.33**	1.30
0.75	0.67	0.75	0.99	**1.24**	**1.44**	**1.41**	1.46	1.31	1.23	1.28
0.73	0.42	0.40	0.54	0.74	**1.00**	1.10	1.13	1.11	1.07	1.16
0.40	0.09	-0.27	-0.20	0.15	**0.54**	0.73	0.89	0.99	0.96	0.82
-0.23	-0.55	-0.88	-0.89	-0.55	**0.34**	0.44	0.72	0.79	0.67	0.62
-0.62	-0.97	-1.38	-1.52	-1.25	-0.57	0.40	0.60	0.64	0.56	0.48

Figure 2c. Getis statistic values computed for each pixel.

1	1	2	3	4	4	4	4	1	1	1
4	2	3	3	4	**1**	1	1	1	1	4
4	1	2	2	1	**1**	4	4	4	3	3
4	1	1	2	1	**1**	2	2	3	2	2
4	1	1	1	**1**	**1**	**1**	1	1	1	1
2	**2**	**1**	**1**	**1**	$\boxed{1}$	**1**	**1**	**1**	**1**	1
2	2	2	1	**1**	**1**	**1**	1	1	1	2
1	1	2	2	1	**1**	2	1	1	2	2
1	1	1	1	1	**1**	1	1	1	1	2
1	1	1	1	1	**4**	1	1	1	1	4
1	1	1	1	1	1	4	1	1	2	4

Figure 2d. Distance value at which Getis statistic value is maximized.

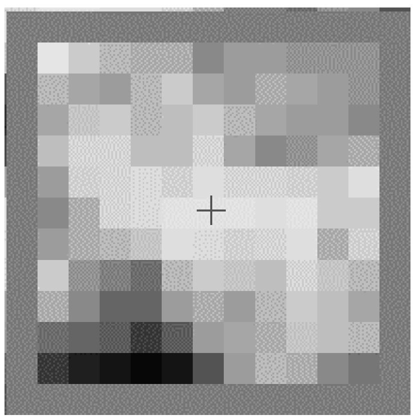

Figure 3a. Sub-set of panchromatic *CASI* digital image data.

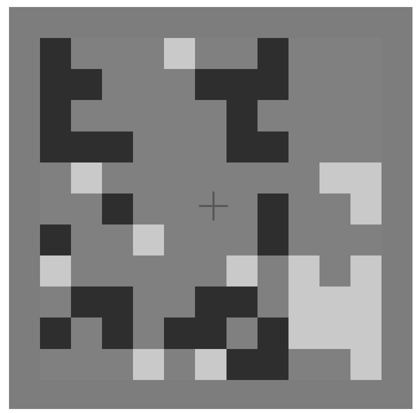

Figure 3b. Semivariance range values computed for each pixel using Rooks case.

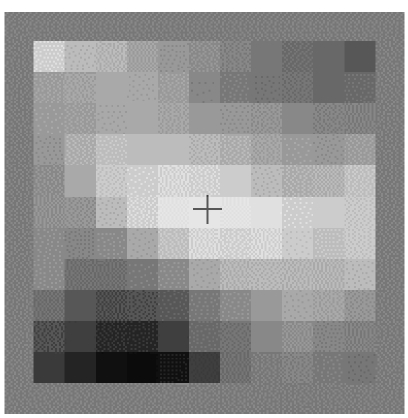

Figure 3c. Getis statistic values computed for each pixel.

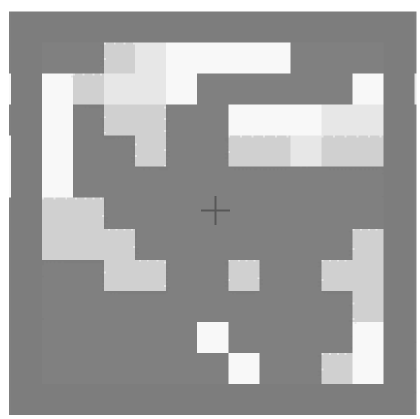

Figure 3d. Distance value at which Getis statistic value is maximized.