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RETRIEVAL OF FOREST CANOPY STRUCTURE FROM HIGH RESOLUTION
AIRBORNE DIGITAL CAMERA IMAGERY

by

Evan D. Seed, BA (Hons)

A thesis submitted to
the Faculty of Graduate Studies and Research
in partial fulfillment of
the requirements for the degree of

Master of Arts

Department of Geography

Carleton University

Ottawa, Ontario

September 1998

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"RETRIEVAL OF FOREST CANOPY STRUCTURE FROM HIGH RESOLUTION
AIRBORNE DIGITAL CAMERA IMAGERY"

submitted by Evan D. Seed, B.A. (Hons)
in partial fulfillment of the requirements for
the degree of Master of Arts

A handwritten signature in cursive script, appearing to read "M. Smith", written over a horizontal line.

Chair, Department of Geography

A handwritten signature in cursive script, appearing to read "Gaylas King", written over a horizontal line.

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September 1998

ABSTRACT

Image structure analysis of multispectral high resolution airborne digital camera imagery and multivariate statistical analysis were used to develop an empirical model of canopy structure based on the linear combination of multiple shadow fractions. This model was capable of predicting ground-based measures of: effective LAI ($R^2 = 0.91$ and $SE = 0.34$), canopy closure ($R^2 = 0.67$ and $SE = 11.26\%$) and basal area ($R^2 = 0.56$ and $SE = 15.3 \text{ m}^2/\text{ha}$) in a boreal mixed-wood forest. It was concluded that the sensitivity of the multiple shadow fractions to the: (1) macroscale and microscale geometry at the individual tree level and (2) vertical and horizontal distribution of vegetation at the canopy level resulted in the ability to predict biophysical variables. Furthermore, this study demonstrated the use of low cost, airborne digital camera technology and image structure analysis as alternatives to more expensive remote sensing technology and sophisticated modeling techniques for retrieval of forest structure.

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CHAPTER 1 INTRODUCTION

The boreal forest is a mixture of coniferous and deciduous trees which forms a fundamental biological unit covering 11% of earth's terrestrial surface (Bonan and Shugart, 1989). It is recognized as a significant biological resource in controlling global carbon cycles (Bonan, 1993) and is of regional economic importance to many communities across North America (Dufour, 1991). Consequently, the boreal forest is of great economic, ecological and cultural value to society. Yet, from a long-term ecological and physiological perspective, anthropocentrically induced impacts from extended use of this resource have resulted in broad-scale changes to the spatial structure of the boreal landscape which are poorly understood (James and Courtin, 1985; Grunwald et al., 1995). Accordingly, if the boreal forest is to be sustained as a valuable resource, there is a long-term need to better understand the physiological and structural response to these impacts in one of the largest vegetated biomes on earth (Powers and Van Cleve, 1991).

1.1 Remote sensing of forest structure

As first recognized by Tansley, (1935) ecosystems are a three dimensional complex of living organisms which cannot be understood in isolation from the characteristics of the space which the organisms occupy. From this viewpoint, spatial structure is regarded as an important attribute of ecosystems and is recognized as a factor which is closely coupled to ecosystem processes. Hence, as an important surface for energy exchange, the forest canopy is sensitive to short term physical (Esseen, 1994; Everham, 1996; Ennos, 1997), chemical (Manning, 1971; James and Courtin, 1985) and biotic factors (Blais, 1968) which can influence canopy structure and reveal information about how forests deal with long term ecological changes at the individual tree, population, stand or ecosystem level (Shields and Bockheim, 1981; Norman and Campbell, 1991; Powers and Van Cleve, 1991).

Forest structural attributes such as stand basal area, leaf area index and crown closure are important descriptive measures for quantifying the distribution, amount and

organization of above ground biomass in the canopy and provide valuable information on plant-environment interactions (Bonan and Shurgart, 1989; Kozlowski et al., 1991; Norman and Campbell, 1991). Quantifying canopy structure spatially and temporally depends on reliable ground-based estimates of forest structural attributes. However, ground-based forest surveys are often difficult to do in remote locations, labour intensive and not economically feasible over expansive areas of the boreal mixed-wood forest.

In recent years remote sensing has received substantial attention as a potential alternative to ground-based surveys for estimating canopy structural attributes in northern temperate and boreal regions (Spanner et al., 1990; Hall et al., 1991; Bonan, 1993; Hall et al., 1995; Chen and Cihlar, 1995; Peddle et al., 1997). The synoptic scale imagery, vertical perspective and wide range of spectral information make remote sensing a suitable tool for extending the spatial estimation of forest canopy structure beyond field-based study capabilities. Attempts to use remote sensing for

empirical modeling of canopy structure have been varied in their approach and include: spectral indices, image texture measures and image structure analysis.

Retrieval of canopy structure from regression based analysis of spectral indices (e.g. NDVI - normalized difference vegetation index: $(\text{near infrared} - \text{red}) / (\text{near infrared} + \text{red})$) has been widely applied but offers mixed results (Sellers, 1985; Smith et al., 1991; Spanner et al., 1994; Nemani et al., 1993; Chen and Cihlar, 1995; Fassnacht et al., 1997). Theoretical limitations on the ability of this technique to extract information under varied or non-ideal conditions confines further investigation to homogeneous canopies with leaf area index (LAI) values below 3 or 4 (Gobron et al., 1997; Hall et al., 1995). In particular, it has been difficult to obtain precise estimates of crown structure in forest stands where LAI values are greater than 7, crown closure is less than 75% or in stands with a mixture of broadleaf and conifer species (Spanner et al., 1990; Spanner et al., 1994; Nemani et al., 1993; Kozlowski et al., 1991). In addition, relationships

which are found between spectral indices and canopy structure are often reported to be curvilinear as spectral indices such as NDVI begin to saturate and become insensitive to changes in LAI at values greater than 3 or 4 (Gong et al., 1995) or crown closure less than 20% (Chen and Cihlar, 1995).

To address these problems with the application of spectral indices and improve the estimation of canopy structure in heterogeneous forest stands, research efforts have concentrated on deriving new surrogate structural information from the addition of image texture. Window-based texture algorithms, which measure the spatial variation of image grey levels within a moving window, are most often used to derive statistical representations of image texture for incorporation into existing spectral analysis (Wulder et al., 1996; St-Onge and Cavayas, 1995; Olthof and King, 1997; Wulder et al., 1998). This approach has shown good success in providing the additional information necessary to improve the precision of LAI estimates in mixed-wood stands.

However, window-based algorithms, such as those

developed by Haralick (1973), require substantial, user-defined input to find optimum texture measures. This constrains their potential for wider application. These texture measures, including semivariance moment texture, (which does not suffer from window-based constraints), also tend to respond quite differently depending on the forest type, spectral band and image scale, making it difficult to extract and relate this information to the three-dimensional structure of a forest canopy (Wulder et al., 1998; Bruniquel-Pinel and Gasteullu-Etchegorry, 1998).

As a result, the application of image radiometric structure analysis in remote sensing research has attracted wide interest from the research community because the method is success in representing the complex three-dimensional structure of forest canopies (Li and Strahler, 1985; Rosema et al., 1992; Gastellu-Etchegorry, 1996; Gerard and North, 1997; Chen and Leblanc, 1997). This method of analysis views the image as a series of discrete objects (trees) which are capable of casting shadows and selectively absorbing and reflecting radiation in various wavelengths depending of the

structure of those objects (Li and Strahler, 1985; Rosema et al., 1992). The basis of this approach is to decompose the image scene into its radiometric components of: (1) sunlit background, (2) sunlit canopy, (3) shaded canopy and (4) shaded background. The end member components or radiometric fractions are then used to develop mathematical models of canopy reflectance for investigating scene bi-directional reflectance factor (BDRF) in hopes of eventually retrieving canopy structural information through the inversion of such models (Li and Strahler, 1985; Li and Strahler, 1992; Deering et al., 1992; Chen and Leblanc, 1997). Indeed, most of these models have improved the theoretical understanding of scene reflectance in forest canopies, yet they remain difficult to apply on an operational basis largely because of their mathematical complexity.

However, more recently image structure analysis has been used in concert with geometric-optical and spectral mixture modeling for the regression-based estimation of canopy biophysical variables (Hall et al., 1995; Peddle et al., 1995; Hall et al., 1996). These studies have shown a

particularly strong empirical relationship between the scene shadow component and canopy biophysical variables in low resolution satellite imagery. The influence of image shadowing on the image scene is widely cited in the remote sensing (Ekstrand, 1994; Danson and Curran, 1993; Franklin et al., 1991;) and photo-interpretation literature (Irvin and McKeown, 1989; Howard, 1991), but the results of Hall et al. (1995) and Peddle et al. (1995) are the first to empirically exploit the relationship between object structure and shadow characteristics for the estimation of forest canopy structure. Indeed, this method holds promise as a simple and operational method for retrieving canopy structural attributes, but it is still not an established alternative to spectral indices or image texture. Research is still needed for verification of this method: (1) in diverse environments (Peddle et al., 1996); (2) for the effects of sensor viewing angle (Walthall, 1997); (3) at scales of imagery capable of resolving sub-canopy architecture in the forest (Chen and Leblanc, 1997).

This thesis advanced previous research by Hall et al.,

(1995) and Peddle et al., (1996) in exploring the relationships between the shadow component and canopy structural attributes in a mixed species forest. The research extended previously known concepts to high spatial resolution imagery capable of resolving within-crown structural information. It also incorporated research by Federer and Tanner (1966), Ranson and Daughtry (1987), and Leblon et al., (1996) investigating the potential for multiple shadow fractions in the scene shadow component.

Overall, the approach to this research was based on the hypothesis that structure analysis of high resolution multispectral digital camera imagery may provide surrogate information on: (1) within-crown image structure and; (2) the horizontal and vertical spatial variance of the forest overstory and understory structure. This information may be used for the remote retrieval of forest biophysical parameters.

1.2 Thesis Objectives

One of the key challenges to applying remote sensing in

forested ecosystems is the need to develop reliable and functional methods to retrieve canopy structural information in diverse environments like mixed-wood forests (Ustin et al., 1993). In order to improve understanding of these related concepts, the specific objectives of this thesis were:

- (1) to determine the statistically separable number of shadow fractions contributing to the scene shadow component in a boreal mixed-wood forest using high resolution standard colour infrared (CIR) digital camera imagery;
- (2) to examine the relationships between the scene shadow fraction(s) and the stand biophysical variables of effective LAI, crown closure, and stand basal area;
- (3) to evaluate the use of low-cost high resolution digital camera imagery for the estimation of forest stand biophysical variables.

1.3 Study area

The study area was located near Kamiskotia Lake Community just northwest of Timmins, Ontario in a band of

boreal forest situated in the province's Clay Belt region. This site was characteristic of a typical well drained, mixed-wood uplands forest in the boreal region of northeastern Ontario. It had a mainly deciduous overstory of trembling aspen (*Populus tremuloides*), balsam poplar (*Populus Balsamifera*) and some jack pine (*Pinus banksiana*) in the drier areas. A conifer understory of white spruce (*Picea glauca*) and balsam fir (*Abies balsamea*) was generally present in the more mature sites with occasional areas of black spruce (*Picea mariana*) in the wetter areas (Legasy et al., 1995). All ground-based data and airborne imagery used in this thesis were collected between May and August 1997, from a series of plots established along a 300 m transect adjacent to an abandoned acid mine tailings (Figure 1-1). The KamKotia Mine site is considered a locally important environmental problem associated with chemical, mechanical and biotic stress agents and continues to be an ongoing site for research into modeling forest ecosystems using digital camera imagery (Gibson, 1976; Kilborn, 1983; Levesque and King, 1995; Blakeman, 1995a; Blakeman, 1995b; Walsworth,

Figure 1-1: Study area at Kam-Kotia mine site

1997; King, 1998).

1.4 Thesis organization

This thesis has been organized into five chapters. Chapter two describes the study area, methodology used in the field, image processing and the statistical analysis of the data. The results are presented in chapter three while chapter four addresses several key questions in a discussion of the results and limitations of the study. Finally, chapter five provides concluding remarks about the major research findings and future research directions.

CHAPTER 2 METHODS

This chapter describes the methods used to collect the ground-measured data including: a description of the study site, study plot establishment and sampling methods for the forest survey. Details are also given on the indirect measurement and derivation of effective leaf area index and canopy closure using the Li-Cor LAI-2000 plant canopy analyzer. Flight planning and related components of the airborne image acquisition using the Kodak DCS 420 CIR camera are presented. In addition, details are presented on the development of a shadow enhancement algorithm, extraction of the shadow fractions and multivariate analysis for forest canopy structural modeling.

2.1 Study site

Mine operations

The KamKotia mine site was an abandoned base metal mine-mill complex which was first explored in 1926 (Gledhill, 1928). In the years of peak production, between 1943-44 and

1961-72, in excess of 6 million metric tons of ore containing copper, zinc, nickel, as well as traces of gold and silver were mined and milled on site (Barnes, 1991). During production, acid producing waste material was discharged by the mill into areas north and south of the mine site. Efforts to contain the discharge through a series of rock berms and containment walls were only temporary and the tailings material subsequently spread into the adjacent forest and nearby Little Kamiskotia River (see Figure 1-1). After operations were closed in 1972, the property remained under private ownership until claims lapsed in 1974. At this time, ownership of approximately 70% of the affected land reverted back to the province of Ontario. The site is currently maintained by the province and continues to be monitored by the Ontario Ministry of Environment.

Scientific research

Studies on the pollution characteristics of the site were started as early as 1976 and over the years the site has been well documented as a severe case of environmental

degradation associated with acid mine drainage (Gibson, 1976; Kilborn, 1983; Blakeman, 1995a; Walsworth and King, 1997; Walsworth, 1997). Despite several attempts to rehabilitate the affected area, the land remains a major source of local contamination to the adjacent forest (Blakeman, 1995a). Indeed, a culmination of mechanical, chemical and biotic stresses may have contributed to the wide ranging canopy structural damage visible at this site (Levesque and King, 1995; Walsworth, 1997; King, 1998).

In an attempt to spatially and temporally document the pollution effects associated with the KamKotia site, a long term research project was set up by Carleton University in 1994 (King, 1997). The study site has since been the subject for ongoing research into modeling of localized stress and development of forest health monitoring methods using spectral, textural and structural (this research) image measures extracted from digital camera imagery (e.g. summarized in King, 1997; Seed and King, 1997). Prior to this thesis, efforts have concentrated mainly on relating spectral and textural characteristics in trembling aspen

canopies to crown damage and a significant soil metal gradient with increasing proximity to the mine tailings (Levesque and King, 1995). Results from this research showed mixed success in monitoring tree health and were difficult to expand beyond homogeneous aspen canopies. However, this early research did highlight the need to develop species-independent models which could be more readily applied to heterogeneous mixed-wood canopies.

2.2 Study plot establishment

In the context of previous research at the KamKotia site and the objectives of this study, the key criteria to study plot establishment for this thesis were to establish a transect in an area: i) representative of a boreal mixed-wood forest, ii) with a range of canopy structures and iii) which was easily accessible. The third criteria was particularly important for canopy structural measurements using the Li-Cor optical instrument (as described in section 2.4).

Dye-sublimation prints of archived digital camera

imagery (50 cm ground pixel resolution) from the previous summer (September, 1995) were used to survey for potential study plot locations along the north-west seep (see Figure 1-1). The images were used to stratified the forest based on visible canopy closure, species composition and density in the overstory. The images were also used to find areas which were readily accessible and provided a sufficiently large clearing for setting up plot location targets and the above canopy Li-Cor measurements (as described in section 2.4). Close access to a large clearing was important, because the Li-Cor 2000 required an unobstructed hemispherical view of the sky for deriving reliable measurements (Li-Cor Inc., 1990). A number of areas were verified on the ground through a series of test plots where density and species composition were estimated.

Fifteen 20 m x 20 m plots (400 m²) were established along a 300 m transect in an area of mixed-wood forest which had a visible range of species densities and understory variability. An abandoned Falconbridge Inc. drilling transect provided easy foot access to the plots and a

reference point on the aerial images. Plots were located on both east and west sides of the transect (Figure 2-1). Elevation differences along the transect were less than 1.5 metres (Walsworth, 1997). At the north end of the transect, plots were grouped into four sets of three plots each, separated by twenty meters of forest. Three plots were also located at the south end of the transect. All plots were offset a minimum of 10 m from the drill path to avoid any immediate edge effects and felled trees. Each plot was considered to be an independent sample of the forest. The decision to locate plots in such close proximity to one another was based on the observed species composition and density along the transect, which were thought to be of sufficient diversity for generating a ground-based data set with a range of canopy structures. Accordingly, it was acknowledged that with several adjoining plots, there was the potential for canopy structural measures from these plots to be similar and show signs of spatial autocorrelation (high correlation of canopy structure between adjoining plots). Indeed, this may have contributed

Figure 2-1: Location of study plots
(next page)

1	4
2	5
3	6

7	10
8	11
9	12

13	ground target
14	

15

to less structural diversity than was intended. However, any similarities in canopy structure between adjoining plots were seen to be outweighed by concerns over work minimization in the field and easy plot identification in the imagery. Finally, the decisions on plot size (20 m x 20 m) and shape were based on the need: i) to include an aggregate measure of several canopy trees, some of which had crown diameters >10 m, ii) to maintain a plot size which was suitably large to accommodate Li-Cor LAI-2000 measurements and iii) to have a sufficient number of pixels to sample for the image structure analysis.

2.3 Sampling methods for forest survey

Sampling criteria

Vegetation surveys were conducted in early June to measure: tree height, stem diameter at breast height (dbh), species composition, stem density and to estimate the woody shrub layer cover. Tree species were identified with the help of reference field guides and plants in the shrub layer were identified where possible (Legasy et al., 1995; Johnson

et al., 1995). A complete census of all trees greater than 2 m tall provided quantitative estimates of forest structure. Woody vegetation under 2 m in height was surveyed for the entire plot to characterize the shrub layer less than 2 m in height. These height criteria were established to survey all woody vegetation which would be included in the Li-Cor LAI-2000 measurements (described below).

Tree height

Tree height is an important indicator of tree growth and a quantitative measure of the vertical structure of the canopy. Direct measurement of height up to 7 m for all individuals was carried out with a graduated measuring stick. Tree heights greater than 7 m were estimated indirectly using a Suunto clinometer. Prior to measurement, the clinometer was calibrated against an object of known height to check for instrument inaccuracies. As well, individuals were periodically re-measured to develop a relative estimate of measurement error which was approximately $\pm 3.5\%$. This observed error compares

favorably with existing estimates in measuring tree heights (Schreuder, 1989). Much of the error produced was a result of tree lean. This was despite efforts to minimize the errors by projecting the tip of the tree onto the ground and offsetting the distance measured from this projected point (Schreuder, 1989). Errors also occurred when measuring tree height directly due to parallax errors.

Density, diameter and basal area

Stem diameter is a measure of individual tree growth. For this research, it was recorded at breast height (dbh or diameter at breast height). Circumference measurements of all trees were taken at 1.4 m above ground with a tape measure and later converted to diameter. Trees that were forked below breast height and not already considered separate individuals required an additional dbh be recorded for each fork (Bonham, 1989).

As a measure of crowding, stand density provides some insight into the spatial structure of the canopy in the study plots. It was measured as the total number of trees

greater than 2 m in each 400 m² plot. Density values were later converted to stems/ha. When recorded by individual species, stand density was used to derive species composition (frequencies) for each plot.

Stand basal area is a measure of stand density which incorporates both stem size and quantity. It is an index of the amount of growing space available in a forest stand and an indirect indicator of stand biomass (Schreuder et al., 1989). It is an especially good quantitative measure for the spatial and temporal comparison of forest stands as it can be easily repeated. Plot basal area was derived from diameter at breast height (dbh) and the number of stems per plot using equation 2-1.

$$\text{Equation (2-1): } G = (\pi/4) \sum (d_i / 100)^2$$

where G = basal area which is expressed in m²/ha and d_i = dbh of tree in centimeters (Schreuder et al., 1989). Plot basal area was calculated as a total of all trees greater than 2 m in height in the plot.

Shrub layer survey

Percent ground cover for all shrub species less than 2m in height was estimated for the entire 400 m² plot using a modified Daubenmire cover scale (Table 2-1a) (Daubenmire, 1959). Individual tree species less than 2 m in height were recorded as part of the shrub layer survey. The approximate height of the shrub layer was also categorized in each of the study plots (Table 2-1b). This information served mainly as a descriptive indicator of the potential contribution and influence of the woody shrub layer to the Li-Cor 2000 measurements.

2.4 Forest structure measurement using Li-Cor LAI 2000 PCA

Purpose of Li-Cor LAI 2000 measurements

In August, canopy measures of effective LAI and crown closure were conducted to coincide with the image acquisition. Canopy effective leaf area and closure were both estimated indirectly for each study plot using the Li-Cor LAI 2000 PCA (Welles and Norman, 1991). Effective leaf area index (L_e) which is defined by Chen and Cihlar

Table 2-1a: Shrub layer cover scale

Rating	Range of cover (%)
P	single individual present
1	<10
2	10-25
3	25-50
4	50-75
5	>75

Table 2-1b: Shrub layer height scale

Rating	Height of species
1	<50 cm
2	50 cm to 1 m
3	> 1 m to 2 m

(1996) as, half the total leaf area per unit ground surface area, was measured indirectly with the Li-Cor LAI- 2000 Plant Canopy Analyzer (PCA) in late August, 1996. It is considered the best predictor and most easily obtained measure of the radiation intercepted by the forest canopy and is temporally less variable than LAI. It has been recommended by Chen and Cihlar (1996) as a basic operational measure of stand structure. The LAI-2000 assumes a random distribution of foliage elements, but this assumption is generally violated in natural forests where vegetation is generally clumped and not random in distribution. Therefore, the LAI-2000 does not provide a true measure of canopy leaf area as it does not consider the clumped distribution of forested canopies (Chen and Cihlar, 1995; Chen and Cihlar, 1996).

Description of Li-Cor LAI-2000 PCA

The Li-Cor LAI-2000 contains fisheye optics which are used to project hemispherical images onto five concentric ring sensors capable of sensing radiation below 490 nm. The

assumption here is that radiation is strongly absorbed by vegetation in this region of the spectrum; therefore the sensor should only see light (sky) and dark (canopy elements) regions. The instrument's total field of view is 148° (Figure 2-2). Rings centred at 7° , 22° , 38° , 52° , and 68° are used to capture the area of dark foliage and homogeneously illuminated sky at different view angles for calculating the average canopy gap fraction. Any combination of rings can be masked in the final analysis to modify the sensor's field of view using the LAI-2000 software. Once masked, the data from that ring sensor are omitted from the leaf area calculations.

The sensor's azimuthal field of view, seen in Figure 2-3, can also be modified with the addition of plastic view caps placed over the outer lens. The main purpose to restricting the sensors azimuthal field of view is to avoid errors associated with averaging two gap fractions linearly within a single below canopy reading e.g. a reading which is one half gap and the other dense foliage (Welles and Norman, 1991). Because LAI is proportional to the logarithm of the

Figure 2-2: Schematic of LAI-2000 PCA sensor head (Welles and Norman, 1991)

Note: FOV is field of view

Figure 2-3: LI-COR LAI-2000 sensor view cone

gap fraction, errors occur when the sensor is viewing and therefore linearly averaging both gap and dense foliage at the same time. Only in thin canopies is this usually not a problem. A complete review of the instrument's specifications and performance is provided by Welles and Norman (1991). As well, other studies have been done to verify results under a variety of forested conditions (Deblonde et al., 1994; Stenberg et al., 1994b; Dufrene and Breda, 1995)

Sampling methods

Careful attention was given to the operation instructions to provide readings which were within 10% of the measured mean values at a 0.95 confidence interval (Li-Cor Inc., 1990). A test designed by Welles and Norman (1991) to calculate the error associated with the linear averaging of gaps was performed in two test plots of boreal mixed-wood forest and revealed potential errors of >40%. Therefore, as recommended by Welles and Norman (1991), a 45° view cap was placed on both of the instrument's sensor heads

to minimize these errors through restricting view cone size and decreasing the azimuthal field of view of the sensor. Two LAI-2000 readings were used to collect the above and below canopy readings. The above canopy reference readings were taken from a unit set up in a large open area approximately 50 m wide and adjacent to the transect. Below canopy measurements were taken 2 m above ground at the same time at flagged intervals within each plot. An extensive shrub layer at approximately 2 m in height at several locations within plots 6, 7, 10, 11 and 12 required the sensor be elevated to 2.5 m for several readings. Vegetation directly in the sensors field of view which could not be avoided through elevating the sensor was pushed back and away from the instrument to minimize inclusion of the shrub layer in the below canopy readings. To minimize errors due to sunlit foliage, all readings were measured under a sky with uniform cloud cover. As well, careful attention was made to keep the measures within the 400 m² plots to minimize the influence of vegetation outside the plot. In total, thirty below-canopy readings were taken to provide a

sufficient spatial average and a representative number of readings for each plot. Five separate measurements were taken at 6 different locations within the study plot (Figure 2-4). Three measurement points were located on the plot boundary every 5 m starting 5 m in from the edge of the plot and again at 10 m into the plot. The sensor was always pointing into the plot to minimize the amount of canopy view from outside the plots. As well, measurements were taken with the sun to the back of the operator (author) at all times to prevent any possibility of intense light entering the sensor, even under the homogeneously cloudy conditions (Li-Cor Inc., 1990).

The ratio of the above:below canopy readings was later used to derive the mean effective leaf area index value for each plot using LAI-2000 software provided with the instrument. For this study, the fifth or outer (68°) ring was dropped from the analysis to minimize the effects of scattering in the blue region of the spectrum at this wide view angle (Deblonde et al., 1994). As well, this decreased the view cone size and helped to minimize the inclusion of

Figure 2-4: Sampling strategy for below canopy measurements with LI-COR LAI-2000

Note: area viewed by sensor is approximate and varies with stand density and height of canopy

neighbouring trees outside the plot boundary. Canopy closure was derived from the first angle range (0° to 15°) of the LAI-2000 such that canopy closure = $(1 - P(7^\circ)) * 100$ (Chen and Cihlar, 1996). Where $P(7^\circ)$ is the gap fraction from the first ring of the LAI-2000 (the ring with a zenith angle midpoint of 7°).

2.5 Airborne image acquisition

Sensor Description

The Kodak DCS 420 CIR was used to acquire all images for this study. It is a digital frame camera originally developed for applications within the US Forest Service. More recently, the camera has become commercially available and is being used for a wider range of applications in environmental surveillance, monitoring and aerial surveys (Eastman Kodak Company, 1996). The Kodak DCS 420 is a charge coupled device (CCD) camera which is capable of producing three 1524×1012 12-bit channels. It has been modified to remove blue sensitivity and add near IR sensitivity to approximate the spectral sensitivity of Kodak 2443 colour IR

film (Bobbe and Zigadlo, 1995). As a result, the bandwidths of the three spectral channels are relatively wide, being approximately 100 nm, with significant spectral overlap. A single area array is used to capture data in three spectral bands. A decal containing red, green and near IR filters on the CCD's surface, limits data capture at each pixel to a single spectral band while camera software interpolates the spectral data for adjacent pixels (Figure 2-5). As a result, the spectral information was registered upon data capture. The single full-frame CCD sensor used in the camera measures 14.0 mm x 9.3 mm with individual pixels sizes of 9 μm x 9 μm . It is sensitive to radiation between 400 nm and 1000 nm (Figure 2-6), but is filtered to provide spectral sensitivity between 500 nm to 800 nm, with nominal band centres at 555 nm (green), 670 nm (red), and 760 nm (near IR) (Birdsall, 1997). The version used in this study was fitted with a Zeiss 28 mm lens and housed in a Nikon 35 mm camera body. A minus blue filter was also fitted on the lens to eliminate light transmission in the blue region. The approximate field of view for this particular camera setup

Figure 2-5: Schematic of data capture in Kodak DCS 420 CIR

A single area array is used to capture data in three spectral bands. A decal containing red, green, and near IR filters on the CCD's surface, limits data capture at each pixel to a single spectral band. As a result, image data are captured in a single spectral band and software interpolates the spectral data for adjacent pixels.

Figure 2-6: Spectral sensitivity of unfiltered sensor in Kodak DCS 420 CIR camera (Kodak, 1996)

was $\pm 14.0^\circ$ in the principal plane and $\pm 9.5^\circ$ in the orthogonal plane.

Flight acquisition parameters

Images were acquired in the green, red and near IR bands at an average ground pixel resolution of 25 cm. The ground coverage per image at this resolution was 381 m x 253 m. The long axis of the camera was positioned along the flight line to maximize potential overlap. The camera was manually triggered at specified intervals along the flight path to provide for 60% overlap between images, and stereo coverage for the entire transect. Images were stored on the camera's disk, which is capable of holding 105 images, and later written to CD in TIFF format. Because of few natural reference points, ground targets were set up every 20 m along a dry creek bed parallel to the 300 m study transect and at several locations within the forest to aid in plot location and flight line navigation. Hi-8 video was also used to record the plot boundary locations from below the canopy and to document the position of natural features for

additional verification. The distances between the ground targets in relation to several plot boundaries was taken with a measuring tape along with detailed field notes. A single flight path along the transect (azimuth = 334°) provided the necessary coverage. Imagery from a second flight path (azimuth 255°) near perpendicular to the first and flown at the north end of the forest transect were also used (Figure 2-7). A total of six images were used in the analysis, four from the first flight line and two from the second flight line. Although the data were acquired approximately 20 minutes apart, solar zenith angle is assumed constant over all images.

Conditions at the time of acquisition in late August 1996, were mostly sunny with occasional periods of scattered low cumulus cloud arriving late in the morning and early afternoon. All images acquired on the first flight line were cloud free, and only cloud-free images were used from the second flight line. No exposure or navigation problems were encountered during image acquisition. This may in part be attributed to a test flight which was used to determine the

Figure 2-7: Flight line coverage of study transect

appropriate exposure settings prior to the acquisition flight. During flight acquisition, an area weighted metering system was used on an aperture priority setting. This setting allowed for the light metering to be weighted over the entire frame while adjustments to exposure were made through changes in the aperture. Exposure times of 1/500th of a second at an aperture of f3.5 and f5.6 produced images with the widest grey level range (DN range) without saturating the forest canopy (e.g. white ground targets were DN = 252, conifer tree shadows over water were DN = 22). Correct exposure was important for producing images with a wide dynamic range. Improper exposure will produce images with fewer distinct grey levels and result in poorer discriminatory capability of the imagery (King, 1995). Finally, it is important to note that no corrections for lens fall-off (vignetting) or bi-directional reflectance were applied to the data and data were not radiometrically calibrated. In this study, both image vignetting and bi-directional reflectance were assumed not to influence the results obtained (discussed further in section 4.3).

2.6 Extraction of the shadow fractions from the digital camera imagery

Preprocessing

Study plots were located on all of the Kodak CIR images using the reference targets set up in the field, photographs and Hi-8 video taken of the plots in the field. Careful attention was paid to selecting the same area for each plot in the different images. Images of the same plot were simultaneously displayed on screen from several different view angles to help ensure the exact same areas were extracted. Distances between plots which were measured in the field were calculated on the imagery to help locate plot corners set off from the main drill road. Because the spectral data were internally registered in the Kodak CIR, all three spectral channels were extracted in one operation. Image cropping tools in Corel Photo-Paint™ 7 (Corel Inc., 1996) were used to select 80 x 80 pixel images of the individual study plots. As well, a single 150 x 150 pixel image centred at nadir was extracted from one of the four full images and used as a training area for the development of the shadow enhancement algorithm and placement of image

thresholds. This subscened training image was located adjacent to the study transect and outside all study plots, but in an area of mixed-wood forest visually similar to that observed along the transect.

Camera view angles were calculated for all study plot locations from the imagery along the principal plane. The total angle of view was first calculated using equation 2-2a:

$$\text{Equation 2-2a: FOV} = \tan^{-1}(\text{view angle}) = \frac{1}{2} \text{ base} / H$$

where the base was equal to the CCD dimensions along the principal plane (14.0 mm) and height was equal to the lens focal length (28 mm). The angle of view (AOV) for each centre pixel in the image subscene was then calculated using equation 2-2b:

$$\text{Equation 2-2b: AOV} = ((P_n - P_{cs}) / P_n) (\text{FOV})$$

where P_n was the number of the pixel at nadir ($\text{AOV} = 0^\circ$) in

principle plane (pixel 756); P_{cs} was the number of the pixel in the centre of subscene image along the principal plane (e.g. pixel 115) and; FOV was the absolute angle of the camera system in the principal plane (14°)

These camera view angle data were then used to determine which of the three or four image subscenes for each plot was closest to nadir along the principal plane and therefore, eventually used for model development. The range of the view angles amongst the selected 15 plots was -4.8° to $+4.5^\circ$. In this study, it was assumed that differences in camera view angle within this small range did not affect the observed relationships between the shadow fractions and biophysical variables.

Algorithm development and image thresholding

The goal of image thresholding was to segment the shadow component and its constituent fractions in the multispectral imagery from a variable background of sunlit image. All shadow fractions were defined and extracted from the spectral information provided by the airborne digital camera

imagery. Ground-measured radiance values were not used to define the shadow component as was the case in Leblon et al. (1996). As a result, there was a need to objectively define and extract the regions of shadowed and sunlit scene entirely from the information provided in each of the red, green and near IR image histograms. Furthermore, in order to minimize the subjectivity and uncertainty associated with extracting the shadow fractions separately in all three spectral bands, the spectral data were merged to create a single multispectral image histogram which was then used for extracting the shadow fractions. This histogram was simply a linear combination of the three spectral bands of the Kodak CIR imagery or in other words it displayed the distribution of the pixels according to the average brightness in the red, green and near IR bands. From this aspect, merging the spectral information was effective in reducing the number of necessary thresholds by two thirds through reducing the number of image histograms requiring segmentation from three to one. This approach also assumed that the best segmentation was achieved by incorporating information

equally from all three spectral bands.

The method for image segmentation developed here followed the approach of similar methods first suggested by Katz (1965) and later Weszka and Rosenfeld (1979), Pal and Pal (1987) and most recently by Breen (1994) and Ryherd and Woodcock (1996). The image histogram is first transformed into one with deeper valleys and sharper peaks before selecting the threshold levels. In this research, this was done using a 3 x 3 (9 pixel window) high pass filter applied to a duplicate copy of a single test image to enhance areas of local contrast smaller than the 3 x 3 window size (Pratt, 1978). For example, shadows within individual tree crowns which were approximately 75 cm in size or understory trees present between the gaps of crowns were enhanced relative to the rest of the image scene. The image filtering was applied to all three spectral bands and was scripted for batch processing of the remaining images (Appendix 1).

In the second step, the filtered multispectral image was integrated with the original image prior to thresholding using the Boolean operator *OR*. This second step of the

algorithm was successful in transforming the multispectral image histogram by weighting pixels in the image according to the local contrast properties of the pixel. Visually, this produced an image with a stepped gradient of shadow brightness where a smooth gradient was present before application of the enhancement algorithm (Figure 2-8). By integrating spatial and spectral information with user defined segmentation this technique was able to capture: (1) the homogenous dark regions of shadow between crowns and (2) the smaller more heterogeneous areas of within-crown shadow which were defined as much by their relative spatial context as by their spectral qualities. Most importantly, it produced a single image histogram with deeper valleys and sharper peaks which provided starting points for a good segmentation (Pearson, 1991; Pal and Pal, 1993). Selection of the threshold level then took place in the bottom of valleys or at breaks in the image histogram where two overlapping unimodal distributions merged. The approach for selecting a threshold level assumed that distinct regions or objects of interest in the image corresponded to unimodal

Figure 2-8: Effects of shadow enhancement algorithm

smooth gradient
of shadow
brightness

Original raw image

stepped gradient
of shadow
brightness

After application of
shadow enhancement
algorithm

peaks separated by valleys or breaks in the image histogram (Sahoo et al., 1988).

Image thresholds were set starting from the first valley in the histogram which represents the darkest shadows or minimum threshold level (T_{min}) (Figure 2-9). Threshold levels were then set at every valley in the histogram until the maximum threshold level (T_{max}) was reached. The maximum threshold (T_{max}) represented the boundary between the shadow component and sunlit component of the image scene. For this purpose, shadow was defined visually in the image as all areas within the image scene which were not directly illuminated by the sun. The threshold levels were used to define the shadow fraction boundaries in the image histogram.

Evaluation and application of shadow threshold technique

Because few recognized quantitative methods exist for evaluating the success of thresholded images, qualitative evaluation methods were adopted for this study (Sahoo et al., 1988; Pal and Pal, 1993; Zhang, 1996). As a result, the

Figure 2-9: Multiple image thresholding applied to the multispectral histogram^a for segmentation of the scene shadow fractions

^a combination of the red, green and near IR bands

^b after application of shadow enhancement algorithm

final segmented images were visually assessed for each plot by overlaying the binary images produced from each threshold level with the original colour infrared image (Appendix 1). This provided a good strategy for visually evaluating each set threshold level based on two criteria: (1) how well small isolated areas of shadow were segmented and (2) how well larger more homogeneous regions of shadow were segmented within the image scene. Thresholds which were close to the boundary of sunlit image were inspected to avoid inclusion of areas which were directly sunlit. Both areas within and between individual crowns were selected for evaluation using the above criteria. Threshold levels which unnecessarily merged heterogeneous regions of shadow or split homogeneous regions were rejected. In total, four threshold levels were selected as acceptable. Table 2-2 shows the characteristics of the selected threshold levels (T-level) and the corresponding shadow fraction which the threshold defines. For example, T3 and T4 define the boundaries for S4. The final segmentation process was scripted so batch processing (using the same selected T

Table 2-2: Image threshold levels used to extract shadow fraction data from Kodak CIR imagery

Threshold	Selected threshold level (DN)	Shadow fraction	Boundaries of shadow fraction (DN value)	
T1 (min)	47	S1	lower	= 0
			upper	= 47
T2	63	S2	lower	= 48
			upper	= 63
T3	87	S3	lower	= 64
			upper	= 87
T4 (max)	111	S4	lower	= 88
			upper	= 111

Note: DN values are from the multispectral histogram

levels) could be applied to the remaining images. Since changes in the mean scene brightness should be negligible from image to image, it was assumed that the same threshold levels could be applied to all image histograms without correcting for differences in image brightness. Finally, the areal proportion of image scene occupied by each shadow fraction was then calculated by doing a count of the number of pixels between the threshold levels defining each shadow fraction (Appendix 1). A forward stepwise multiple regression analysis was then used to determine the number of statistically significant shadow fractions needed to model the ground-measured variables.

2.7 Forest canopy modeling and multivariate analysis

Model development

A multiple regression analysis using forward stepwise selection procedures was used to determine shadow fraction combinations which were most strongly associated with the forest biophysical parameters of effective LAI, canopy closure and basal area. The multiple regression analysis was

useful in that it allowed model development to be driven by statistical significance and provided an objective and flexible strategy for both: (1) determining the number of statistically significant shadow fractions needed to model scene variance and (2) assessing the relations between the extracted shadow fractions and the ground-measured variables.

In each model, the forest biophysical variable was defined as the dependent variable while the areal percentages of the scene represented by the extracted shadow fractions were defined as independent variables. For example, the percent of S1, percent of S2 or percent of [S1 + S2] etc. In total, ten separate variables were created from the combination of different merged shadow fractions and entered as independent variables. Table 2-3 lists the independent variables which were input into the stepwise multiple regression analysis. In the stepwise procedure, the variable with the single largest simple correlation was first added. At each successive step in the building of the regression equation, variables were either deleted or

Table 2-3: List of independent variables used in stepwise multiple regression analysis

Independent Variable	Shadow Fraction
1	S1
2	S2
3	S3
4	S4
5	(S1+S2)
6	(S3+S4)
7	(S2+S3)
8	(S1+S2+S3)
9	(S2+S3+S4)
10	(S1+S2+S3+S4)

re-entered into the regression equation based on the ranking of all variables using partial correlation coefficients and controlling for the variables already entered (Dillon and Goldstein, 1984; Neter et al., 1985). Statistical significance of each variable was determined using both the overall and partial F values at each step in the regression process. Independent variables were entered at an F probability significance value of 0.05 and removed from the regression at an F probability significance value of 0.10 for the effective leaf area model and F to enter of 0.15 and 0.20 for the crown closure model. However, due to the low statistical significance of the individual shadow fractions in developing a best-fit regression model for basal area the stepping criteria for variable entrance was altered to allow more variables to enter into the model (for basal area only). Accordingly, the F probability significance to enter was set at 0.75 and the F probability significance to remove was set at 0.85. In particular, the higher F probabilities allowed shadow fractions S3, S4, S5 and (S3 + S4) to enter into the pool of acceptable variables. This selection

process for all models was terminated when no further variables could be entered or deleted from the final regression equation. In other words, the process was terminated when no new statistically significant information (shadow fractions) could be entered into the model equation.

The selected regression models were then inspected to make sure the input shadow fractions were meaningful and most importantly not overlapping. For example, variables 1 and 10 overlap as they both contain S1. In most cases, the selection procedures (i.e., tolerance level which is the reciprocal of the variance inflation factor) for detecting multicollinearity amongst the independent variables were sufficient to filter out these combinations of variables (Neter et al., 1985; SPSS, 1996). However, when these problems did occur, the tolerance criterion was set more strictly to 0.0001 eliminate the variable causing problems. The final regression equations were denoted in the following form:

$$\text{Equation 3-3: } Y = b_0 + b_1x_1 + b_2x_2 + \dots b_kx_k$$

where Y denotes the predicted biophysical variable, b_0 is a constant, b_i is the i th partial regression coefficient and x_i is the predictor (independent) variable ($i = 1, \dots, k$).

Selection and evaluation of a best-fit model

In order to determine the statistically significant number of shadow fractions, model comparison tests were conducted on the three best-fit models selected by the stepwise multiple regression. The best-fit model was chosen based on the following criteria: (1) the highest adjusted R^2 value (coefficient of determination), (2) lowest standard error (SE) and (3) with the overall goal of achieving parsimony (using as few variables as required). From a model fitting point of view the adjusted R^2 provided a more reliable indicator of the goodness of fit than R^2 as it took into account the number of predictor variables entered into the model (Dillion and Goldstein, 1984). As a rule, R^2 will always increase with the addition of a new variable, but the adjusted R^2 will continue to increase only as long as the t -value for the coefficient of an added variable is

absolutely >1 in value. An analysis of variance (ANOVA) table was also constructed to test whether the variables in the best-fit model were indeed related to the dependent variable. This provided an overall significance test for the regression model which was expressed as a P -value (Neter et al., 1985).

As a final evaluation of the aptness of the selected best-fit regression models, a series of residual plots were constructed to check for any departures in linearity or trends in the residuals (e.g. curvilinear residuals). Normal probability plots were also constructed of the residuals and examined for deviations from normality. Then, a casewise analysis of the residuals was conducted for each of the selected best-fit models to observe any potential outliers (>2 standard deviations).

Description of shadow fractions in best-fit model

Spectral and descriptive information were collected on each fraction from the best-fit model. Spectral data were calculated from a sample of 150 pixels per shadow fraction

distributed across the fifteen plots. Descriptive information was recorded on the tone and texture of each fraction. As well, each fraction was physically associated to the forest scene at the individual tree or canopy level. This was in an effort to identify the biophysical reasons behind any discovered relations. Shadows were characterized by their: (1) position in the forest canopy, (2) tonal and textural qualities and (3) association with canopy architecture or species composition. Specific names were assigned to each fraction based on their relation to the forested scene. For example, within-crown shadowing was identified most frequently within individual tree crowns.

CHAPTER 3 RESULTS

In this chapter, data are presented which describe forest canopy structure using the ground-based measurements and canopy structural attributes of the study plots. A series of select multiple regression models with different numbers of shadow fractions are also compared. From this group of models, a single best fit model containing three unique shadow fractions is selected for further evaluation with the dependents L_e and crown closure and a model containing two unique shadow fractions is selected for further evaluation with basal area. Physical connections between forest canopy structure and the three shadow fractions are emphasized and insight is provided into the possible information content these shadow fractions contribute in estimating L_e , crown closure and basal area. The relative importance of each shadow fraction is investigated through analysis of the R^2 contribution for each fraction. The linearity and direction of the relationship these shadow fractions have with the ground-

based measures are revealed in analysis of partial regression coefficients. Finally, a series of residual plots are used to provide some insight into the aptness of each selected best-fit regression model.

3.1 Description of forest structure in study plots

The data in Table 3-1 summarize the ground-based measurements collected for each of the fifteen study plots and together with Table 3-2 provide descriptive information on forest canopy structure and species composition. Table 3-3 presents a descriptive summary of the shrub layer survey. The overall differences observed amongst the individual plots are assumed to reflect different canopy structures within the boreal mixed-wood forest. Of particular interest are the measures of basal area, L_e and crown closure.

Basal area

The results presented in Tables 3-1 and 3-2 in part describe the horizontal stratification of the canopy within

Table 3-1: Summary of field data for the 15 study plots

Plot	Basal area (m ² /ha)	DBH (cm)	Height (m)	Stem density (stems/ha)	L _e ^a	Crown closure ^b (%)
1	2.3	34.9	28.7	125	1.12	26.4
2	13.6	17.6	14.4	600	1.59	67.4
3	36.5	16.1	13.0	1075	2.18	69.9
4	15.1	19.4	17.9	525	1.88	73.1
5	14.5	20.8	16.6	525	2.13	68.6
6	54.4	19.7	16.3	1075	2.69	67.4
7	32.0	15.4	13.9	1050	3.30	73.1
8	16.0	18.3	14.2	625	3.40	69.9
9	38.3	22.2	16.6	800	2.72	78.7
10	7.8	22.9	14.0	350	2.90	48.2
11	35.2	26.2	21.1	650	2.58	76.0
12	56.6	18.5	15.0	1125	3.98	89.2
13	76.7	12.7	11.0	1950	3.36	87.3
14	40.2	21.1	16.9	850	3.53	91.5
15	53.0	19.1	15.4	1075	4.92	94.9
Mean	32.7	20.2	16.3	825	2.82	72.1

^a L_e (effective LAI) is calculated using rings 1,2,3,4 of the LAI-2000

^b crown closure = (1-P(7°)*100) where P(7°) is the gap fraction in the first angle range (0° to 15°) of the LAI-2000

Table 3-2: Relative species composition of trees >2 m in height for the 15 study plots

Plot	Deciduous species		Conifer species			
	A	BP	BF	BS	JP	WS
1	0.80	0.00	0.00	0.00	0.20	0.00
2	0.33	0.00	0.46	0.17	0.00	0.04
3	0.33	0.00	0.42	0.23	0.00	0.02
4	0.39	0.00	0.35	0.17	0.04	0.04
5	0.38	0.00	0.29	0.19	0.05	0.09
6	0.44	0.00	0.42	0.14	0.00	0.00
7	0.24	0.00	0.45	0.26	0.00	0.05
8	0.12	0.00	0.36	0.36	0.08	0.08
9	0.38	0.03	0.28	0.12	0.03	0.16
10	0.14	0.29	0.29	0.14	0.00	0.14
11	0.04	0.02	0.08	0.11	0.00	0.11
12	0.18	0.15	0.56	0.09	0.00	0.02
13	0.05	0.15	0.69	0.08	0.01	0.01
14	0.06	0.20	0.47	0.09	0.09	0.09
15	0.04	0.02	0.26	0.33	0.03	0.08
Mean	0.26	0.09	0.36	0.17	0.03	0.08

A = trembling aspen (*Populus tremuloides*), B = balsam poplar (*Populus balsamifera*), BF = balsam fir (*Abies balsamea*), BS = black spruce (*Picea mariana*), JP = jack pine (*Pinus banksiana*), WS = white spruce (*Picea glauca*)

Table 3-3: Shrub layer cover and height classes for the study plots

Plot ID #	Shrub layer	
	Cover class	Height class
1	1	2
2	1	2
3	1	2
4	4	1
5	2	2
6	5	3
7	5	3
8	5	2
9	2	2
10	4	3
11	3	3
12	4	3
13	1	2
14	2	2
15	1	1

the study plots. Comparisons within the ground-based data show a higher than average total basal area in plots 3, 6, 9, and 11 to 15. Either a higher than average stem density or larger than average dbh contribute to the observed values in these plots. Plot 13 showed the highest mean basal area but the lowest mean dbh and mean height of all study plots which is indicative of the abundant number of balsam fir in the understory. Plot 12 showed a similar understory structure with the addition of an extensive shrub layer covering 50-75% of the plot (Table 3-3). In fact, much of the shrub layer in this plot consisted of balsam fir <2 m in height which were included in the shrub layer survey. At the same time, plots 1, 5, and 9 through 11 show a lower than average composition of balsam fir in the understory layer. Generally, the understory layer is less developed in these plots, although a dense shrub layer of speckled alder (*Alnus rugosa*) persists in plot 10 and to a lesser extent in plot 5. The canopy structure of these plots is best summarized in the higher than average mean dbh, lower than average stem densities and higher relative percentage of canopy level

species such as trembling aspen, and white spruce in these plots. Of the remaining observations, plots 1 and 10 show a distinctly lower than average total basal area. Plot 1 had the lowest stem density, but highest observed mean DBH and height which characterizes a single layered overstory canopy. Similarly, plot 10 typifies a single layered overstory canopy, but with greater species diversity and shrub layer cover than plot 1.

Effective leaf area index

Effective leaf area index was a stable and good predictor of radiation interception in forest canopies (Chen and Cihlar, 1996). In this context it was a good summary variable which provided information on canopy structure. Over the full range of L_e (1.12 to 4.92) the highest values were seen in plots 7, 8, 12, 13, 14 and 15 (Table 3-1). Likewise, the lowest L_e values were seen in plots 1 and 3. These observed differences and other similarities (e.g. plots 7 and 8) in L_e are most likely attributed to relative differences in species composition within the plots rather

than differences in tree size or stem density (Table 3-2). For example, the higher than average L_e values observed in plots 7, 8 and 12 through 15 are coupled with a relatively high percent composition of conifer species (balsam fir, black and white spruce) and lower percent composition of deciduous species. There was also a distinct trend of lower than average L_e with a higher than average composition of trembling aspen in plots 1 through 6. Accordingly, the results of a correlation matrix shown in Table 3-4 reveal a significant negative relationship at ($r = -0.76$ at 0.001 level) between L_e and percent trembling aspen and a significant positive correlation ($r = 0.63$ at 0.05 level) between L_e and total percent conifers. Indeed, these results make apparent the importance of species composition in determining L_e . This is especially important from a remote sensing perspective, because if L_e is to be successfully estimated, models should likely be developed that account for variations in species composition (Bonan, 1993).

	% trembling aspen	% balsam poplar	% balsam fir	% jack pine	% white spruce	% black spruce	L _v	crown closure	basal area	total stem density	conifer stem density	deciduous stem density	mean height
% trembling aspen	1.00	-0.46	-0.41	0.53	-0.37	-0.36	-0.76	**	-0.73	-0.48	-0.49	* -0.51	* 0.62
% balsam poplar	1.00	0.32	-0.13	-0.13	0.28	-0.36	0.36	*	0.11	0.18	0.14	0.15	-0.27
% balsam fir		1.00	-0.51	-0.33	0.09	0.38	0.58	*	0.59	0.77	0.76	**	**
% jack pine			1.00	-0.13	-0.27	-0.31	-0.50	-0.44	-0.50	* -0.37	-0.31	-0.24	* 0.74
% white spruce				1.00	0.17	0.20	0.13	-0.24	-0.34	0.07	0.22	-0.39	-0.07
% black spruce					1.00	0.41	0.29	-0.06	0.07	* 0.63	-0.02	-0.49	L _v
L _v						1.00	0.73	**	0.64	0.55	**	* 0.68	* 0.49
crown closure							1.00	0.73	**	0.69	0.31	-0.58	0.49
basal area								1.00	0.92	**	0.84	* 0.62	-0.45
total stem density									1.00	0.96	**	* 0.54	**
conifer stem density										1.00	0.27	-0.67	**
deciduous stem density											1.00	-0.18	-0.18
mean height												1.00	mean height

* significant at 0.05 level

** significant at 0.001 level

Table 3-4: Correlation matrix for stand attributes

Crown closure

Crown closure provided information on the percent vegetation cover within each plot. In this respect, it rendered a statistical description of the amount of open space or gaps between tree crowns in the study plots. Table 3-1 shows a wide range of closure existed (approximately 70%) within the plots. Yet, there was a substantial similarity among two groups of plots (e.g. 12 through 15; and 2 through 8). These results suggest a minimal diversity in crown closure amongst the majority of study plots, and consequently a relatively uniform amount of forest cover. Still, there were differences in the species composition of the forest cover between plots with similar crown closures. So, although the amount of cover was relatively consistent the canopy structure was still influenced a great deal by the differing crown geometries which form the upper canopy. For instance, plots 6 and 8 have similar crown closures at 67.4% and 69.9% respectively but very diverse species compositions (Table 3-2). Plot 6 was characterized by a dominant upper canopy composed almost entirely of trembling

aspen. Contrary to this, the species composition of the upper canopy in plot 8 is dominantly black spruce, jack pine and white spruce.

Finally, results of the correlation analysis shown in Table 3-4 revealed several interesting observations including: (1) a highly significant negative relationship between crown closure and % trembling aspen in each plot; (2) a moderately significant positive relationship between crown closure and % balsam fir in each plot; (3) a highly significant positive correlation between crown closure and basal area and; (4) a highly significant positive correlation between crown closure and conifer stem density. Together, these relations suggested that it was the amount, size and type of species which were the most important contributing factors to the amount of vegetation cover in the plots. In other words, the more conifers and less deciduous trees the higher was the crown closure, fewer were the number of gaps or smaller were the size of gaps between tree crowns. Again, from a remote sensing perspective, these results suggested that species

composition coupled with size and density were important factors to be accounted for in model development.

3.2 Comparison of the goodness of fit and standard errors for selected multiple regression models

Table 3-5 compares the coefficients of determination, adjusted coefficient of determination and standard error of the predictive equation for the best-fit multiple regression models. Results are shown as dependent variables for effective leaf area index, basal area and canopy closure. Statistical significance is reported for R^2 values, along with a list of the independent variables in each model. The results described here were used to determine a single best-fit regression model based on the highest goodness of fit (GOF) using the adjusted R^2 .

The highest GOF with the dependent variables L_e and canopy closure was obtained from models which included the same three independent shadow fractions S_1 , S_2 and $(S_3 + S_4)$. In contrast to this, the highest GOF obtained when modeling basal area was with model 4 which contained only shadow fractions S_1 and S_2 . In fact, the addition of a third

Table 3-5: GOF for a series of multiple regression models fitted with effective leaf area index, canopy closure, and basal area

Independent variables in multiple regression model	Summary statistic		
	R^2	$\bar{R}^2$	SE
	effective leaf area index		
Model 1. (S1),(S2),(S3 + S4)	*** 0.906	0.881	0.337
Model 2. (S1),(S2),(S3),(S4)	*** 0.907	0.870	0.353
Model 3. (S1),(S2),(S3)	*** 0.876	0.843	0.388
	basal area ^a		
Model 4. (S1),(S2)	* 0.556	0.482	15.30
Model 5. (S1),(S2),(S3)	* 0.565	0.446	15.82
Model 6. (S1),(S2),(S3 + S4)	* 0.561	0.441	15.89
	crown closure ^b		
Model 7. (S1),(S2),(S3 + S4)	** 0.668	0.577	11.26
Model 8. (S1),(S2),(S3),(S4)	* 0.686	0.560	11.49
Model 9. (S1),(S2)	* 0.600	0.490	12.37

* significance = 0.05

** significance = 0.01

*** significance = 0.001

R^2 coefficient of multiple determination

$\bar{R}^2$ adjusted coefficient of multiple determination

^a standard error is expressed in m²/ha

^b standard error is expressed as a percentage

shadow fraction such as $S3$ or $(S3 + S4)$, resulted in a lower goodness of fit and higher standard error when modeling basal area. Even so, the results show only minor differences amongst the models.

Comparisons amongst the three dependent variables clearly show the highest GOF was obtained when modeling L_e , and to lesser extent crown closure. In fact, all three models for L_e were very effective in reducing the sum of squares and accounted for as much as 90% of the observed variance. The strong relations reported here for L_e and crown closure were both highly significant ($p = 0.001$ and $p = 0.01$ respectively). Similarly, the lowest SE have been achieved in the regression of L_e followed by regression models of crown closure. For instance, L_e was estimated to within ~9% and crown closure estimated to within ~16% of the actual ground-measured values. Last, all three models used to estimate basal area showed the lowest GOF amongst all estimated dependents. When compared, the best-fit regression model with basal area accounted for approximately 40% less variance than the best-

fit counterpart with L_e . Still, the results with basal area showed a significant relationship ($p = 0.05$) with the selected shadow fractions and suggested the models were at least partially successful in accounting for the observed variance.

Furthermore, the links between light interception and stemwood production are much weaker than those observed between light interception and canopy leaf area. For instance, leaves project more shadow per unit area than stems or branches, thus intuitively the information provided by the scene shadow component is unlikely to be as directly important to estimates of basal area as it would be for L_e . In fact estimates of basal area may be inherently more difficult to retrieve given the weak relationship between light interception and stemwood productivity and theoretically should only be as strong as the efficiency with which the current year's leaf area represents the measured stand basal area (Stenberg et al., 1994a). Indeed, for this very reason it is hypothesized that the strength of the relationship observed between basal area and the canopy

shadowing model was presumably a product of the moderate ($r = 0.64$) and significant ($p = 0.05$) relationship observed between effective leaf area index and stand basal area amongst the fifteen study plots (see Table 3-4). Of course this remains to be rigorously tested, but it does raise an interesting question. That is, whether or not in future if stand basal area is indeed worth efforts to develop predictive equations for independently or whether estimates of stand basal area would be more readily inferred from models of predicted L_e .

Finally, after comparing the adjusted R^2 values and overall significance amongst the three models for each of L_e , basal area and crown closure, models 1, 4 and 7 were selected for further investigation. All three models contained the same two independent variables S_1 and S_2 , while models for L_e (model 1) and crown closure (model 7) both contained a third independent variable ($S_3 + S_4$). In all cases, the selected models were also those showing the highest adjusted R^2 value and lowest overall standard errors.

3.3 Description of the shadow fractions from the best-fit multiple regression models

Physical relation to forest canopy

Table 3-6 identifies a number of descriptive characteristics for each of the three statistically significant shadow fractions defined in the previous section. Each shadow fraction has been identified with a name more descriptive of its relation to the image scene.

For instance, the shadow fraction S1 was identified as deep shadow (abbreviated as S_d), based on its tonal characteristics. Transitional shadow (abbreviated S_t and formerly identified as S2) was named and identified for its most frequent position in the forest scene as was within-crown shadowing (abbreviated S_{wc} and formerly identified as (S3 + S4)). That is, transitional shadows were most often on the edges of tree crowns and usually between both deep and within-crown shadows. Figure 3-1 is a stereo paired image which illustrates the relative position of each fraction within the forested scene.

Deep shadow was the only fraction to be considered as

Table 3-6: Qualitative criteria for characterizing the three forest shadow fractions on the basis of Kodak CIR digital camera imagery

Shadow fraction	Image tone	Image texture	Physical relation of to the forest canopy
Deep (S_d) Note: Formerly fraction (S_1)	dark black	clear and smooth	full shadow which is cast between crowns by entire trees and groups of trees; shadows cast onto the lower canopy and a herbacious ground layer; often but not always associated with conifer trees
Transitional (S_t) Note: Formerly fraction (S_2)	black to dark grey	smooth to mottled	diffusely illuminated shadow which is cast between crowns from entire trees and groups of trees and within the crowns from branching structure; shadows cast in the lower to mid-canopy and onto a sunflecked herbacious ground layer
Within-crown (S_{wc}) Note: Formerly fraction ($S_3 + S_4$)	light grey	lightly mottled	diffusely illuminated shadow which is cast within the individual tree crowns from branching structure; shadow furrows are created in the upper canopy and occasionally onto a herbacious ground layer; shadow on the ground is sunflecked as a result of the transmittance of light between branches, shoots and leaves; often, but not always associated with deciduous trees

Figure 3-1: Position of shadow fractions in forest scene

(next page)

full shadow and most often occurred deeper in the canopy between crowns in canopy gaps. Even so, it should be noted that canopy gaps were not exclusive to deep shadow. In fact, shadows falling in canopy gaps may have been all transitional shadowing depending on the understory height, biomass, size of the gap and its shape in relation to the sun angle.

The remaining transitional and within-crown shadow fractions were considered partially or diffusely illuminated shadow. The term diffusely illuminated has been used to better describe the tonal values of these shadow fractions. It was believed that the presence of sunflecks or penumbra (small disc shaped spots or patches of sun which appear on the ground and are created when gaps in the canopy are smaller than the apparent size of the sun's disc) and the occurrence of multiple scattering events in the canopy and within individual crowns tended to lighten the tone of some shadows (Leblon et al., 1996). As noted by Stenberg et al. (1994a), the penumbra had the effect of evening out the spatial distribution of light in the canopy by bringing

sunflecks to the deeper canopy layers. Therefore, this phenomena was suggested to be a very important part of the transitional shadow fraction. Likewise, it was believed that within-crown shadowing was potentially influenced by the penumbra in areas where this fraction was present as diffusely illuminated ground shadowing.

Finally, it was an interesting observation that at least two of the three shadow fractions were often visually associated with either conifer (deep shadows) or deciduous trees (within-crown shadowing). This specific association with species type was hypothesized to be a result of: (1) differing crown morphologies and (2) leaf absorption characteristics observed in conifer versus deciduous trees.

In terms of crown morphology, trembling aspen and balsam poplar crowns tended to have larger branches and more open crowns with the foliage being attached in clumps much further from the main stem. As a result, deciduous trees tended to have branching morphologies which favoured within-crown shadowing. In contrast, most conifer species such as white spruce and especially black spruce tended to have

smaller branches and relatively dense foliage often very close to the main stem and hence, a very efficient crown structure for absorbing radiation and one which effectively produced more deep shadowing adjacent to conifers. This observation has been at least partially verified through earlier studies of Federer and Tanner, (1966) and more recently Bonan, (1993) and Leblon et al. (1996).

Furthermore, the association of conifers to the production of deep shadows was believed to be an effect of the more efficient radiation absorption characteristics in the red and near IR spectral regions of conifer needles versus deciduous leaves. This increased ability to absorb radiation resulted in less radiation passing through the crowns of conifers and therefore the effect of darker shadows (Leblon et al., 1996).

Spectral composition of shadows

Several significant points can be recognized by examining the spectral composition of the three shadow fractions in Figure 3-2. First, it can be seen that a

Figure 3-2: Mean DN and standard deviation at nadir of each shadow fraction: $\blacksquare$ S_{wc} - within crown shadow, $\circ$ S_t - transitional shadow, $\square$ S_d - deep shadow. Band nominal centerwidths of Kodak DCS 420 CIR are: 555 nm (green), 670 nm (red) and 760 nm (near IR). All values were calculated from a sample of 150 pixels per shadow fraction distributed across the 15 nadir view plots.

gradient of brightness exists amongst the three shadow fractions. For example, within-crown shadow consistently displayed the highest DN values for all spectral bands, followed by transitional shadow. Deep shadow had the lowest DN values for all spectral bands, which indicated an increase in the absorption of radiation toward the deep shadow fraction. Second, there was an increase in the ratio of red to near IR brightness from within-crown shadow to deep shadow, indicating a relatively larger increase in near IR reflectance than the corresponding increase in red reflectance across this gradient. For instance, the ratio of red : near IR brightness (DN values) was ~0.67 for within-crown shadowing and increased considerably to ~0.85 for deep shadowing. Indeed, this suggests that the association of deep shadow with increased canopy depth and conifers is correct. Conversely, the high DN value observed in the near IR coupled with a relatively low DN value in the red (chlorophyll absorption band) indicates within-crown shadows are likely cast onto a foliated surface from structural elements within the individual crown. Transitional shadow

was cast between within-crown shadow and deep shadow and occupied the mid-canopy layer, straddling both individual crowns and canopy gaps. Spectrally, this was interpreted by a similar relative pattern of behavior in the DN values to within-crown shadowing (near IR > green > red), but with lower overall brightness values similar to those observed in deep shadowing.

Trends in the amount of shadow for each study plot

Variations in the mean amount of deep, transitional and within-crown shadow are illustrated in Figure 3-3. The areal percentage of each shadow fraction is reported along with camera view angle for each study plot. In comparing the three shadow fractions for all plots, it is apparent that the deep shadow fraction tends to have a wider range of observations than either transitional or within-crown shadowing respectively. For example, the range amongst the observations is ~20% for deep shadow, ~16% for transitional shadow and only ~14% for within-crown shadow. From a regression modeling point of view this suggests the deep

Figure 3-3: Areal percentage of deep shadow, transitional shadow and within-crown shadow for the study plots

(next page)

Plot 1

$S_{wc} = 29.44\%$
 $S_t = 17.61\%$
 $S_d = 6.72\%$
 $\alpha = +3.2$

Plot 2

$S_{wc} = 32.05\%$
 $S_t = 16.68\%$
 $S_d = 7.25\%$
 $\alpha = -2.0$

Plot 3

$S_{wc} = 35.04\%$
 $S_t = 13.45\%$
 $S_d = 5.50\%$
 $\alpha = -1.6$

Plot 4

$S_{wc} = 36.23\%$
 $S_t = 14.19\%$
 $S_d = 6.84\%$
 $\alpha = -4.8$

Plot 5

$S_{wc} = 36.30\%$
 $S_t = 13.26\%$
 $S_d = 4.58\%$
 $\alpha = -4.1$

Plot 6

$S_{wc} = 39.09\%$
 $S_t = 7.60\%$
 $S_d = 1.88\%$
 $\alpha = -3.9$

Plot 7

$S_{wc} = 35.23\%$
 $S_t = 19.55\%$
 $S_d = 14.67\%$
 $\alpha = -2.9$

Plot 8

$S_{wc} = 43.16\%$
 $S_t = 11.28\%$
 $S_d = 4.64\%$
 $\alpha = -3.6$

Plot 9

$S_{wc} = 38.86\%$
 $S_t = 14.69\%$
 $S_d = 6.84\%$
 $\alpha = -4.7$

Plot 10

$S_{wc} = 33.96\%$
 $S_t = 14.79\%$
 $S_d = 8.19\%$
 $\alpha = -0.9$

Plot 11

$S_{wc} = 37.12\%$
 $S_t = 17.42\%$
 $S_d = 9.41\%$
 $\alpha = -2.3$

Plot 12

$S_{wc} = 32.55\%$
 $S_t = 23.19\%$
 $S_d = 23.05\%$
 $\alpha = -3.7$

Plot 13

$S_{wc} = 38.22\%$
 $S_t = 8.04\%$
 $S_d = 3.52\%$
 $\alpha = +3.4$

Plot 14

$S_{wc} = 32.83\%$
 $S_t = 15.56\%$
 $S_d = 15.00\%$
 $\alpha = +2.1$

Plot 15

$S_{wc} = 29.25\%$
 $S_t = 21.12\%$
 $S_d = 22.82\%$
 $\alpha = +4.5$

shadow fraction is a relatively effective explanatory variable. That is, with its greater range of observations it can potentially account for more variance in the dependent variable(s) than either transitional or within-crown shadowing.

It is also interesting to note that deep shadow was more consistent for plots 1 through 5 and compared to within-crown shadowing, poorly distinguishing these plots from each other. For instance, the absolute range of values amongst plots 1-5 for within-crown shadowing is approximately 7% compared to <3% for deep shadow. Plots 1 through 5 have similar species compositions with upper canopies of trembling aspen and the occasional spruce or jack pine (see Table 3-2). The within-crown shadow fraction appears to separate these plots much better than either the deep shadow fraction or transitional shadow fraction. Likewise, the deep shadow fraction appears to separate the dominantly conifer plots (plots 7, 12, 14 and 15) quite well from the dominantly deciduous plots (plots 1 through 5). Statistically, Figure 3-3 reveals substantial information

about the effectiveness of each fraction and its ability to account for the observed variance in the dependent variables. That being, the greater the separation amongst the shadow fractions in the individual plots, the greater the ability to predict the biophysical variables and to predict with less error. Furthermore, it shows how multiple shadow fractions are effective in allowing a mixture of species compositions to be studied with a single model.

3.4 Nature and significance of the relations in the best fit multiple regression models

The partial contribution to R^2 , partial correlation coefficient and significance level for each shadow fraction are shown in Table 3-7 for the L_e , crown closure and basal area best-fit multiple regression models. Comparisons are made amongst all three dependent variables for the deep and transitional shadow fractions and between crown closure and L_e for within-crown shadowing. Within-crown shadowing did not contribute information to the best-fit model for basal area.

Table 3-7: Contribution to R^2 , partial correlation coefficient and significance level for best fit multiple regression models with effective leaf area index, basal area and crown closure

Shadow fraction	ΔR^2	r	P -value	
	effective leaf area index			
	S_D	0.463	0.881	0.000
	S_T	0.379	-0.445	0.005
	S_{wc}	0.065	0.255	0.018
	basal area			
	S_D	0.079	0.744	0.309
	S_T	0.477	-0.667	0.004
	crown closure			
	S_D	0.238	0.794	0.065
	S_T	0.338	-0.563	0.009
	S_{wc}	0.093	0.467	0.108

ΔR^2 is change in R^2 with inclusion of variable or contribution to R^2

r is partial correlation coefficient

Partial contribution to R^2 and significance

Judging from the contribution to R^2 and relative significance levels of S_t and S_d , it seems that both shadow fractions are important sources of information for modeling canopy structure. In terms of the contribution to R^2 , the deep shadow fraction accounted for as much as ~46% of the variance in L_e and ~24% of the variance in crown closure. Even so, S_d appeared to play a reduced role in accounting for the observed model variance in basal area. In fact, S_t actually made the most significant contribution to R^2 when estimating basal area and accounted for almost half of the observed model variance. Equally important to the estimation of L_e and crown closure, S_t accounted for ~38% and ~34% respectively, of the observed model variance for both of these dependent variables. Indeed, the contribution of both S_t and S_d are the most significant reasons why the estimation of canopy structure was so successful in this study. Nevertheless, the within-crown shadow fraction did contribute new information not accounted for by either, S_t or S_d , to the estimation of L_e and crown closure. Although

less significant, S_{wc} accounted for as much as 9% of additional model variance.

Partial correlation coefficients

It can be seen from Table 3-7 that the partial correlation coefficients provide unique information about the strength and direction of the observed relations between the biophysical variables and each shadow fraction. Accordingly, interpretation of the coefficients provides some insight into the nature of the observed relationships and the linearity of each independent variable when all other variables in the model are accounted for.

The partial correlation coefficients for S_d and S_{wc} were both positive for the best-fit L_e and crown closure regression models. However, those relations with S_d were much stronger than the relations observed for S_{wc} . Statistically, this again indicated that S_d was a much better predictor variable than S_{wc} based on the greater range of observations and sensitivity of S_d . A positive partial correlation also existed between basal area and S_d ,

although it was not significant as were those observed with L_e and crown closure.

The positive relations observed with (i) S_d and L_e , basal area and crown closure and (ii) with S_{wc} , L_e and crown closure, fit well with what is already described about these shadow fractions. Indeed, increased values of L_e and crown closure were interpreted to mean higher amounts of vegetation cover within the canopy; hence, canopy structural conditions favourable to the creation of S_{wc} in the image scene. Likewise, higher values of S_d were interpreted as being an effect of canopy structural conditions suitable for the creation of deep shadows. For example, increased values of L_e caused by increased numbers of conifers were often associated with deep shadows and increased values of basal area caused by an increased density of conifers or tree size were also associated with deep shadowing.

By far, the most interesting relationship amongst those presented in Table 3-7 is that between S_t and the biophysical variables. This negative relationship was not anticipated, and the underlying reasons for it require

further detailed investigation. However, the importance of this relationship to understanding the models developed in this research warrants interpretation. For example, interpreting the results from the crown closure model the following are hypothesized to explain the negative correlation coefficient: (1) a decrease in crown closure resulted in an increase in the number or size of canopy gaps which contributed to a canopy structure more favourable to the production of S_c and less to favourable for S_d and (2) a similar decrease in crown closure resulted in less vegetation cover, therefore conditions less favourable to the creation of S_{wc} . In other words, it was hypothesized that as the canopy became more open due to changes in species composition or stem density etc., the increased number or size of canopy gaps resulted in a canopy structure more conducive to the creation of S_c and less conducive to S_{wc} and S_d . Statistically, S_c works in the opposite manner as S_{wc} and S_d . A similar interpretation was used to explain the negative partial correlation coefficients between S_c and L_e and basal area. Such that, as basal area and L_e decreased,

the canopy structure was altered in favour of conditions for the creation of S_e rather than S_d in basal area and S_d and S_{wc} in L_e .

3.5 Aptness of the best-fit multiple regression models

Figures 3-4 through 3-6 present plots of the standardized residuals against each of the dependent variables: effective leaf area index, basal area and crown closure. In each plot, all case labels correspond to the study plot ID numbers. The residual plot for the best-fit L_e model showed no systematic variation or trends from the regression line. Most residuals tended to fall within ± 1.5 standard deviations of the regression line and all observations were < 2 standard deviations from the line. Hence, there were no outlier observations (> 2 standard deviations). The residual plot for the best-fit crown closure model showed that most residuals were again within ± 1.5 standard deviations of the regression line, but there were some indications that plots with lower crown closures were more prone to estimation errors. For example, plots 1,

Figure 3-4: Residual plot from best fit multiple regression model of effective leaf area index

Note: case labels correspond to the study plot ID #

Figure 3-5: Residual plot from best fit multiple regression model of basal area

Note: case labels correspond to the study plot ID #

Figure 3-6: Residual plot from the best fit multiple regression model of crown closure

Note: case labels correspond to the study plot ID #

2, 8, 10 and 6 had the lowest crown closures and showed the greatest estimation errors. Even so, there were a lack of sample points at the lower range of crown closures to confirm that the error variance was larger for more open canopy conditions. Otherwise, the residual plot for the crown closure model showed no serious outliers or trends from the regression line. Contrary to this, the residual plot for the best-fit basal area model showed that a definite linear trend was still evident in the residuals. For example, there was a tendency for the regression to overestimate the predicted values in those plots with a lower basal areas (plots 4,5, 10 and 8) and underestimate in those plots with higher basal areas (plots 13, 12, and 6). This suggested the model was not effective in accounting for (removing) all the observed variance in basal area. However, it was not an indication the selected model was inappropriate, only that it was not sufficient.

Figures 3-7 to 3-9 are normal probability plots of the residuals for the best-fit multiple regression models of L_e , basal area and crown closure. Plots which are nearly linear

Figure 3-7: Normal probability plot of residuals for best fit multiple regression model of effective LAI

Figure 3-8: Normal probability plot of residuals from best fit multiple regression model of basal area

Figure 3-9: Normal probability plot of residuals for best fit multiple regression model of crown closure

are indicative of normality. The heavy weighted line on each plot represents a situation of perfect linearity. Small departures from linearity did occur in both normal probability plots of crown closure and L_e . The departures in the plot for L_e appeared to be minimal and isolated to no more than a few data points. However, the departures shown for crown closure were more consistent and suggest the linearity of the error terms is weaker for the crown closure model than for either L_e or basal area models. Even so, this was not likely a serious indication of non-normality in the error terms. Finally, the normal probability plot for the basal area model showed strong linearity and suggested the error terms were indeed normally distributed.

Indeed, there were strong indications from the results presented in this section that the best-fit multiple regression models were appropriate models for estimating effective leaf area index, basal area and crown closure.

CHAPTER 4 DISCUSSION

This chapter attempts to further an understanding of the use of multiple shadow fractions for retrieving canopy structure from high resolution airborne imagery. The results presented in the previous chapter are situated in context with the literature and the objectives outlined in the introduction are further explored. To this end, the discussion addresses several key questions central to this thesis: (1) How did the results obtained in this study compare with results in the literature? (2) Why were the shadow fractions effective sources of information in modeling canopy structure? (3) What were the errors and limitations of this study?

4.1 Comparing approaches to canopy structural modeling

Comparisons amongst results from similar studies using high resolution imagery are often difficult. Different methodological approaches, sample sizes, pixel ground resolutions and forest conditions often make comparison

incomplete at best. Yet, these studies offer one of the few benchmarks from which to compare and contrast the results obtained in this thesis. For the most part, LAI is readily comparable, but few studies in the literature routinely estimate forest stand basal area or crown closure. Results are compared in the context of other high resolution imagery largely from *casi* (Compact Airborne Imaging Spectrometer).

Spectral and textural modeling

In one of the few comparative studies using high resolution optical imagery in a mixed forest situation Wulder et al. (1996) were able to predict LAI in fourteen study plots over a range of 4.6 with a r^2 of 0.67 and standard error of 0.70 using the NDVI on 2 m *casi* imagery. Again, in the same study and using image texture measures, r^2 values of 0.56 and a standard error of 0.77 were reported. It was only with the addition of image texture measures and spectral indices in a multivariate analysis that R^2 values of 0.92 approached those reported in this study. Likewise, the results presented in this thesis showed

improvements in the standard error of the predictive equation of approximately 50% over the estimation error of 0.68 or 15% of the observed range in LAI reported in Wulder et al. (1996). Accordingly, this demonstrates the comparable use of multiple shadow fractions to image texture and spectral indices for the estimation of LAI. It also emphasizes the potential of digital camera imagery for modeling canopy structure in a mixed-wood forest.

Nonetheless, caution should be taken in comparing these results which are based on different sensors and in different forest ecotones. In the study presented by Wulder et al. (1996) the species composition was different (subalpine forest), less diverse and unlike this study included pure stands of lodgepole pine (*Pinus contorta*) and trembling aspen (*Populus tremuloides*). As well, the ground-based measures of LAI were obtained using allometric equations in Wulder et al. (1996) compared to Li-Cor measures of effective LAI in this thesis.

In a similar study on forest LAI estimation in mixed-wood conditions, Wulder et al. (1998) reported identical,

although weaker findings than those in Wulder et al. (1996). Using a bivariate regression between LAI and NDVI calculated from *casi* imagery with a 1 m ground pixel resolution, Wulder et al. (1998) reported r^2 values of 0.01 and SE of 1.62 in a mixed-wood forest with LAI ranging from 1.52 to 9.43. Similar results were reported from bivariate regression between LAI and several texture derivatives as measured in the red and near IR including: semivariance (r^2 ranging from 0.28 to 0.39) and first and second order co-occurrence measures (maximum r^2 of 0.34). However, it was only with the inclusion of both textural and spectral indices in a multivariate analysis that the goodness of fit was significantly improved with a R^2 of 0.51 and SE of 1.26 or 16% of the observed range in LAI. These results did not compare as favourably with results reported in this thesis. The overall strength of the best fit model was significantly stronger ($p = 0.001$) at $R^2 = 0.91$ and the standard error of 0.35 or ~9% of the observed range in effective LAI was lower than those reported by Wulder et al. (1998).

Even so, site conditions and sensor type differences

between Wulder et al. (1998) and the results reported in this thesis were evident. As once again a mixture of different species was reported between the two studies, with Wulder et al. (1998) estimating LAI in stands which are composed predominantly of jack pine (*Pinus banksiana*), white and red spruce (*Picea glauca* and *Picea rubens*), balsam fir (*Abies balsamea*), red maple (*Acer rubrum*) and white birch (*Betula papyrifera*).

While most studies of forest LAI estimation concentrate on deriving LAI from simple regression analysis of sensor spectral data, few studies have investigated the potential of multivariate analysis in estimating forest LAI. For example, Gong et al. (1995) compared several regression based techniques for LAI estimation from spectral data and vegetation indices for spatial mode *casi* data with a ground pixel resolution of 1-2 m. The best fit equations were obtained from a piece-wise multiple regression analysis where significant R^2 values of 0.87 and RMSE (root-mean square error) estimates were 1.4 or ~13% of the actual ground measured values in dominantly conifer stands along

the Oregon transect (see Runyon et al., 1994). In this case, LAI estimates were derived from the Li-Cor LAI 2000 and like this study were not actual but effective estimates of leaf area index. Indeed, the reported range of effective LAI values were greater in Gong et al. (1995) being from greater than 10 to less than 1. It was encouraging to note the similar relative errors and strength of the relations reported between the two studies. This comparison highlighted the use of image structure analysis and digital camera imagery as alternatives to spectral modeling with more expensive airborne sensors.

In an earlier study, using various airborne spectral data and indices derived from *casi* imagery with a 5 m ground pixel resolution, Gong et al. (1992) reported R^2 values ranging from 0.81 to 0.98 in stands of ponderosa pine. Standard errors of the predictive equation were consistently less than 0.3 or 10% of the actual ground measured range of LAI which was 3. The results presented in this thesis compared quite favourably with the results from Gong et al. (1992). Both sensors were capable of estimating LAI with

similar accuracies, although Gong et al. (1992) were limited to pure stands of ponderosa pine.

Yet another study by Spanner et al. (1994) along the Oregon transect showed far less favourable results when estimating LAI from calibrated *casi* imagery with a ground pixel size of 2-3 m. Relationships between the simple ratio of red (676-682 nm) to near IR (784-790 nm) were strong with an R^2 of 0.92. However, with a standard error of 2.15, LAI could only be predicted to within ~20% of the actual ground measured values. Using airborne spectrometer data (SE590) acquired with similar spectral bands in the red and near IR, improvements were realized in the standard error which was reported at 1.37 or measurable to within ~13% of the actual ground-measured LAI values.

Indeed the relative results from this thesis were comparable to those obtained by Spanner et al. (1994), but as was emphasized by the authors, it was the estimation of LAI values >7 which tended to cause the most difficulty. The LAI values in the dominantly conifer forests along the Oregon transect were more diverse than those reported in

this thesis. For instance, the range of LAI values observed were from a minimum of 0 for stands of red alder (*Alnus rubra*) to a maximum of 10.6 in mixed-wood stands of Douglas fir, white oak (*Quercus garryana*) and big-leaf maple (*Acer macrophyllum*). This raised some question as to whether the range of LAI values in this thesis was actually wide enough to fully test the shadow fraction model. Furthermore, as suggested by an earlier study along the Oregon transect from Spanner et al., (1990) the relatively good results obtained in this thesis may well have been influenced by the mostly closed canopy conditions of the forest. With an average closure of ~72%, forest conditions observed in this thesis were similar to the range of closure in which the authors reported the strongest relations with LAI (>75% closure).

Image structural modeling

Of the few empirical studies using scene radiometric components to model canopy structure, none have been completed in mixed-wood stands or with multiple shadow fractions. As well, neither Peddle et al., (1997) nor Hall

et al., (1995) used high resolution digital imagery to extract the scene radiometric components. Nonetheless comparisons are made, if only to emphasize the strength of this method in estimating canopy structure in diverse environments and with different sensors.

In Hall et al., (1995), a helicopter mounted radiometer was used in conjunction with aerial photography to extract the scene shadow component in near pure boreal stands of black spruce (*Picea marianna*). Results indicated that both LAI and dbh were best estimated using the scene shadow component at sun zenith angles (SZA) of 30° and 45°. In fact, LAI was estimated with $r^2 = 0.72$ and a SE = 0.58 or to within ~12% of the ground measured values and dbh was estimated with $r^2 = 0.54$ and a SE = 1.97 cm or to within 19% of the ground measured values. It is interesting to compare the relative accuracy of the LAI estimates versus the estimates for dbh and how they are very similar to estimates observed in this thesis; where for example, L_e was estimated to within 9% of the ground measured values and basal area to within 20% of the ground measured values. These results

verify the inherent difficulty in estimating stem biomass (dbh or basal area), and equally important, the precision with which estimates of LAI can be obtained with empirical modeling of the scene shadow component(s). Again, the results in this thesis compare quite favourably to those presented in Hall et al., (1995), especially given the more heterogenous canopy conditions in which the models in this thesis were derived.

Finally, Peddle et al., (1997) used geometric-optical modeling to estimate the areal percentage of the scene shadow component with both cone and spheroid models for 31 stands of black spruce. Results were also corrected for SZA and similar to Hall et al., (1995) showed the best results in modeling canopy structural attributes were at SZA's = 30° and 45°. LAI was estimated with $r^2 = 0.82$ and a SE = 0.47 or to within ~10% of the ground measured values. In short, the results verify the use of the scene shadow component for estimating canopy structure. At the same time, they also highlight the different approaches to scene fraction verification. Comparing the results from Peddle et al.,

(1997) to those of Hall et al., (1995) and this thesis, it is evident that all three methods of extracting the scene shadow component are valid. However, given the low costs, multispectral capability and high ground pixel resolutions capable with digital camera imagery, they are the most cost-effective solution to scene component validation for plot-based studies.

4.2 Effectiveness of multiple shadow fractions

It is apparent from the observed results that the multiple shadow fractions provided surrogate information on the spatial distribution of forest structure within the study plots. The effectiveness of the multiple shadow fraction approach appeared to be based on: i) the inherent link shadows provided between crown structure at the individual tree level and crown productivity and, ii) links to the horizontal and vertical distribution of vegetation at the canopy level. Because the quality of the shadow information is critical to the success of this approach, the effectiveness of the shadow fractions was also reliant on

the shadow extraction technique.

Surrogate information at the individual tree level

At the individual tree level, the dependency of light interception by crown structural properties occurred at different scales. Both the macroscale and microscale geometry of trees influenced the absorption, transmittance and reflectance of light. It is suggested that the combination of the three shadow fractions' sensitivities to crown shape and size (macroscale geometry), as well as within-crown architecture (microscale geometry), provided the predictive ability of the multiple shadow fractions.

Macroscale geometry of individual trees was thought to influence the amount and type of shadowing in the image scene through features such as crown shape and size. (Okerblom and Kellomaki, 1982; Kuuluvainen and Pukkala, 1987; Stenberg et al., 1994; Peddle et al., 1997; Chen and Leblanc, 1997). For instance, conical or cylindrical shaped crowns typical of boreal conifers are generally narrow and tend to have a relatively high crown height-to-width ratio.

In the forest scene, this equates to a relatively small surface area of the crown being exposed to the upper canopy. Hence, a very sudden transition occurs between sunlit canopy and shadow and conditions which tend to favour the production of shadows with high contrast (i.e., deep shadows). On the other hand, spherical shaped crowns which are typical of boreal deciduous trees, have a lower crown height-to-width ratio. Consequently, a larger surface area of the crown is exposed in the upper canopy. This creates conditions favourable for the production of transitional or within-crown shadows, which are lower in contrast and more gradual in their shading effects as compared to deep shadows.

Links between the crown size and the amount of shadow in the image scene are more intuitive. That is, larger crowns will project a relatively larger area of shadow and smaller crowns will project a relatively smaller area of shadow. This is a simple, but powerful link between crown structure and image shadowing. When exploited, this link provides a fundamental source of information which drives the

empirically based models of canopy structure.

Equally important are the links between shadow type and crown microscale geometry. The microscale geometry of trees such as branching patterns, foliage clumping and crown transparency, influence the type of shadows produced in the image scene through links to crown architecture, light penetration and absorption (Ross, 1981; Oker-Blom and Kellomaki, 1983; Rosema et al., 1992; Stenberg et al., 1994; Leblon et al., 1994; Chen and Leblanc, 1997).

Individual crowns are organized into stems and branches. Their particular arrangement or crown architecture creates a sub-canopy structure which is important in determining the type of shadow projected onto the ground or created within individual tree crowns (Oker-Blom and Kellomaki, 1983; Leblon et al., 1994). This is particularly important in terms of providing surrogate information. Conifers and deciduous trees have very different sub-canopy structures and therefore produce shadows which may be unique to each type of tree.

For example, deciduous trees are characterized by an

open crown architecture where the branches and clumps of foliage are located further from the main stem than in the more closed crown architectures common to black and white spruce. This more open crown architecture in deciduous crowns creates conditions which are more favourable for the creation of sunflecks or penumbra on the understory layer, as well as within-crown shadows. These sunflecks have the effect of increasing the shadow brightness by adding a mixture of sun-shadow to the projected shadow area (Leblon et al., 1994). Although many of these sunflecks are no larger than a few centimeters and maybe up to 10 cm, they may have a profound effect on the spectral characteristics of the forest shadow component (e.g. the creation of transitional shadowing or within-crown shadows). Likewise, the more closed crown architecture and clumping of foliar elements in conifers creates conditions less favourable for the creation of large sunflecks, and hence a sub-canopy structure more favourable for the creation of deeper shadows or transitional shadows. It is suggested that the sensitivity of the multiple shadow fractions to the

microscale structure of individual crowns provided additional predictive information in modeling canopy structure.

In future, research efforts should be concentrated on verifying the effects of microscale geometry on the creation of multiple shadow fractions. These studies should include an investigation of the penumbra and more detailed spectral verification of the types of shadows projected by deciduous and conifer trees.

Surrogate information at the canopy level

At the canopy level, it is suggested that the multiple shadow fractions are providing information on the horizontal and vertical distribution of vegetation in the different canopy layers. In comparison to other canopy structural modeling, multiple shadow fractions more closely represent the distribution of light within the forest canopy. This sensitivity to the three dimensional structure of the canopy is reflected in the gradient of light which the three shadow fractions represent. For example, S_d was created deep in the

canopy between crowns, S_c was created in both canopy gaps and on the edges of trees, and S_{wc} was created most often in the upper canopy (see figure 3-1). Through their collective positions in the image scene the three shadow fractions are inherently linked to canopy depth and the presence of understory vegetation. It is this sensitivity to canopy depth and the light regime of the forest that is suggested to be providing surrogate information about the horizontal and vertical distribution of vegetation in the different canopy layers.

Dependency on shadow extraction technique

It is apparent that the degree of success of the individual shadow fractions to account for variance in the ground-measured variables was a consequence of the method used to extract the fractions. Although the shadow enhancement algorithm and thresholding generally provided a good segmentation of the shadow fractions, it was not as effective in extracting all within-crown shadowing. As shown in Figure 4-1, the areas of shadowing within the individual

Figure 4-1: Segmented image comparing the area of deep shadow, transitional shadow and within-crown shadow for the training area subscene.

a) Original image

b) Segmented shadow fractions

crowns are only partially extracted. For example, the large aspen crown(s) on the bottom right of the image show a moderate amount of within-crown shadowing which was not extracted, particularly on the sunlit side of the crowns. In comparison, essentially all areas of deep and transitional shadowing were extracted from the image scene. Within-crown shadows are inherently more difficult to extract from the image scene because of their relative position next to the sunlit canopy. Even so, if future efforts can improve upon the extraction of within-crown shadows, the full potential of multiple shadow fractions may be realized. It is believed that within-crown shadowing plays a larger role in the forest scene than was indicated by this study.

4.3 Sources of error in study

In any research study involving the collection, measurement and analysis of data, there is potential for errors to arise. While every effort has been made to eliminate or minimize errors in this study, several sources of error are recognized as having influenced the results.

These errors and their implications are discussed in the context of the results obtained in this study.

Li-Cor 2000 PCA Measurement of effective LAI

Measurements acquired with the Li-Cor 2000 PCA were considered accurate to within 10% of the measured mean values at a 0.95 confidence interval (Li-Cor Inc., 1990). While efforts to minimize sources of error have already been described in chapter 2, it was believed that errors in L_e did occur from the inclusion of an understory shrub layer (speckled alder) in plots 8 and 10. Both plots had a relatively low stem density and lower than average crown closure, but the L_e values for these plots seem unusually high for such open canopies. During operation the understory shrub layer was pushed aside by the operator to minimize this influence on the readings; however, it is believed that the Li-Cor sensor still recorded information from the shrub layer from the outer ring sensors (e.g. rings 5,4 and 3 and possibly 2). At these larger view angles, vegetation was likely still visible to the sensor. So, while the shrub

layer directly above the operator was viewed as being open by the sensor at the first angle range (0° to 15° - ring 1), the remaining rings likely recorded information about the understory shrub layer.

Furthermore, it is believed that the inclusion of canopy level information from outside the plot boundaries could have also affected the accuracy of the measurements in all plots, but again particularly plots 8, 10 and 1. The more open conditions in these plots meant that the sensor viewed a wider area of canopy, as vegetation from within the plots did not serve to block the view into adjacent plots. The extent of this error is believed to be relatively small and confined to the aforementioned plots.

In future, indirect estimates of LAI will remain unduly affected by the inclusion of understory shrub layers which reach in excess of 2 m (or height of operator). Indeed, there is no sure way to eliminate this source of error without disrupting the natural state of the vegetation. However, errors from the inclusion of vegetation from outside the plot boundaries and from understory shrub layers

may be minimized with the use of newer instruments which have a narrower azimuthal field of view, such as the TRAC (tracing radiation and architecture of canopies) (Chen and Cihlar, 1995).

Subjectivity associated with image segmentation

Segmentation of the shadow fractions relied on the subjective placement of the threshold levels. In this regard, two sources of error are derived: i) from subjectively determining which valleys were thresholded and ii) from subjectively determining where to set the threshold level within the chosen valleys of the image histogram.

While the shadow enhancement algorithm was seen to improve the precision of which valleys could be detected and included in the multiple regression analysis by making the peaks and valleys more distinct, it did not effectively reduce the error from determining where in the valley the threshold levels should be set. For instance, if the valley which separated the transitional shadow fraction from the deep shadow fraction is ~5 pixels wide, where should the

threshold level be set? Shifting the threshold level higher or lower will alter the areal percentage of both shadow fractions. Thus, the subjective placement of the threshold level within the designated valley(s) that was not properly addressed in during image segmentation. Nonetheless, multiple regression analysis at least allowed the process of selecting the final shadow fractions to be statistically driven.

In future, criteria should be developed to define which valleys are included for thresholding and for determining where in the valley the threshold level should be set. For example, a valley could be defined by standardized changes in the pixel frequency such that, a valley is considered only if a set percentage drop has occurred in the pixel frequency and remains for a set minimum number of consecutive DN values. The introduction of criteria to minimize the subjectivity of the threshold process should further reduce errors associated with user interpreted boundaries.

Radiometric calibration and lens vignetting effects

Additional errors were believed to be caused by assuming lens vignetting effects were constant over all images. The accuracy with which images were segmented was likely influenced by applying the same threshold levels universally to each plot regardless of lens vignetting effects in the images. Although minimized through the selection of plots close to nadir, failure to account for vignetting effects inherently altered the accuracy with which the threshold levels could be applied to all images. For example, changes in image brightness due to lens vignetting effectively produced a shift in the image histogram DN values amongst the plots. While this did not greatly affect the shape of the image histogram or the information it contained, it did shift the relative position of the valleys and peaks in the histogram. Therefore, in universally applying the same threshold levels (DN value) to all images, it was possible that segmentation was not optimized in some images. In fact, any increases in the amount of shadowing with camera view angle may have in part been a product of lens vignetting.

Because this progressive darkening of the image toward its edges (from light absorbed by the lens walls) is independent of the imaged scene and canopy geometry, it is theoretically possible to correct for this shift in image brightness (King, 1992). Attempts at such a correction might yield improvements in the accuracy with which threshold levels could be applied, especially at larger camera view angles.

Finally, it is important to remember that all threshold levels in this study were applied to the raw digital number (DN) values which were not radiometrically calibrated or atmospherically corrected. The selected threshold levels were considered independent of calibration requirements and atmospheric effects. A similar number of thresholds would be found in calibrated data which are simply linearly related to the raw data (King, 1992). The advantage of calibration would be greater consistency of threshold determination, but with the increased costs associated with instrument calibration. Similarly, atmospheric correction would have led to greater consistency of threshold determination, but

at costs not necessarily justified for local application of the models. Consequently, it is believed that while these sources of error exist, they are small and are of less concern than other errors mentioned in this study.

Effects of camera view angle

Investigations were carried out as to the effects and potential errors camera view angle had on the observed relationships between the shadow fractions and the biophysical variables.

In general, Figure 4-2 provides insight into the potential errors caused by assuming a constant view angle. As camera view angle increases toward the direction of the sun in the forward scattering direction, the overall amount of image scene in shadow will increase as more of the shadowed side of the tree is revealed to the sensor. In the backward scattering direction, as the camera view angle increases away from the sun, the overall amount of shadow will decrease as more of the sunlit crowns are viewed by the sensor. These changes in the areal percentage of shadow with

Figure 4-2: Sun-object-image angular relationship

camera viewing geometry may have influenced results obtained.

For this purpose, a limited analysis of these effects was carried out on the shadow fraction data used in this study to gain practical insight into the potential source and amount of error within a $\sim 10^\circ$ field of view surrounding nadir (0°).

That is, the amount of within-crown shadowing was seen to increase in the forward scattering direction and decrease in the backward scattering direction. It was believed that this was in part due to the increased saturation of crowns on the sunlit side. This would have the effect of decreasing the amount of within-crown shadowing viewed by the sensor and in combination with an ineffective algorithm would mean the extraction of less within-crown shadows on the sunlit side of crowns. Indeed, this could be in part the reason why plots 1 ($+3.2^\circ$), 13 ($+3.4^\circ$) and 15 ($+4.5^\circ$), which were all located in the sunlit zone of the image, showed the lowest percentage of within-crown shadowing amongst all plots (see figure 3-3). Likewise, transitional shadowing also showed

similar trends, with higher amounts recorded in plots on the shadowed side of the image versus the sunlit side. Yet, the amount of deep shadow was seen to increase in both viewing directions. This may have been caused by real differences in the deep shadow component as parts of the image scene were revealed and hidden at changing camera view angles. It may also have been an indication that lens vignetting had unduly influenced the amount of deep shadow extracted from the image at camera view angles greater than $\pm 5^\circ$ off nadir. In fact, it is difficult to separate the effects of camera viewing geometry and bidirectional reflectance from those observed from lens vignetting.

On a closing note, it is comforting to find that early attempts to normalize the relationships for camera view angle effects appear to indicate that on average, the strength and precision of the estimates are not greatly affected. For instance, when normalized for a camera view angle range of $\pm 5^\circ$ off nadir, the resulting relation of shadow fractions with L_e produced a $R^2 = 0.88$ and $SE = 0.36$. This equated to a decrease in the R^2 of only 0.02 and an

increase in SE of only 0.03. Similar magnitudes of change were also seen for the normalized relationships between basal area and canopy closure.

4.4 Limitations of the study

While the methods investigated in this thesis demonstrate the capability for retrieving canopy structural attributes from multiple shadow fractions, there are limitations to the spatial and temporal application of this approach. As such, caution should be exercised as to the interpretation of these results beyond the context of the objectives outlined in this thesis.

This thesis focused on the development of an empirical model to further the understanding of relations between image structure and forest structure in a boreal mixed-wood forest. Research for this thesis originated from the need to develop methods to remotely estimate forest structure in a boreal mixed-wood forest to quantify canopy structural damage occurring adjacent to an acid mine tailings site. While acknowledging an acute environmental problem in a

structurally damaged ecosystem at the study site (Gibson, 1976; Kilborn, 1983; Levesque and King, 1995; Walsworth, 1997), attempts to draw causal links between observed structural damage and forest stress agents were considered beyond the scope of this thesis.

Furthermore, image structure analysis was explored as complementary to other proposed methods of remotely estimating canopy structural attributes. In this regard, no one method is yet considered suitable for all types of forest conditions. Therefore, it is recommended that this approach be used in conjunction with other more traditional approaches such as image textural and spectral measures. Until the regression models developed in this thesis are rigorously verified and tested with a larger sample size, application of the models should remain limited to the data set obtained for this thesis and the localized area surrounding the KamKotia mine site.

In addition, observations and conclusions obtained in this study may not be temporally replicated without rigorously investigating the influence of solar azimuth and

solar zenith angles. These effects have been verified under homogeneous canopy conditions and with a single shadow component. For example, at large solar zenith angles, the amount of shadow in the image is known to increase and weaken the observed relations of the shadow component to LAI, and stand basal area in pure stands of black spruce (Peddle et al., 1995). However, extension of these results to mixed-wood stands with multiple shadow fractions is not likely recommended, given the more variable shadowing conditions under mixed-wood canopies (Leblon et al., 1996).

Again, if the methods are to be applied temporally there should be some consideration given to relative radiometric calibration of data sets. For example, deep lakes and other natural pseudo-invariant targets could be used to perform a relative calibration on data sets collected at different time periods. In this manner, increased consistency could be obtained without the additional costs associated with more intensive absolute instrument calibration.

CHAPTER 5 CONCLUSIONS

The retrieval of forest canopy structural attributes such as LAI, basal area and crown closure from remotely sensed imagery are a particular challenge in boreal mixed-wood forests. The increased structural complexity arising from a mixture of crown geometries and horizontal stratification of the canopy presents a forest scene which has been difficult to model and thus far poorly addressed in the literature. Accordingly, traditional approaches such as spectral indices and, more recently, image texture measures in combination with spectral indices, have shown limited success. Yet, these methods have remained the focal point of research into modeling canopy structure in mixed-wood stands. For this purpose, it was hypothesized that an analysis of the shadow component in high resolution multispectral digital camera imagery would provide surrogate information suitable for the estimation of LAI, basal area and crown closure in the boreal mixed-wood forest. This thesis demonstrates that there is information in the shadow

component of high resolution multispectral digital camera imagery that can be used to estimate the amount and distribution of vegetation in a boreal mixed-wood forest. This conclusion is based on the following assessments made from work completed in this thesis:

(1) A linear combination of three statistically significant shadow fractions was found to be sufficient for modeling effective LAI and crown closure. In addition, a linear combination of two statistically significant shadow fractions was found to be sufficient for modeling stand basal area. Together these findings support the use of multiple shadow fractions such as deep shadow, transitional shadow and within-crown shadow for modeling canopy structure in the boreal mixed-wood forest.

(2) The information contained in the deep shadow fraction and transitional shadow fraction accounted for a majority of the observed variance in the ground-measured variables of effective LAI, stand basal area and crown closure. Within-

crown shadowing accounted for substantially less variance in modeling effective LAI and crown closure, but still provided a significant contribution to both models. The within-crown shadow fraction did not include significant information to the estimation of stand basal area. It was believed that ineffective segmentation of the within-crown shadow fraction may have contributed to these results. Finally, it was suggested that the overall sensitivity of the three shadow fractions to i) the macroscale and microscale geometry at the individual crown level and ii) the vertical and horizontal distribution of vegetation at the canopy level resulted in the ability of the shadow fractions to predict canopy structural attributes.

(3) High resolution imagery from the Kodak 420 CIR camera was capable of resolving scene structural information within individual crowns. This information could be extracted from simple image processing techniques from uncalibrated multispectral imagery. Indeed, this was the first research to demonstrate the use of high resolution multispectral

digital airborne imagery for scene fraction verification. The advantages to this data source are the low cost of the imaging technology as well as its digital format which is suitable for statistical image processing.

In future, this approach to canopy structural modeling could be optimized through a larger sample size, and validation in a wider range of forest canopy conditions. Further study is also needed in the ground-based validation of the identified multiple shadow fractions using a spectral radiometer. Such research should also include an investigation of the penumbra and its importance in the spectral composition of the shadow fractions. Again, improvements in the segmentation and extraction of the shadow fractions would also likely be realized if image vignetting effects were to be accounted for. In addition, relative calibration of the digital imagery should be performed based on pseudo-invariant ground targets (e.g. deep water, pavement) if this method is to be repeated both spatially and temporally. Finally, the effects of solar zenith, solar azimuth and camera view angle and indeed bi-

directional reflectance should be further investigated.

APPENDIX 1: INSTRUCTIONS FOR IMAGE PROCESSING AND ANALYSIS IN COREL PHOTO-PAINT 7

The following are a detailed listing of the steps and input parameters used for image processing and analysis in Corel Photo-Paint™ 7.

STEP 1: HIGH PASS FILTERING

Purpose: to create and run a 3 x 3 high pass filter on the raw image file.

(i) Select menu and program options

- ▶ 'open' the raw image file (eg. A06.cpt)
- ▶ 'click left' on the image to activate the file window
- ▶ 'select' the Effects menu
- ▶ 'select' 2D ▶ Userdefined options from the menu

(ii) Use the following input parameters

- ▶ 'click on' Symetric and 'input' Divisor = 1
- ▶ 'input' cell weights into window (see Figure A1-1)

Figure A1-1: Cell weights for 3 x 3 convolution mask

-1	-1	-1
-1	9	-1
-1	-1	-1

(Pratt, 1978)

Note: the brightness values located around the eight outer cells were multiplied by the filter weights assigned to each cell (-1). This value was then assigned to the center cell of the convolution mask and divided by the center weight (9).

► 'select' Okay to accept and 'save as' eg. A06Highpass

Note: this step is repeated for each threshold level and can be scripted for batch processing of image files (see Corel, 1996).

STEP 2: COMBINE IMAGES USING LOGICAL OR

Purpose: to combine the original raw image with the filtered output image from step 1.

(i) Select menu and program options

- ▶ 'select' the Image menu
- ▶ 'select' Calculations from the menu

(ii) Use the following input parameters

- ▶ 'input' a file name for Source 1 (eg. A06raw.cpt) and
 'input' a file name for Source 2 (eg. A06highpass.cpt)

Note: user must input the raw image file and filtered image file output from step 1.

- ▶ 'click on' the Use all channels option
- ▶ 'input' Opacity = 100
- ▶ under the Method option 'select' Logical OR
- ▶ 'select' Okay to accept and 'save as' eg. A06combine

STEP 3: THRESHOLDING IMAGES

Purpose: to threshold the output image from step 2 (eg. A06combine.cpt) into a binary image for visual evaluation.

(i) Select menu and program options

- ▶ 'open' image file output from step 2
- ▶ 'click left' on the image to activate the file window
- ▶ 'select' the Image menu
- ▶ 'select' the Adjust ▶ Threshold from the menu

(ii) Use the following input parameters

- ▶ 'select' Bi-level thresholding
- ▶ 'input' High level = 255 and Low level = 0
- ▶ 'select' Threshold level = eg. 111
- ▶ 'select' Okay to accept and 'save as' eg. A06T111

Note: this step is repeated for each threshold level and can be scripted for batch processing of image files (see Corel, 1996).

STEP 4: COMPARING THRESHOLD IMAGE TO RAW IMAGE

Purpose: to overlay a single thresholded image (eg. output from step 3) with the raw image for visual inspection of the threshold boundaries.

(i) Select menu and program options

- ▶ 'select' the Image menu
- ▶ 'select' the Calculations from the menu

(ii) Use the following input parameters

- ▶ 'input' a file name for Source 1 (eg. A06raw.cpt) and
 'input' a file name for Source 2 (eg. A06T111.cpt)

Note: user must input the raw image file and thresholded image file output from step 3.

- ▶ 'click on' the Use all channels option
- ▶ 'input' Opacity = 100
- ▶ under the Method option 'select' Logical AND
- ▶ 'select' Okay to accept and 'save as' eg. A06T111raw

Note: repeat this step for all threshold levels or to contrast the difference between two threshold levels in an image follow step 5.

STEP 5: COMPARING TWO THRESHOLDED IMAGES

Purpose: to overlay two thresholded images for visual inspection of the difference between the two thresholds.

(i) Select menu and program options

- ▶ 'select' the Image menu
- ▶ 'select' the Calculations from the menu

(ii) Use the following input parameters

- ▶ 'input' a file name for Source 1 (eg. A06T96.cpt) and
 'input' a file name for Source 2 (eg. A06T111raw.cpt)

Note: user must input a thresholded image file from step 3 and the output image file from step 4.

- ▶ 'click on' the Use all channels option
- ▶ 'input' Opacity = 100

- ▶ under the Method option '*select*' Logical AND
- ▶ '*select*' Okay to accept and 'save as' eg. A06T111T96

STEP 6: AREAL PERCENTAGE OF SHADOW FRACTIONS

Purpose: to display the areal percentage of a shadow fraction or to display spectral band information of a shadow fraction.

(i) Select menu and program options

- ▶ '*left click*' on the output image from step 2
(eg. A06combine.cpt) to activate the file window
- ▶ '*select*' the Image menu
- ▶ '*select*' the Histogram option from the menu

Note: DN values which are displayed are linear average of the DN values of the 3 spectral channels (in this study the green, red and near IR). The image histogram and DN values for the individual spectral bands can be displayed by selecting the appropriate RGB channel which the band is displayed in eg. select the red channel to display data from

near IR spectral band.

(ii) Use the following input parameters

- ▶ *'Move cursor on screen'* to minimum DN value which defines the shadow fraction eg. DN = 96
- ▶ *'Click left and hold'* on the minimum DN value and *'move cursor'* to maximum DN value which defines the shadow fraction eg. DN = 111. The total image between DN 96 and DN 111 is displayed in percent along with mean and median DN value for DN range selected eg. S7 = 10.53%.

APPENDIX 2: REGRESSION EQUATIONS FOR BEST FIT MODELS

Independent variables in multiple regression model	Regression equation
	effective leaf area index
Model 1.(S1),(S2),(S3 + S4)	$Y = 0.497 + 0.255X_1 - 0.216X_2 + 0.0913X_3$
Model 2.(S1),(S2),(S3),(S4)	$Y = 0.358 + 0.255X_1 - 0.217X_2 + 0.846X_3 + 0.101X_4$
Model 3.(S1),(S2),(S3)	$Y = 2.97 + 0.255X_1 - 0.263X_2 + 0.0889X_3$
	basal area
Model 1.(S1),(S2)	$Y = 89.47 + 4.643X_1 - 6.43X_2$
Model 2.(S1),(S2),(S3)	$Y = 72.39 + 4.65X_1 - 6.51X_2 + 0.969X_3$
Model 3.(S1),(S2),(S3 + S4)	$Y = 66.18 + 4.648X_1 - 6.276X_2 + 0.525X_3$
	crown closure
Model 1.(S1),(S2),(S3 + S4)	$Y = 19.3 + 3.866X_1 - 3.387X_2 + 1.929X_3$
Model 2.(S1),(S2),(S3),(S4)	$Y = 3.94 + 3.857X_1 - 2.895X_2 + 1.185X_3 + 2.995X_4$
Model 3.(S1),(S2)	$Y = 104.77 + 3.847X_1 - 4.518X_2$

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IMAGE EVALUATION TEST TARGET (QA-3)

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