Optical remote-sensing techniques for the assessment of forest inventory and biophysical parameters

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Abstract: Forests are the most widely distributed ecosystem on the earth, affecting the lives of most humans daily, either as an economic good or an environmental regulator. As forests are a complex and widely distributed ecosystem, remote sensing provides a valuable means of monitoring them. Remote-sensing instruments allow for the collection of digital data through a range of scales in a synoptic and timely manner. Accordingly, a variety of image-processing techniques have been developed for the estimation of forest inventory and biophysical parameters from remotely sensed images. The use of remotely sensed images allows for the mapping of large areas efficiently and in a digital manner that allows for accuracy assessment and integration with geographic information systems. This article provides a summary of the image-processing methods which may be applied to remotely sensed data for the estimation of forest structural parameters while also acknowledging the various limitations that are presented. Current advancements in remote-sensor technology are increasing the information content of remotely sensed data and resulting in a need for new analysis techniques. These advances in sensor technology are occurring concurrently with changes in forest management practices, requiring detailed measurements intended to enable ecosystem-level management in a sustainable manner.

This review of remote-sensing image analysis techniques, with reference to forest structural parameters, illustrates the dependence between spatial resolution to the level of detail of the parameters which may be extracted from remotely sensed imagery. As a result, the scope of a particular investigation will influence the type of imagery required and the limits to the detail of the parameters that may be estimated. The complexity of parameters that may be extracted can be increased through combinations of image-processing techniques. For example, multitemporal analysis of image radiance values or multispectral image classification maps may be analysed to undertake the assessment of such forest characteristics as area of forest disturbances, forest succession and development, or sustainability of forest management practices. Further, the combination of spectral and spatial information extraction techniques shows promise for increasing the accuracy of estimates of forest inventory and biophysical parameters.

Key words: forest structure; forest inventory; forest biophysical parameters; optical remote sensing; image processing
Introduction

Forests and woodlands are the most widely distributed vegetation ecosystem on the planet, covering approximately 40% of the global land surface (Westoby, 1989). The economic importance of forests is clear, as through either consumption or utilization of some product or service forests affect the everyday life of most humans (van Martin, 1984). Less clear is the impact of forests upon the global environment through processes such as the regulation of the global climate, storage of carbon, conversion of carbon dioxide to oxygen and energy exchange with the atmosphere (Gates, 1990). For example, it is known that deforestation and the combustion of fossil fuel contribute more than 7 billion metric tonnes of carbon to the atmosphere each year above the natural flux, mostly in the form of CO₂ (Jarvis and Dewar, 1993). Forests annually produce 70% of the net global terrestrial carbon accumulation (Peterson and Running, 1989) which results in the uptake of carbon from the atmosphere and the conversion of the greenhouse gas CO₂ to O₂ (Perry, 1994). Sustainable forest management policies have been initiated to reconcile the competing aims for the use of forests (Toman and Ashton, 1995). Intergenerational responsibility dictates a need for monitoring of forests, as anthropogenic forces are potentially responsible for significant changes in ozone levels, desertification, deforestation and loss of biodiversity.

The temperate northern forests found in Canada serve as an example of the role of forests both in economic and environmental terms. Canada contains approximately 10%, or 417.6 million hectares, of the global forest cover (Westoby, 1989) with Canadian forest products accounting 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 $2.6 \times 10^{10}$ tonnes of biomass and $2.4 \times 10^{10}$ m$^3$ of gross merchantable timber (Brand, 1990). This importance of forests, both environmentally and economically, has necessitated a change in Canadian forest 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 demonstrates the shift in global forest management priorities from stand management to ecosystem management (NRC, 1995). A key result of this change in priorities is the monitoring of complete natural ecosystem areas – not just 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 has increased, requiring information on soils, productivity and habitat requirements. Further, 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 nontimber values, such as potential for employment and recreation (CCFM, 1995).

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). Techniques such as multisensor fusion (Franklin et al., 1994), multitemporal analysis (Qi et al., 1993), increased spectral resolution (Gong et al., 1992) and increased spatial resolution (Leckie et al., 1995) may assist in providing the level of detail desired for the formulation of forest management decisions. The utility of remotely sensed data for
forest management is indicated by the Canadian forestry community, which is the largest market for satellite data in Canada of any application field, accounting for approximately 22% of the annual sales of satellite imagery (Leckie, 1990).

This article is chiefly concerned with optical satellite and airborne remote-sensing methods and applications for the estimation of forest inventory and biophysical parameters. The promise of high spatial resolution sensors in satellite orbit in the near future (Aplin et al., 1997) will increase the utility of satellite data in the forest remote-sensing context and will likely increase the amount of users of remotely sensed data for forest management. This article is intended as a resource to current and potential users of high spatial resolution optical remotely sensed data to extract digitally forest-related information. To provide a spatial resolution context for this review, the $30 \times 30$ m pixel of the Landsat Thematic Mapper (TM) is the image spatial resolution range which is considered upper bound, with aerial photographs as the lower bound. A survey of currently available methods and applications is provided, as well as research issues and techniques which are pertinent to the high variance imagery which is collected by high spatial resolution imagery. High spatial resolution airborne remotely sensed data have provided for the development of methods and applications for the assessment of forests resulting in a rich information source for potential users of high spatial resolution satellite data.

The role and progress of radar remote sensing in forestry are acknowledged, yet the focus of this article is upon analysis of the visible and near-infrared wavelengths, also considered as optical imagery. The behaviour of the spectral response in the microwave region differs from that which occurs in the optical wavelength region, requiring specialized techniques for image preprocessing and analysis. A review of microwave remote sensing in the assessment of forest structure may be found in Leckie (1998).

The ability to use remotely sensed spectral data for the assessment of forest structure is related to the changes in incoming solar radiation that is absorbed by the forest in the visible and near-infrared wavelengths. For example, the amount of light available to the lower portions of trees is restricted by the level of the canopy closure; mutual shading of trees results in differing light intensity available for interception by tree canopies; and, commonly, the amount of light penetrating through the canopy is inversely proportional to the number of trees per unit area. As a result, measures have been developed which relate light transmission in individual stands to such stand density measures as leaf area index, trees per unit area, crown closure, basal area and stem density (Curran, 1980).

1 Forest structure through inventory and biophysical parameters

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). Accordingly, the ability to assess the structure of a forest permits insights into the environmental factors, such as hydrology, albedo, productivity and soils. Understanding of the forest structure allows for the ability to monitor, model and predict 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 vigour, 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 (see Table 1 for list of typical inventory parameters). Forest biophysical parameters provide data on the productivity, structure and amount of forest resources (Table 2 presents and defines the most common forest biophysical parameters). These measures are most commonly used as they are often correlated measures and can also be applied to any plant canopy and may be integrated into regional-scale models (Running and Hunt, 1994). Forest biophysical parameters are an attempt to simplify the measurement of forest structure into a single measure, such as leaf area index (LAI). 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). 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.

### Table 1  Typical provincial forest inventory parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale</td>
<td>Normally 1:12,500 to 1:20,000</td>
</tr>
<tr>
<td>Species</td>
<td>Abbreviated species or tolerance level</td>
</tr>
<tr>
<td>Development stage</td>
<td>Development description, including elements such as cut, burn, regenerating and mature</td>
</tr>
<tr>
<td>Crown closure</td>
<td>Percentage classes from 10 to 30% to greater than 90%</td>
</tr>
<tr>
<td>Volume</td>
<td>Volume of timber per unit area and by species</td>
</tr>
<tr>
<td>Basal area</td>
<td>Total cross-sectional area per unit area measured at 1.37 m above ground</td>
</tr>
<tr>
<td>Height</td>
<td>Mean tree height per unit area and by species</td>
</tr>
<tr>
<td>Stand indicators</td>
<td>Brief site description</td>
</tr>
<tr>
<td>Nonforest conditions</td>
<td>Nonforest characteristics, such as agricultural, mining, gravel and cut blocks</td>
</tr>
<tr>
<td>Ownership</td>
<td>Land ownership characteristics</td>
</tr>
<tr>
<td>Map symbol legend</td>
<td>Explanation of the symbols used</td>
</tr>
</tbody>
</table>

*Source: After Gillis and Leckie (1993).*

### Table 2  Typical forest biophysical parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAI</td>
<td>Leaf area index – is a measure of area of foliage per unit area of ground</td>
</tr>
<tr>
<td>Biomass</td>
<td>Biomass – is the total of absolute amount of vegetation present (often considered in terms of the above-ground biomass)</td>
</tr>
<tr>
<td>NPP</td>
<td>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</td>
</tr>
</tbody>
</table>

*Source: Definitions after Bonham (1989).*
2 Background for the remote sensing of forests

Optical remote-sensing instrumentation for spatial data collection of forests ranges from analogue aerial photographs to complex spaceborne digital multispectral instruments. A complete discussion of remote-sensing instruments is beyond the scope of this review – for a description of instruments, see Jensen (1996); for a problem analysis of the use of remote sensing for vegetation management, see Pitt et al. (1997). In general, optical remotely sensed data are a result of a complex series of interactions between the electromagnetic radiation emitted by the sun reflected off the earth’s surface and received by a sensor. In the forestry context, this complex series of interactions encompasses factors such as the optical properties of the stand, spatial resolution (scale), stand object relationship to scale and spatial aggregation.

The interpretation of remotely sensed data of forest canopies requires knowledge of the factors affecting their optical properties, which may be internal or external to the forest stand (Guyot et al., 1989). External factors that have an affect on the reflectance of forests are the size of the viewed area, orientation and inclination of the view axis between the surface and sensor, sun elevation, nebulosity and wind speed. Factors internal to the stand that have an effect on reflectance are canopy geometry, optical properties of the background and row orientation (Guyot et al., 1989). Terrain also has an effect upon stand reflectance (Craig, 1981; Civco, 1989) resulting in variations in reflectance based upon the sun/surface/sensor geometry (Schaaf et al., 1994). The spatial resolution of a remotely sensed measurement is determined by the sensor’s instantaneous field of view (IFOV), the area of the target which is viewed by a sensor in an instant of time. With imaging sensors, this quantity is normally expressed as a pixel size. Using this definition, spatial resolution is analogous to scale (Woodcock and Strahler, 1987).

Scale is a fundamental concept in remote sensing and plays an important role in determining the type and quality of information that can be extracted from an image. Marceau et al. (1994a) present the concept of decreasing variance with lower spatial resolution, the scale and spatial aggregation problem in a forestry context, and the effect scale changes have upon classification accuracy. The need for the sampling grid to correspond to cover type is suggested, based upon computation of minimum spectral variance to assess the scale and aggregation characteristics of the cover type (Marceau et al., 1994b). The sampling grid, as dictated by the sensor, dictates the spatial variability, and has an effect upon classification accuracy and potential information extraction (Irons et al., 1985; Chavez, 1992). Woodcock and Strahler (1987) present semivariograms as a means to investigate optimal resolution for a particular investigation.

The relationship between the spatial resolution and the forest objects of interest influences the information content as the elements which comprise an image are represented in detail as a function of the scale. Strahler et al. (1986) propose the concepts of H-resolution and L-resolution to characterize scene models based on information content. The H-resolution case occurs if the objects of interest in the scene are larger than the image resolution. The L-resolution case occurs when the resolution cells are larger than the objects, resulting in an inability to resolve individual elements. The terms high and low resolution often carry an absolute connotation of a pixel size, not of information content. Differing abilities for analysis exist depending on the initial image data content. As a result, there is an implicit limit to the information content associated with a particular sensor through knowledge of the spatial resolution of the sensor. For example, with Landsat TM data the 30 m pixel results in a combined spectral response
representing an area, such as trees, understory and leaf litter. The L-resolution pixel results in a low-variance environment with marked spatial association between neighbouring pixels. While an H-resolution situation, as sensed with an airborne multispectral scanner or digital frame camera, may collect image data at a spatial resolution of less than 1 m, results in a high-variance environment often with great variability between neighbouring pixels. In an H-resolution situation, a group of pixels may combine to represent an individual tree rather than the characteristics of an entire stand. As a result, it is the relationship between the ground objects of interest and the sensor resolution that dictates the information content. For example, 1 m spatial resolution data may allow for an H-resolution image spatial structure when sensing large mature trees, yet not for smaller trees which are not large enough to comprise a number of pixels.

Remotely sensed instruments typically discretize a continuous natural surface into a uniform grid of equally sized and shaped pixels (Jupp et al., 1988; Fisher, 1997). As a result, there is no intrinsic geographical meaning to the spectral measures recorded by remote-sensing systems, with each image that is collected being a unique sample of the surface features. This problem is demonstrated in the difficulty in extracting accurate, reproducible information from images of varying resolutions, and in this respect is similar to a phenomenon understood to human geographers as the modifiable areal unit problem (MAUP) (Openshaw, 1984). The MAUP is two sets of interacting problems which are related to the spatial scale of the data and any need for aggregation of the spatial data. There are two primary problems within the MAUP:

- A variety of different results may be computed for the same data as they are increasingly aggregated (scale problem).
- The data may also be aggregated in a variety of ways (aggregation problem).

The scale problem refers to the variation of results that can be obtained when the same areal data are combined into progressively larger units of analysis, and indicates a failure to discriminate the objects of geographical inquiry. The aggregation problem arises from the large number of ways in which these areal units can be combined, and reflects the complexity to account for the processes at work between scales. Knowledge of the potential factors affecting the spectral response of forest canopies assists in the application of the most appropriate image analysis technique. In a remote-sensing context, the MAUP is related in varying image spatial resolution, combined with arbitrary grid partitioning of the natural surface. Further, the MAUP must also be considered when relating data collected on the ground to image data; the ground data must represent an areal extent similar to that collected by the remote-sensing instrument.

The information content of remotely sensed imagery, as previously discussed, is directly related to the relationships between the image spatial resolution and the size of the objects of interest on the ground. The spatial resolution ranges commonly found for a series of instruments are presented in Table 3, from aerial photographs, to airborne multispectral, to satellite-borne instruments.

a  **Aerial photography:** The human assessment of aerial photographs continues to be the remote-sensing inventory method of choice. Conventional methods of interpretation are both time consuming and costly and results may vary between analysts. The development of inventory techniques based upon the image processing of multispectral satellite imagery increases the potential for reduced costs and automation. Leckie (1990)
presents a summary of the costs per unit area of remotely sensed data, which relates the trade-off between costs and detail, with aerial photographs being the most costly while providing the greatest amount of information on the forest, with satellite data being the least expensive per unit area with the least amount of detail. Yet, the high level of information afforded by aerial photography is not always necessary; the lesser detailed and lower-costing satellite imagery may be appropriate for particular applications.

Aerial photography is the oldest and most frequently utilized form of remote sensing, originating with the merging of a photographic camera and a balloon platform in 1859. The spatial resolution of aerial photographs is very high and is limited mainly by film properties. The spectral resolution is normally panchromatic (from 0.25 to 0.7 μm) with the potential for collection of other spectral ranges (Avery and Berlin, 1992). The quality of airphotos is influenced by factors such as atmospheric scattering, aircraft motion and vibration, and the resolving power of the film. Aerial photography is the most frequently utilized remote-sensing tool for the assessment of forests (Gillis and Leckie, 1996). The use of aerial photography in the estimation of biophysical parameters is infrequent in the literature in comparison to usage for forest inventory.

The interpretation of air photos is generally an analogue procedure requiring an experienced specialist to extract forest inventory information (Watts, 1983). As may be

<table>
<thead>
<tr>
<th>Type or photo scale</th>
<th>Approximate range of spatial resolution (m)</th>
<th>General level of plant discrimination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common satellite images</td>
<td>30 (Landsat)</td>
<td>Separation of extensive masses of evergreen versus deciduous forests (stand-level characteristics)</td>
</tr>
<tr>
<td></td>
<td>20 (SPOT multispectral)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10 (SPOT panchromatic)</td>
<td></td>
</tr>
<tr>
<td>Small satellites</td>
<td>&gt; 1 (panchromatic)</td>
<td>Recognition of large individual trees and of broad vegetative types</td>
</tr>
<tr>
<td></td>
<td>&gt; 3 (multispectral)</td>
<td></td>
</tr>
<tr>
<td>Airborne multispectral scanners</td>
<td>&gt; 0.3</td>
<td>Initial identification of large individual trees and stand-level characteristics</td>
</tr>
<tr>
<td>Airborne video</td>
<td>&gt; 0.04</td>
<td>Identification of individual trees and large shrubs</td>
</tr>
<tr>
<td>Digital frame camera</td>
<td>&gt; 0.04</td>
<td>Identification of individual trees and large shrubs</td>
</tr>
<tr>
<td>1:25 000 to 1:100 000</td>
<td>0.31 to 1.24*</td>
<td>Recognition of large individual trees and of broad vegetative types</td>
</tr>
<tr>
<td>1:10 000 to 1:25 000</td>
<td>0.12 to 0.31</td>
<td>Direct identification of major cover types and species occurring in pure stands</td>
</tr>
<tr>
<td>1:250 to 1:10 000</td>
<td>0.026 to 0.12</td>
<td>Identification of individual trees and large shrubs</td>
</tr>
<tr>
<td>1:500 to 1:250</td>
<td>0.001 to 0.026</td>
<td>Identification of individual range plants and grassland types</td>
</tr>
</tbody>
</table>

Notes:
‘Small satellites’ are the new generation of commercial high spatial resolution satellites (Fritz, 1996; Aplin et al., 1997).
*Based upon a typical aerial film and camera configuration utilizing a 150 mm lens.
Source: After Avery and Berlin (1992); Pitt et al. (1997).
expected, the results of the interpretation of air photos by photo interpreters are expensive, time consuming and inconsistent. Digital methods have been developed in an attempt to streamline the photo interpretation process (Leckie, 1990; Dymond, 1992). The ability to produce digitally a complete forest inventory from airphotos is not yet mature enough for complete automation, with the need for the judgements of an experienced photo interpreter still required to account for unusual or unforeseen image characteristics (Leckie et al., 1998).

b Airborne remote sensing: Airborne remote sensing provides a flexible operational and experimental tool. The ability to sense the surface of interest remotely at a desired time with the chosen technical specifications is the key feature of airborne remote sensing. Yet, airborne remote sensing has limitations due to such factors, as the instability of the platform and limited ground coverage. Due to low flying altitudes, high-spatial resolution and sensor engineering, airborne multispectral remote-sensing instruments often have a narrow image width often resulting in the need for mosaicking. The requirements of a particular project dictate the spectral characteristics, the desired resolution, flight line azimuth and location, desired illumination conditions and acceptable flight conditions (Wulder et al., 1996a). In applications requiring less spectral coverage, digital frame cameras provide a usually lower cost alternative to multispectral scanners (see King, 1995, for a comprehensive review of digital frame camera technology). The high-resolution data collected from airborne platforms often create an H-resolution environment with the associated increase in variance over present satellite systems. The increase in variance creates problems in the application of traditional remote-sensing techniques, such as a multispectral classification (Gougeon, 1995a).

c Satellite remote sensing: With the launch of the first Landsat satellite in 1972 systematic, synoptic, repetitive, 80 m resolution multispectral images of the earth’s surface were available from space. Data capture, transmission, storage and analysis technologies have increased substantially since the first Landsat, with a wide variety of spectral, spatial and temporal options available to users of satellite image technology. The use of satellite data in the estimation of forest structure has been directed at the estimation of biophysical parameters and the accurate estimation of forest inventory parameters. The L-resolution sensors which have been available up to this point have not provided the high accuracy inventory information required by forest managers (Gillis and Leckie, 1996).

The knowledge acquired from the analysis of airborne high-resolution data will soon be applicable to a new suite of proposed high spatial resolution satellites (Aplin et al., 1997). In the near future, high spatial resolution satellites will provide spatial data at a resolution of approximately 4 m multispectral and 1 m panchromatic. The ability to estimate some elements of a forest inventory and to perform structural analysis from a stable satellite platform with an image footprint of greater than 10 km may soon be possible (Fritz, 1996).

d Image data-preprocessing considerations: Prior to the analysis of optical remotely sensed data a variety of considerations related to the integrity of the image data must be addressed to account for image geometric and radiometric characteristics. To allow for the locating of ground features on imagery, or the comparison between a series of
images, a geometric correction procedure is undertaken to register each pixel to real-world co-ordinates (Jensen, 1996). The concept of image radiometry is related to the spectral characteristics of the imagery. Radiometric corrections are applied to convert the sensor-specific digital numbers to radiance values. Image radiometry is also affected by the atmosphere intervening between the ground surface and the sensor. The magnitude of the scattering, absorption and emission effects upon the signal received by the satellite varies by wavelength, resulting in a requirement for wavelength range-specific correction procedures (Avery and Berlin, 1992). In the visible wavelengths the main consideration is the scattering caused by atmospheric haze, while in the infrared wavelengths it is the water vapour resulting in atmospheric absorption of radiation, with different techniques appropriate for satellite (de Haan et al., 1991; Teillet and Fedosejevs, 1995) and airborne (van Stokkom and Guzzi, 1984) collected data.

II Image-processing techniques for the assessment of forest structure

Studies involving remotely sensed data normally have data collection, processing and analysis stages which relate the remote measure to ground-based validation measures (Steven, 1987). The data collected by multispectral remote-sensing instruments are in a digital form, allowing for mathematical analyses and manipulations. The information content of remotely sensed data is enhanced by the ability to apply image analysis techniques to extract subtle structural information. Image processing provides the means to assess the inter-relationships between pixel location and values. The following is an overview of the image analysis techniques that have been used, or are in development, for the extraction of forest structural information from digital imagery. The suite of image-processing techniques which has been developed to generate forest biophysical information from spectral information may be integrated with the newly developed object-based approaches which may be applied to H-resolution data.

1 Spectral relationships

Relative changes in spectral response indicate variability in the groundcover. Spectral response is often related to the ground validation data allowing for the extrapolation of the calibration relationship to the entire image. Yet, due to the complexity of the interaction between the downwelling radiation with the forest canopy and how this relationship is recorded by remote-sensing instruments, the relationship between the image spectral response and the ground validation data is often poor (Danson and Curran, 1993; Baulies and Pons, 1995). Remotely sensed data are collected from above the forest, resulting in an inability to account for any vegetation characteristics not visible from above. As a result, the degree of canopy closure often has an effect on stand reflectance, especially in the near-infrared channels (Spanner et al., 1990). Further difficulties in relating field validation data to image data are based upon such factors as the dynamic range of the ground data in relation to the image data and the areal extent of the ground validation data compared to the image data. The use of spectral response to estimate forest structure is likely the most common data extraction technique due to the simplicity of the approach.

A test case for operational mapping with the low-resolution Landsat MSS demonstrated good agreement between the image estimates and ground measured parameters
when considering the scale of analysis (Bryant et al., 1980). A comprehensive estimation of forest stand parameters, including volume, from Landsat TM reflectance data found results comparable to conventional timber inventory methods (Franklin et al., 1986). In general a poor relationship is found between spectral response and volume (Gemmel, 1995); yet Ripple et al. (1991), utilizing both SPOT and TM data, found through correlation and regression analyses a significant relationship between softwood volume and the log of reflectance data. Correlation methods are a common approach to the estimation of the inventory parameters of diameter at breast height, canopy closure, height, density and age (Danson, 1987; de Wulf et al., 1990). Correlation studies are also undertaken for the estimation of the forest biophysical parameter of leaf area index. When estimating leaf area index with spectral values, caveats to consider are the presence of understory vegetation, within-stand shadowing, bidirectional effects and stand density, as well as the canopy closure. Common to studies which estimate LAI from remotely sensed data is a difficulty in estimating LAI once the foliage within the stands begins to overlap (Baret and Guyot, 1991).

2 Spectral vegetation indices

Characteristically, green plants strongly absorb visible electromagnetic radiation and strongly scatter near-infrared radiation (Curran, 1980). This is as a result of pigments, especially chlorophyll, which absorb visible wavelengths, while the air–water interfaces between the intercellular spaces and cell walls cause multiple refraction, resulting in high net reflectance values in the near-infrared wavelengths (Gausman, 1977). Vegetation indices have been developed to emphasize the difference between the absorption in the visible and reflectance in the infrared through mathematical processing of multispectral bands, such as ratioing and differencing. The normalized difference vegetation index (NDVI) is a commonly used vegetation index, calculated from the red (R) portion of the visible and near-infrared (NIR) radiation in the form of:

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}}$$

This was initially developed as a measure of green leaf biomass (Tucker, 1979). NDVI has also been demonstrated to assist in compensation for changing illumination conditions, surface slopes and viewing aspects (Avery and Berlin, 1992). Canopy interception dictates the upper limit for vegetation to utilize available sunlight for photosynthesis which further drives production (Law and Waring, 1994). NDVI captures information relating to the amount of radiation absorbed in the visible (red) and reflected in the infrared (NIR) by vegetation. NDVI has a range of $-1$ to $1$, where values which approach 1 are the result of a high NIR value and low R value, indicating dense vegetation, whereas low and negative values indicate such situations as low vegetation density or nonvegetated surfaces.

Vegetation indices, such as NDVI, may be viewed as a surrogate for scene vegetation content and are applied in an attempt to relate to physical measures of vegetation, such as LAI. Other vegetation indices may be utilized with some success – such as RVI, demonstrated by Spanner et al. (1994) to be well related to LAI. Nemani et al. (1993) utilized the middle infrared of the Landsat TM sensor to apply a correction for the effects of changes in the level of canopy closure on the computation of NDVI. There are many different vegetation indices which may related to particular characteristics in a given case.
(Heute, 1988; Myneni et al., 1995; Chen, 1996). Chen and Guilbeault (1996) found that in relationships between a vegetation index and LAI, the indices based upon simple ratios of two bands were best correlated with ground measurements of LAI and fraction of photosynthetically active radiation (FPAR). Limiting the effectiveness of vegetation indices in the estimation of forest structure is that relationships are frequently nonlinear and reach an asymptote at an LAI value of approximately 3 (Asrar et al., 1984; Franklin, 1986; Running et al., 1986; Baret et al., 1988; Baret and Guyot, 1991; Spanner et al., 1990; 1994; Wulder et al., 1996b). Further, NDVI may even decrease as LAI increases due to increased mutual shadowing in a mature stand.

Based upon the aforementioned considerations the application of NDVI in the estimation of vegetation characteristics should be undertaken with caution. Additional information, such as texture, may be used to provide a context for improved estimates of forest structural parameters with NDVI.

3 Texture

Image spectral values alone are of limited utility in the estimation of forest structural parameters as the spatial element of the imagery is not considered. In the context of image analysis, texture has many definitions, with the theme to the varied descriptions of texture generally indicating the spatial variation in neighbouring pixel values. The addition of texture (the spatial variation in tones) may add structural information to estimates of forest stand parameters. The textural values act as surrogates for the actual physical canopy composition through representing the distribution of the vegetation. Texture has been demonstrated to add structural information to the spectrally derived vegetation indices and to improve estimates of LAI (Wulder et al., 1996b; Wulder et al., 1998). Texture has been utilized in remote sensing as ancillary information in multispectral classifications of L-resolution imagery of vegetation cover (Frank, 1984; Franklin and Peddle, 1990; Kushwaha, 1994) and H-resolution estimation of forest structure (Hay and Niemann, 1994; Wulder et al., 1996b; Wulder et al., 1998). The variation in texture is related to changes in the spatial distribution of terrestrial vegetation. Textural derivatives are supplemental to the image data that provide an additional information source.

When assessing the textural characteristics of imagery, the spatial resolution of the imagery is an important consideration as L-resolution data have less potential for texture than do H-resolution data. The suppressed variance environment captured by L-resolution data incorporates much of the variation in vegetation within a single pixel, thus reducing the texture. H-resolution data, which comprise pixels that are smaller than the objects of interest, are often highly textured.

The section on spectral vegetation indices summarized the shortcoming of NDVI in the estimation LAI due to an asymptotic relationship for LAIs greater than $\approx 3$. The vegetation index values saturate as a function of being derived from a remote platform which may only view the horizontal expression of a stand as seen from above. As LAI values increase, the vertical complexity of the stand also increases, proving difficult to measure from a nadir-viewing remote platform. For example, stands with differing vertical levels of complexity may appear the same to a horizontal viewing sensor. The vertical structure refers to tree height distribution and the horizontal distribution pertains to stand density and spatial distribution (St-Onge and Cavayas, 1995). Stand stratification is primarily the result of variations in time and method of establishment and growth rate.
of species. Accordingly, stands with varying vegetation composition and structure may have similar vegetation index values due to a similar vertical expression. The introduction of spatially sensitive image texture variables in the estimation of LAI increases the accuracy of LAI values obtained remotely in relation to field-collected data, especially for LAI values greater than 3 (Wulder et al., 1996b).

4 Multispectral image classification

Multispectral image classifications are based upon finding patterns in the spectral response in relation to land-cover groups known to be present. The creation of a thematic map of forest characteristics is often the goal of an image classification in a forestry context. Image classification procedures group pixels into classes, or categories, based upon distinctive patterns of digital numbers. Image classification procedures are normally categorized as either supervised or unsupervised. A supervised land-cover classification uses training data input by an analyst which are based upon a priori knowledge of land cover at a given location. The spectral values found at the training sites are then applied to a multispectral classification procedure, such as maximum likelihood, which enables the portions of the image not directly surveyed to be put into classes based upon similar spectral characteristics to the training areas (Jensen, 1996). Unsupervised classifications do not depend on the input of a training data set, and generate classes based upon clustering of the spectral values present into groups based upon similarity (Lillesand and Kiefer, 1987). Once the spatial clusters are generated an analyst often attempts to determine the nature of the clusters and to provide labels.

The most commonly applied classification procedure is the maximum likelihood procedure. Maximum likelihood is a statistical decision rule that examines the probability of a pixel in relation to each class with assignment of the pixel to the class with the highest probability (Lillesand and Kiefer, 1987). The maximum likelihood procedure has an underlying assumption of a normal distribution to the data within each class and may be biased by unequally sized training classes. Visual image enhancements may be utilized to aid in the interpretation of imagery or for assistance in creation of training data (Beaubien, 1994). The maximum likelihood procedure may be computed upon spectral values alone, or with the inclusion of ancillary data, such as a digital elevation model. Knowledge of the environmental characteristics of plant growth, such as an elevation gradient to tree species presence, indicates the utility of the incorporation of a digital elevation model to increase the accuracy of a multispectral image classification (Strahler et al., 1978; Franklin et al., 1986).

Contextual classifiers also allow for classification decisions to be based upon more information than spectral values alone. Contextual classifiers utilize both the spectral and spatial characteristics of a pixel. In contextual classification methods the classification of an individual pixel is influenced by the characteristics of the surrounding pixels (Gong and Howarth, 1992). Sharma and Sarkar (1998) have demonstrated a contextual classification technique that is modifiable for either high or low-resolution imagery. Evidential reasoning is similar to contextual classification methods in its attempt to provide an increase in information to the classifier. In a classification based upon evidential reasoning, evidential support for a given pixel is generated based upon the observed frequency of occurrence within the training data set to create decision rules which enable an image classification (Peddle et al., 1994). Evidential reasoning has been developed to account for the complexity of environmental data as a tool that is robust to
large numbers of input layers from diverse sources at a variety of spatial scales and with
differing measurement scales (Peddle, 1995).

Peddle et al. (1994) undertook a comparison of artificial neural networks, evidential
reasoning and maximum likelihood classifiers upon an alpine forest environment, where
the neural network results were found to be superior. Neural networks are an artificial
intelligence modelling technique which attempts to emulate the computational abilities
of the human brain. In the remote-sensing context, neural networks have been applied
because neural networks have no underlying assumptions on the distribution of the data
and also allow for the inclusion of ancillary data in the analysis (Hepner et al., 1989).
Hepner et al. (1989) demonstrated the robust nature of neural networks for a land-
cover classification. In a forestry classification context, Ardö et al. (1997) found results
when classifying forest damages to be comparable to those of a traditional classifier.
Fuzzy classification methodologies have been developed to account for the tendency of
classification algorithms to produce artificially abrupt boundaries between classes (Gath
and Geva, 1989).

The spatial resolution of the imagery processed for classification will influence the
level of detail which may be categorized through the classification procedure. The
classification system developed by Anderson et al. (1976) acknowledges the variability in
information content at different scales, based upon the ability to extract greater classifi-
cation detail from higher-resolution imagery (or larger-scale photos). The Anderson
classification levels have become a common reference to the level of detail of ground
cover captured by an image classification. Accuracy assessment of the classification
results allows for investigation of the integrity of the resultant image classification.
Congalton (1991) provides, in a forestry context, a review of accuracy assessment
protocols allowing for a procedure for transparent appraisal of classification results.
Further, an overview of accuracy assessment procedures and general guidelines may be
found in Stehman and Czaplewski (1998).

The availability of H-resolution data has resulted in the need to reassess the common
approaches to the classification of remotely sensed imagery. Traditional classification
methods are generally based upon the lower variance image structure found with
L-resolution imagery, yet with increases in spatial resolution per pixel classifiers do not
necessarily produce higher classification accuracies (Martin and Howarth, 1989). The
increase in variance with H-resolution imagery precludes a bitmapping approach to
training a supervised classifier. Trees of the same class will often have variable spectral
response because of such characteristics as position in the stand, age, height and health.
Each tree crown which is distinguishable on H-resolution imagery will have a sunlit and
shaded portion with the resultant variable spectral response. The stand areas which are
in shadow or have understory species growth will also have variable spectral response.
Strategies for H-resolution image classification generally require the separation of tree
crowns from the background (Gougeon, 1995b). Once trees have been delineated through
the application of digital methods, further information is available based upon the digital
numbers found within each crown. Spectral information may be extracted from each
individual tree crown to enable classification to species types based upon the observed
spectral response. Traditional classification tools, successfully applied to L-resolution
data (Robinove, 1981; Congalton, 1991), assume pixels to be independent and normally
distributed, which is not the case with the spectral values found within an individual
tree crown. Gougeon (1995a) presents a comparison of possible multispectral classifi-
cation schemes for individually delineated tree crowns.
5 Change detection

Change detection, or multitemporal image assessment, allows for the monitoring of the
temporal aspect of forests, through the comparison of a given location at differing points
in time. Analyses of change between images often require accurate geometric registration
and attention to the radiometric characteristics present in the images (Varjo, 1997).
Change detection analysis may be undertaken upon either classified thematic maps, image
spectral values or transformations of the image spectral values. Change detection upon
classified thematic maps requires a similar classification strategy between images and has
the potential for problems based upon varying training data and placement of bound-
aries. Lark (1995) found that the combination of multiple classifications may result in an
increase in error classes with the number of classes in each classification. Spectral methods
for assessing the change between pixels of corrected and coregistered images may be
undertaken through subtraction of pixel values for a temporal difference image, or
division for a temporal ratio image ( Muchoney and Haack, 1994). For example, Olsson
(1994) demonstrates a spectral differencing technique to assess changes in reflectance
caused by forest thinning, where the measured reflectance, in reference to a benchmark
image, decreased due to the removal of deciduous trees and increased as time progressed
after thinning. Leckie et al. (1992) assessed a time series of 13 Landsat MSS images to
demonstrate the potential of predicting future stand conditions based upon an actual
change trend. Other methods for assessing change between images include analysis of
principal components of single bands from multiple date imagery ( Fung and LeDrew,
1987), change vector analysis ( Lambin and Strahler, 1994) and fuzzy sets ( Gong, 1993).

6 Data fusion

Data fusion may be undertaken between differing wavelengths of remotely sensed
imagery or between remotely sensed data and meta-data. Electromagnetic data fusion is
an attempt to exploit differing wavelengths to provide unique information to the
extraction of forest structural parameters. The fusion of optical and SAR data marries
the optical data which are sensitive to the vegetation reflective characteristics with the
SAR data which are the result of the forest structural characteristics ( Franklin et al., 1994).
Meta-data fusion is the incorporation of remotely sensed data with geographic data
intended to provide unique locational information, such as soils or climate data ( Davis
et al., 1991). The meta-data are often stored in a geographical information system (GIS),
which is a geographically referenced database. The integration between remotely sensed
and GIS data allows for powerful modelling and analysis ( Ehlers et al., 1989). The data
stored in a GIS are often detailed and extensive yet static, while remotely sensed data may
be current. As a result, remotely sensed data may be used to update the forest stand data
stored in a GIS. In a similar fashion, remotely sensed data may be used to break down, or
decompose, forest stand polygons stored in a GIS based upon remotely sensed data of a
higher resolution ( Wulder, 1998a). Remotely sensed data also may provide current
information on vegetation extent and structure to computer models of forest productivity
( Running and Hunt, 1994).

7 Linear mixture modelling

Linear mixture modelling, also known as spectral mixture analysis, is the reconstruction
of pixel digital numbers based upon the spectral characteristics of the objects found
within the L-resolution pixel. In linear mixture modelling, an assumption is made that a small number of materials can reproduce the observed spectra when mixed together in various proportions (Adams et al., 1993). The small number of materials is referred to as endmembers, or components (Gong et al., 1994). Normally a spectroradiometer is utilized to collect spectral endmembers in situ. Milton (1987) provides a summary of the steps for in situ spectral data collection. The general procedure for spectral mixture analysis requires the collection of pure spectral signatures for all the vegetation which may be found within the study area. The endmembers, as collected with a spectroradiometer in the field or lab, may then be used to reconstruct the pixel. The form of models utilized for spectral mixture analysis may be either linear (Adams et al., 1993) or nonlinear (Shimabukuro and Smith, 1994). The ability to reconstruct pixels based upon endmember information is not a trivial task, often suffering from an oversimplification of the pixel spectral contents.

The requirement for mixed pixels to compute spectral fractions requires L-resolution data as a portion of the analysis. The potential of H-resolution data in spectral mixture analysis is in the collection of image-based endmembers. The ability to utilize H-resolution airborne or satellite data will increase the ability to collect spectral endmembers which characterize the region that is to be unmixed, providing a link between local and regional data sources. The ability to decompose the L-resolution pixel effectively decreases the scale of the analysis. Hall et al. (1995) demonstrate the ability to discern the spectral contents of a pixel, in conjunction with geometrical optical modeling, to estimate forest biophysical parameters.

8 Bidirectional reflectance methods

The fundamental physical property governing the reflectance behaviour of any surface is the bidirectional reflectance distribution function (BRDF). The BRDF relates irradiance from a given direction of incidence on a surface to the reflected radiance in the viewing direction. The specific geometric and mathematic definition refers to directional radiation in infinitesimally small elements of solid angle which precludes its direct measurement (Deering, 1989). The BRDF is commonly thought of as being integrated into larger quantities of the solid angle, yielding the bidirectional reflectance factor (BRF) measures actually acquired by field instruments (Milton et al., 1994). Walthall et al. (1985: 383) define BRF in simpler terms as the ‘reflectance at a multitude of possible view angles at a given time or solar position’. Accordingly, the ability to collect BRF measurements allows for spectral analyses that are not altered by sun/instrument geometry. Yet, to characterize the BRF of a surface, multiple spectral measurements are required from a series of azimuths and incidence angles creating the need for directable instruments (Ranson et al., 1994) and generating large data volumes (Walthall et al., 1985). The problem implied by the presence of the BRDF is that the reflectance of the same forest varies based upon the location of the sensor in relation to the sun and such factors as the underlying topography. The potential benefits of collecting BRF measurements are normally out-weighed by the measurement difficulties encountered, such as the need for specialized instruments. The understanding of BRDF characteristics of forest canopies is important for relating remote-sensing observations of biomass, species, stand structure and albedo (Kimes et al., 1987). Ranson et al. (1994) demonstrated a relationship between forest structure, PAR albedo and BRF values.
9 Geometrical-optical models

A number of geometric-optical models has been developed to assess canopy bidirectional characteristics (see Goel, 1987, for a review), with the Li and Strahler (1985) model, developed for conifer environments, the most commonly used. The Li–Strahler series of models treats vegetation canopies as an assemblage of discrete, three-dimensional objects illuminated at a specific angle and casting shadows on a contrasting background. The areal proportions of following basic components of sunlit and shaded tree crowns, sunlit and shaded background, are determined by geometric optics and Boolean set theory. The directional reflectance of the forest is estimated by the proportion of each component weighted by independently determined spectral signatures, normally acquired in the field, effectively performing a three-dimensional pixel decomposition. Ongoing improvements of the basic model have incorporated the effects of mutual shadowing at high solar zenith angles (Li and Strahler, 1992), topography (Schaaf et al., 1994), and the use of radiative transfer principles to describe multiple scattering effects within tree crowns (Li et al., 1995). Woodcock et al. (1997) have developed a technique for inversion of the Li–Strahler model, which allows for estimation of reliable estimates of forest cover, yet improvement is required for estimates of tree size. A mapping project based upon Landsat TM imagery and inversion of the Li–Strahler model is described in Woodcock et al. (1994).

10 Hyperspectral image analysis

Other information which may be remotely sensed to provide insights into the state of forest vegetation is hyperspectral image data. Imaging spectrometers provide spectral information for a large number of narrow spectral bands for each pixel, resulting in a full spectral curve for each pixel (Vane and Goetz, 1993). Research with spectroradiometer data has demonstrated the potential for detailed analysis of vegetation spectral characteristics based upon absorption features (Curran, 1989), spectral characteristics (Bracher and Grant, 1994), or derivative spectroscopy (Demetriades-Shah et al., 1990). Distinct absorption features relate to chemicals that are found at discrete locations on the electromagnetic spectrum. Of interest in the assessment of forest structure are the locations of chlorophyll \( a \) and \( b \), which are found at 0.64 and 0.66 \( \mu m \) (Curran, 1989) and that provide an indication of tree health and vigour. The ability to collect full spectral information allows for the detailed assessment of the spectral characteristics of plants, such as the ‘red edge’ which relates to plant vigour and chlorophyll (Bracher and Grant, 1994). Derivative spectroscopy is an analysis technique borrowed from analytical chemistry used for the elimination of unwanted background signal and for resolving and enhancing overlapping spectral features (Demetriades-Shah et al., 1990).

At present there are more than a dozen airborne and spaceborne imaging spectrometers (Vane and Goetz, 1993). Johnson et al. (1994) assessed the utility of Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) in the prediction of canopy biochemistry as a component of the OTTER project. The red-edge spectral region was found to be strongly related to LAI, canopy total nitrogen, and canopy chlorophyll content, while insignificant results were found for starch concentration. As a component of the OTTER project, Gong et al. (1992) found a strong relationship between \( \text{casi} \) hyperspectral data and a LAI from 0 to 3. A limitation that has hampered existing instruments for detailed forest structural analysis is L-resolution pixel size, which is often also irregularly shaped.
due to longer along-track integration time in comparison to across track. Niemann (1995) investigated the relationship between stand age with L-resolution hyperspectral data. The analysis found a poor relationship between red edge, derivative spectra, and band ratios with age classes.

11 Individual tree isolation

The ability to delineate tree crowns of a forest digitally allows for improved estimation of inventory elements such as density, volume and canopy closure. Forest stand density estimation has been attempted on L-resolution data with an accuracy too low for inventory usage, but high enough for regional density characterization (Franklin, 1994; Wu and Strahler, 1994). Methods are being developed to estimate forest structure directly through the delineation of the actual objects of interest. Once delineated, trees may be classified, separated from the understory or spectrally assessed. An international forum on the ‘Automated interpretation of high spatial resolution imagery for forestry’ demonstrated several current approaches to the delineation of tree crowns, such as valley following (Gougeon, 1998), radiance peak filtering (Niemann and Adams, 1998), edge finding (Pinz, 1998), template matching (Pollock, 1998), morphology (Barbezat and Jacot, 1998), and clustering (Culvenor et al., 1998; Wulder, 1998b).

An example of the valley-following approach to stem counting and classification has been demonstrated upon H-resolution MEIS (Multi-detector Electro-optical Imaging Sensor) multispectral scanner data of conifer forests. Image-processing techniques are applied for the isolation of conifer tree species (Gougeon, 1995b), and subsequent classification schemes for the crowns delineated on the H-resolution imagery (Gougeon, 1995a). The tree delineation approach outlined by Gougeon (1995b) considers the dark understory areas between trees as ‘valleys’ and attempts to join together the comparatively low valley digital numbers. An iterative approach to the joining of valley pixels results in nearly delineated trees requiring further sharpening with a rule-based strategy. The rule-based classification is based upon spatial discrimination of the trees considered as objects, and applying techniques borrowed from manual aerial photo interpretation.

A stem isolation approach based on radiance peak filtering has been presented by Hay et al. (1996). Radiance peak filtering is based upon the premise that each tree in an H-resolution scene has a bright pixel which represents the apex of the tree. Passing a filter over the image and seeking the highest digital number within the filter kernel provide an estimate of tree stem locations (Dralle and Rudden, 1997). Normally a kernel of a fixed size is passed over the image, which does not account for the presence of trees of a variety of sizes. Hay et al. (1996) used semivariance to customized the kernel size for the extraction of the radiance peaks. Daley et al. (1998) dynamically allocated the kernel size for each pixel location based upon the local scene structure. The problem common to radiance peak filtering is a large number of pixels indicated as trees that are not. The problem of false positives has been investigated by Burnett et al. (1998) through the introduction of spatial autocorrelation and spectral directionality.

Edge-finding techniques for the isolation of tree crowns often work in conjunction with a radiance peak filter. Once the radiance peak is isolated, the edges to the image object may be delineated based upon an iterative search approach (Pinz, 1998). Template-matching approaches are based upon the spectral characteristics found within an image scene compared to synthetic image templates. The synthetic image templates are generated based upon known stand characteristics which may be matched to image
scenes to indicate the crown distribution present in the imagery (Larsen, 1998; Pollock, 1998). The morphology of digitized airphotos has also been presented as a means to extract tree crowns (Barbezat and Jacot, 1998).

The overlap of foliage common to deciduous species results in difficulty in the delineation of individual stems. The foliage of codominant species is found to overlap, while suppressed growth beneath the more dominant trees provides confusion spectrally. Wulder (1998b) has approached the problem through generation of clusters based upon spatially dependent groups of pixels. On 1 m spatial resolution imagery of a deciduous forest the clusters represent either a large single tree or a cluster of spectrally similar trees. The clusters of trees may be spectrally classified, provide clues to crown closure and also indicate the stand-level structure. Culvenor et al. (1998) demonstrate a hybrid approach to clustering assisted by valley following to isolate the clusters.

The interest by the forestry and ecological communities to possess an accurate accounting of all trees within a management unit or an ecosystem is illustrated by the variety of tree crown delineation approaches. Factors which affect the remote sensing of forest canopies also have an effect on the efficacy of the tree crown delineation approaches. The relationship between the image resolution and the tree size is important, as the ability to reconstruct trees with a number of individual pixels is often required. Cover type is also important as conifers are generally more readily delineated than deciduous species. The difficulty in finding an automated approach to tree crown delineation that is robust to forest conditions indicates the utility of a system which pairs the automated crown detection approaches with a photointerpretation approach (Leckie et al., 1998).

12 Spatial discriminators

Shape information has been shown to increase the accuracy of image classification results with L-resolution imagery (Xia, 1996). The utility of shape information has been seen as a means to increase the ability to discriminate spatially between objects which have been isolated on H-resolution imagery. The ability to discern individual conifer trees has been demonstrated in the previous section, based upon spectral differences between the overstory and understory and the implementation of rule-based procedures. The rule-based procedures which are implemented attempt to introduce techniques utilized in the visual interpretation of aerial photographs based upon shape, size and distribution (Gougeon, 1995b). Fournier et al. (1995) present a catalogue of spatial discriminators for potential implementation of a rule-based delineation procedure based upon crown outline, bright areas, crown radiometric profiles and tree shadows. Visual discrimination of stems was undertaken on 40 cm MEIS data to assess the utility and validity of the catalogue of spatial discriminators. The accuracies found from visual interpretation of the MEIS imagery based upon the spatial discrimination classification rules were found to be below the accuracies obtained from spectral information in comparable studies (Leckie and Dombrowski, 1984; Leckie et al., 1995). The image spatial information shows potential for future integration to rule-based crown identification procedures as higher spatial resolution imagery becomes available.

13 Image semivariance

A variogram describes the magnitude, spatial scale and general form of the variation in a given set of data (Matheron, 1963). 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; Woodcock et al., 1988a). A thorough review of semivariance and geostatistics in remote sensing is presented in Curran and Atkinson (1998). Variograms have been the tool used to link models of ground scenes to spatial variation in images (Woodcock et al., 1988b). Semivariograms are a graphical representation of the spatial variability, and provide a means of measuring the spatial dependency of continuously varying phenomena. Figure 1 illustrates the general form of a semivariogram, where the nugget is a measure of the intrapixel variation, the sill is a the point at which variance peaks and the range indicates the number of lags, or distance, to reach the sill. Accordingly, the range represents the point at which the similarity of the pixels to the initial pixel is no more marked than to other pixels along the calculation transect. Cohen et al. (1990) describe the semivariance response in terms of forest canopy structure.

Image semivariance has been used extensively in the assessment of L-resolution forest structure (see Cohen et al., 1990; Bowers et al., 1994, for examples; Ramstein and Raffy, 1989, for the theory). In analysis of H-resolution forest imagery each pixel represents near pure spectral characteristics of an object. Image semivariance has been demonstrated to represent 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 on simulated H-resolution data (1995) and MEIS data (1997), which are also both strongly related to LAI. Semivariance response has also been exploited in the multivariate estimation of LAI as an image textural indicator based upon extraction of discrete points from the semivariance response curve (Wulder et al., 1998), or similarly as a textural classifier (Carr and Myers, 1984).

14 Spatial autocorrelation

Spatial autocorrelation is present when a particular value, or attribute, is found to exhibit some degree of dependence to location. Thus, the measurement of spatial autocorrelation involves the simultaneous consideration of both locational and attribute information.
(Goodchild, 1986). In the case of remotely sensed images, the locations are pixels and the attribute data are the digital numbers. As remote-sensing methods regularize continuous landscapes into a grid of equally sized and regularly spaced data in the form of pixels (Fisher, 1997), it is anticipated that there will be some degree of dependency between pixels. Further, this dependency is likely to take the form of positive spatial autocorrelation, with similar values found in close association. In general, the level of spatial autocorrelation is not dependent of the scale at which these data are analysed, with negative spatial autocorrelation being more sensitive to scale changes (Chou, 1991).

The autocorrelated nature of imagery was noted early in the assessment of remotely sensed data (Craig, 1979) and the effect that image autocorrelation would have upon traditional classification techniques was noted by Campbell (1981). Later, studies of image spatial autocorrelation examined pixel inter-relationships using a scanline technique (Labovitz and Masuoka, 1984). This approach, however, only allows spatial dependency to be assessed in a limited number of directions. In another approach, semivariance is often applied in the assessment of autocorrelation, with the observations found within the range considered as the limit of autocorrelation (Jupp et al., 1989; Franklin et al., 1996). Wulder and Boots (1998) summarize the traditional methods that have been applied to assess autocorrelation in remotely sensed imagery and present a complementary approach based upon the spatial dependence exhibited between pixels.

Spatial autocorrelation may be measured using either global or local statistics. Global indicators provide a single measure summarizing all the spatially referenced inter-relationships. These measures may prove unreliable if the nature and extent of spatial autocorrelation vary significantly over the study area (Haining, 1990). To remedy these concerns, local indicators of spatial association (LISA) have been developed (Anselin, 1995). Getis (1994) investigated the potential of the spatial dependency relationships of remotely sensed imagery. Wulder and Boots (1998) present a statistic and procedure for the extraction of spatial dependence information from remotely sensed imagery. In one study, investigation of the spatial dependence characteristics of Landsat TM image of a managed forest region indicates a strong Landsat TM channel and cover-type dependence to local spatial autocorrelation. Analyses of H-resolution forest imagery demonstrate a local spatial dependency of image objects, which allow for the extraction of trees and clusters of trees (Wulder, 1998b).

III Summary

The future composition of forests due to the effects of climate variability can currently only be hypothesized upon. Monitoring changes in forest structure will provide the ability to assess forests from a measurement baseline and assess changes against this baseline. The techniques made possible through the collection of remotely sensed data and image processing provide the ability to assess changes in forest structure. The incorporation of techniques and methods from forest science and inventory with H-resolution imagery is providing for unique solutions to persistent problems. Successful assessment of forest structure with high spatial resolution instruments may borrow from the established L-resolution satellite techniques and develop new techniques suited to the properties of the new technology. Yet, in many applications the potential increase in accuracy of estimates from higher-resolution imagery may be offset by the regional coverage which is possible with lower-resolution sensors.
The image-processing techniques presented illustrate the availability of a variety of potential information extraction options dependent upon the goals of a particular application. Also demonstrated by the presentation of image-processing techniques is the greater maturity of spectral techniques in relation to spatial techniques. Spatial information extraction techniques, especially for H-resolution imagery, provide for stronger relationships to be created between the image and ground data. The relationships developed between image spectral response and forest inventory parameters may now be augmented with detailed spatial information. Parameters may be estimated empirically, such as with regression-based models, or in a more deterministic fashion, such as deriving stem counts from an image of isolated tree crowns. The combination of empirical and deterministic approaches may provide for an increase in the ability to estimate forest inventory and biophysical parameters. Spatial statistical techniques may allow for an improved linkage between image spectral and spatial information.

Due to the environmental and economic importance of forests, the demand for information related to the structure and composition of forests will only increase with time. The increasing sophistication of techniques for analysis has resulted in increased accuracy in the prediction of forest inventory and biophysical parameters from remotely sensed imagery. The addition of high-resolution satellites to the currently available suite of aerial photographs, airborne multispectral imagery and existing satellite instruments will provide for continued growth in the use of remote-sensing technologies in forestry.

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