IMPACTS OF RADIOMETRIC CORRECTIONS ON EMPIRICAL MODELLING
OF BIOPHYSICAL VARIABLES WITH AIRBORNE MULTISPECTRAL
DIGITAL CAMERA IMAGERY

By

Robert Kyle Bemrose

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ABSTRACT

Modelling forest attributes using empirical remote sensing methods can be affected by variations in image brightness within individual images. This research evaluates how distortions in high-resolution colour infrared (CIR) airborne imagery influence the empirical modelling of biophysical variables. The main research objectives were to: 1) correct variations in image brightness of airborne multispectral data caused by bi-directional reflectance variation, topography, and optical light fall-off, and 2) compare stepwise regression models of field measured forest variables derived from raw image spectral and texture data versus models derived from corrected image spectral and texture image data. Biophysical measurements of forest structure and health were made in the Gatineau Park northwest of Ottawa, Canada, which is an area of unmanaged temperate hardwood forest on the southern edge of the Canadian Shield. Regression models produced for average diameter at breast height (DBH), basal area and effective leaf area index (ELAI) improved using image data corrected for bi-directional variation and light fall-off. ELAI models improved with the correction of image brightness caused by topographic variations. This research provides a first step towards understanding how regression based biophysical models of forest structure and health derived from image spectral and texture information change with the reduction of image brightness distortions.

DEDICATION

This thesis is dedicated to my Father who always provided encouragement throughout my pursuit for higher education. He will be greatly missed.

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LIST OF ABBREVIATIONS

ABS	: Absolute Value
AOV	: Angle of View
APC	: Antenna Pattern Compensation
ASM	: Angular Second Moment (Image Texture Measure)
AvgDBH	: Average Diameter at Breast Height
AvgH	: Average Health Score
BA	: Basal Area
BRDF	: Bidirectional Reflectance Distribution Function
BRV	: Bidirectional Reflectance Variation
CIR	: Colour Infrared
CON	: Contrast (Image Texture Measure)
COR	: Correlation (Image Texture Measure)
DBH	: Diameter at Breast Height
DBIW	: Database Input Window
DEM	: Digital Elevation Model
DIS	: Dissimilarity (Image Texture Measure)
DN	: Digital Number
ELAI	: Effective Leaf Area Index
ENT	: Entropy (Image Texture Measure)
FOV	: Field of View
GNDVI	: Green Normalized Difference Vegetation Index
GPS	: Global Positioning System
HOM	: Homogeneity (Image Texture Measure)
LAI	: Leaf Area Index
NAD	: North American Datum
NCC	: National Capital Commission
NDVI	: Normalized Difference Vegetation Index
NIR	: Near-Infrared
PCC	: Percent Canopy Cover
RMSE	: Root Mean Square Error
SAIL	: Scattering by Arbitrary Inclined Leaves
SE	: Standard Error
TPs	: Tie Points
UTM	: Universal Transverse Mercator
VAR	: Variance (Image Texture Measure)
VIF	: Variance Inflation Factor

1.0 INTRODUCTION

Measuring and mapping of the vertical and horizontal structure within a forest stand is important in several applications such as silviculture, biodiversity assessment, carbon sink monitoring and wildlife habitat analysis. Forest structure is defined in numerous ways throughout the literature, but the main reoccurring concept is associated with geometrical representation of a forest (Oliver and Larson, 1990; Stone and Porter 1998). It is described through many mensuration techniques that attempt to characterize the size, aerial coverage, and spatial density of trees or canopy foliage. The estimation of forest structure is a common objective in many remote sensing studies because images acquired above the canopy can provide spectral and spatial information related to the forest measurements taken on the ground. Models are often derived from remotely sensed imagery to provide a generalized representation of certain structural characteristics that relate to biological processes occurring within a forest. To develop such models, quantitative data collection, processing and analysis stages are required to relate the remote measures to ground-based validation measures (Steven, 1987). These models can then provide a means to analyze and map large areas with relatively little fieldwork. In order to develop the strongest possible models between image variables and field variables, factors that reduce the optical quality of the remotely sensed imagery need to be understood and data processing needs to be implemented to reduce the noise (undesired variance) that these factors contribute.

Airborne sensors, as with all remote sensing instruments, have particular properties that both promote and limit their usefulness for modelling and mapping forest structure. Imagery acquired from airborne sensors can be affected by several distortions that need to be corrected to ensure that image-based models of forest structure are representative of the area being examined. Currently, many studies to develop empirical predictive models of forest variables are conducted without correcting the imagery, which may lead to misinterpretations, poor prediction and low map accuracy. Images are often not corrected due to a lack of familiarity concerning the distortions that may be present or because suitable correction techniques are not available. There are several factors that need to be addressed that influence the quality of the imagery. The radiometric (brightness) information acquired by an airborne optical sensor can be influenced by the sensor's lens (vignetting), sensor bit-depth (radiometric resolution) and electronic noise, the atmosphere (scattering, absorption and clouds), target illumination interactions (bi-directional reflectance variation), and topography (slope and aspect) (Edirisinghe, 1997; Holopainen and Wang, 1998; Pellikka, 1998; Fischer, 2001). Each of these factors has an impact on the imagery, which can lead to unfavourable modelling results if not recognized and corrected. Before extracting information from remotely sensed imagery, each of these factors should be evaluated to determine if correction is required.

Vignetting causes an overall gradual fading of image brightness from the centre of the image to the edge (Edirisinghe et al., 2001; Yu et al., 2004). This can often be modelled using a simple function relating brightness to view angle. Radiometric resolution refers to the sensor's sensitivity to differences in reflected,

emitted or scattered radiation (Jensen, 2005). Higher radiometric resolution is generally achieved if electronic noise is low and increases the precision with which forest field variables can be modelled and predicted. The atmosphere acts as a reflector itself in the visible by adding scattered radiance to the ground radiance and by absorbing radiation in certain spectral regions (Singh and Saull, 1988). Bi-directional reflectance variations cause brightness changes across an image resulting from the position of the sun in relation to the sensor's field of view. Topography causes slopes facing away from the sun to be darker than slopes facing towards the sun in the image.

There are a number of methods that have been developed to correct these distortions. This research applies methods to correct distinct deterministic spatial variations in image brightness: bi-direction reflectance variation, topography and vignetting. The corrections are evaluated both in terms of how well the spatial variations are reduced by their effectiveness in statistical modelling of vegetation structure and health.

1.1 Research Goal, Objectives and Scope

The overall goal of this research was to determine how much image correction techniques can improve biophysical models of forest structure variables derived from remotely sensed imagery. More specifically, the research objectives were to:

- (1) correct variations in image brightness of airborne multispectral data caused by bi-directional reflectance variation, topography, and optical vignetting;

Atmospheric and noise/bit depth effects were excluded from this research because for the former, the small view angle of the data would not produce significant spatial variations in brightness, and for the latter, noise was expected to be mostly spatially random.

- (2) compare stepwise regression models of field measured forest variables derived from raw image spectral and texture data with models derived from corrected image spectral and texture data.

To achieve these objectives, airborne multispectral data were acquired and corrected for: 1. bi-directional reflectance variation, 2. topography, 3. the combined effects of bi-directional reflectance, topography and vignetting using a net correction, and 4. bi-directional reflectance variation correction followed by the net correction to remove residual noise. Stepwise regression was then used to develop relationships between field variables (stem density, diameter at breast height, basal area, effective leaf area index, percent canopy cover and a tree health score) and image variables (near-infrared, green, green normalized difference index, and texture measures). The regressions were first derived for raw image data and then again after each of the image correction methods was applied. All models were compared to determine the impact of each correction on the model correlation coefficient (R^2), significance (P -value), and standard error (SE).

1.2 Thesis Structure

The thesis is structured into five chapters. The second chapter provides background information on image correction techniques and regression-based biophysical modelling. The third chapter develops the ideas from the background by presenting the research methodology including study site selection, field plot measurement of forest variables, image data acquisition and processing, and regression modelling of forest image relationships. Chapter four presents the results. Chapter five discusses the main findings of the research, its limitations, future directions and conclusions of the research.

2.0 BACKGROUND

2.1 Biophysical modeling of Forest Attributes in Remote Sensing

Biophysical modeling of forest attributes with the use of remotely sensed imagery can be performed using empirical or theoretical methods. Empirical remote sensing models typically relate two datasets representing image measurements (e.g. a vegetation index) to field measurements interest, in often a statistical fashion (Strahler et al., 1986; Schlerf and Atzberger, 2006). Theoretical models (generally termed ‘physical’ based reflectance models) consider the relationship between canopy structure, leaf orientation and the scattered and emitted radiation. As this thesis focuses on empirical modelling, only a short summary of physical models is provided below.

2.1.1 Physical Models

Goel (1988) distinguished four types of canopy reflectance models: 1) geometric-optical; 2) turbid medium; 3) hybrids of geometric-optical and turbid; and 4) computer simulations. The choice of canopy reflectance model depends on the nature of the surface under investigation and how the model is to be used (Gemmell, 1998). The Li and Strahler (1985) model is one of the most common geometrical-optical models. This model treats vegetation canopies as an assemblage of discrete, three-dimensional objects illuminated at a specific angle and casting shadows on a contrasting background (Strahler et al., 1986). The vegetation canopy is described

using opaque geometric shapes (cones or cylinders), which cast shadows on the ground (Schlerf and Atzberger, 2006). Norman and Welles (1983) used the geometric approach to model orchards and wide row crops as a collection of discrete ellipsoids (Strahler et al., 1986). Turbid medium models (e.g. SAIL model of Verhoef and Bunnik, 1981) describe the canopy as a horizontally homogenous and semi-infinite layer that contains small vegetation elements which are treated as absorbing and scattering particles of a given geometry and density (Schlerf and Atzberger, 2006). Radiative Transfer Theory is used to model radiation interactions with the canopy in various spectral bands. Hybrid models may have advantages over simpler models in terms of realism since these models take into account both geometric structure and radiative transfer considerations (Gemmell et al., 2002). Computer simulation models compute the path of photons through the canopy to determine the direction of the incident rays and the scattering direction (Schlerf and Atzberger, 2006). These models are applied to remotely sensed data by inversion. Inversion involves adjusting model parameters until the modeled reflectance best matches the measured image reflectance (Gemmell, 1998).

2.1.2 Empirical Models

Empirical models have been used extensively in forestry remote sensing applications to relate variables of interest (e.g. LAI, basal area) to predictor variables extracted from imagery. Spatial and spectral measurements are most commonly the measurements extracted. Regression is typically used to determine the form and strength of relationships between variables (Cohen et al., 2003). It has been

recognized that empirically based methods have a number of drawbacks, including site and scene dependency, as well as the difficulty of taking into account the effects of extraneous factors (Gemmell et al., 2002).

Both the physical and empirical approaches have advantages and disadvantages depending on the particular application. Empirical methods are not considered to be the best from a theoretical standpoint because they often produce relationships between image and field variables that are hard to explain. However, they are often used for almost all studies because of their ease of implementation and simplicity. It is well known that the radiation reflected, emitted, absorbed or scattered is not captured properly through empirical methods because the energy interactions within a forest environment are very complex, and several parameters are involved, often in a non-linear way (Rosema et al., 1992). A physically based approach could solve many of the limitations related to empirical methods if it could be shown to work accurately enough (Gemmell and Varjo, 1999; Schlerf and Atzberger, 2006). Physical models are useful to study the effects of varying forest structure on reflectance, but they are often constrained by the input data, and oversimplification of the canopy that reduces spatial extension of predictive capability, particularly with high-resolution imagery. The study of canopy reflectance models is still in the preliminary research stages and a substantial amount of work is still required before the methods can be introduced into more operational modelling and mapping applications. This study used empirical methods because they are most commonly applied in practise, and implementation of complex canopy reflectance models would

have forced the research to focus on the models themselves instead of the image correction methods.

2.1.3 Spectral Information

Spectral analysis is based on the development of a deterministic relationship between the amount of electromagnetic energy reflected, absorbed, emitted or back-scattered in specific bands or frequencies and the chemical, biological and physical features of the phenomena under investigation (Jensen, 2005). Spectral information describes the average tonal variations in various portions of the electromagnetic spectrum, which are strongly associated with the surface being sensed (Haralick et al., 1973). The analysis of spectral information can be conducted independently through the direct relationships to surface features or can be enhanced by generating spectral indices.

Spectral indices enhance certain qualities of the surface being sensed by using different combinations of spectral information through a mathematical ratio or difference calculation. The most common information sought after with spectral indices is related to vegetation (i.e. vegetation indices). Vegetation indices make use of the fact that live green vegetation absorbs solar radiation particularly well in the visible wavelengths (due to the presence of chlorophyll and other absorbing pigments in the leaves) and strongly scatters solar radiation in the near-infrared (NIR) due to interactions with leaf cell structure (Verstraete and Pinty, 1996). The normalized difference vegetation index ($NDVI = (NIR-RED) / (NIR+RED)$) is the most widely used index that utilizes this relationship (Rouse et al., 1974).

2.1.4 Spatial Information

Spectral information alone does not always provide enough information to model biophysical properties of a forest. Additional information can be found in the spatial arrangement of pixel spectral values. One of the main components of spatial information present in remotely sensed imagery is texture. Texture refers to the impression of roughness or smoothness created by the variation of tone or repetition of visual patterns across an image (Irons and Peterson, 1981). The tonal variations describe the spatial distribution of the subject being sensed (Haralick et al., 1973). There are several texture calculations available to extract different information pertaining to a variety of spatial configurations.

2.2 Radiometric Corrections

The brightness of imagery acquired from an optical remote sensor is affected by, amongst many factors, the relative geometry of the sun, target surface, atmosphere and lens system. If these effects can be reduced or removed, images can more closely represent actual surface reflectance (as measured using reflectance instrumentation) and relationships between image information and field data will be more realistic and stable.

Radiometric corrections attempt to remove undesirable brightness variations or “noise” in an image and correct the pixels to their “natural” state (Edirisinghe, 1997). Correction means changing a pixel reflectance or brightness value to what it would have been if the sun and sensor geometry were a fixed standard pair rather than

at varying angles over the image extent (Jupp and Strahler, 1996). Corrections that have been developed range from highly complex procedures that require several inputs, to simple empirical techniques. This research focuses on the radiometric correction of brightness variations caused by topography, bi-directional reflectance variation (BRV) and light fall-off. The correction of atmospheric effects was not included for reasons stated in Section 1.1. The background concepts and theory for the techniques used in this research are summarized in the following sections.

2.3 Bi-directional Reflectance Variation (BRV)

When sensing the complex reflectance properties of the Earth's surface, variations in brightness across a field of view are inevitable. Solar energy reaching the surface can be absorbed, transmitted or reflected. Optical sensors deal with the portion of sun's energy reflected from the earth's surface. When sensing non-lambertian surfaces such as forests, the average reflectance is direction dependent with the highest reflectance coming from the forest surface facing the sun (Figure 1).

Figure 1. Forest reflectance in relation to the sun.

When acquiring imagery from an airborne system, the position of the sun in relation to the sensor's field of view produces a brightness variation across the area sensed. The brightest area on the image occurs on surfaces where radiation is reflected back towards the sensor (back-scatter) with the darkest areas occurring where the surface reflects radiation in the same direction that it was incident to the surface (forward-scatter). Figure 2 displays how the relative azimuth between the sun and sensor governs the brightness variation over the extent of the image.

Figure 2. Image brightness variation associated with the sensor's field of view and position of the sun in relation to the surface being sensed.

This brightness variation is termed bi-directional reflectance variation (BRV) or the bi-directional reflectance distribution function (BRDF) (Lillesand and Kiefer, 2000; von Schonermark, 2004). BRDF is defined by Girolamo (2003) as the ratio of the radiance scattered by a surface in a specified direction to the unidirectional irradiance incident on a surface. Both back-scatter and forward-scatter cause surfaces exhibiting the same quality to have variations in image brightness. The variation is dependent upon the viewing position, solar position and wavelength (Figure 3).

Figure 3. Sun-sensor relationship (Lillesand and Kiefer, 1979; Pickup et al., 1995a).

where

θ_s = solar zenith angle;

θ_v = viewing zenith angle;

ϕ_s = solar azimuth angle;

ϕ_v = viewing azimuth angle;

X_c, Y_c = nadir pixel position;

X, Y = position of pixel off nadir.

The position of the surface in relation to the sun and sensor can cause two other variations in reflectance that result in localized areas of high reflectance. The hotspot occurs when the sun is directly behind the sensor, resulting in a high back-scattering effect (Trotter and Brown, 1999). The second can occur when the sun's

radiation is directly reflected back to the sensor from water surfaces or other specular surfaces (Pellikka, 1998). This localized high reflectance effect is termed the sunspot.

2.3.1 BRV Reduction

There are several different ways to reduce the effects caused by BRV but there is no simple method to completely correct it because the problem not only relates to the sun-sensor-surface geometry, but also to shape and texture of the surface and how radiation is either absorbed, scattered or reflected. Two main methods to normalize the reflectance variation involve empirical (e.g. Pickup et al., 1995a; Stow et al., 1997; Pellikka, 1998; Holopaonen and Wang, 1998) or physically based techniques (e.g. Li and Strahler, 1992; Nilson and Kuusk, 1989). Empirical methods are used when information on the directional reflectance properties of the surfaces are unknown, and to avoid time-consuming atmospheric corrections (Jackson et al., 1990). They usually involve fitting the variation in general brightness to a parametric function (using least squares or some other criterion) and then normalizing by the combination of additive and multiplicative image transformation (Jupp and Strahler, 1996). The simplest methods involve fitting polynomials to average variations over the image frame and subtracting or dividing out the general level to ‘flatten’ the data (Jupp and Strahler, 1996). Empirical methods suffer from that fact that different surface types interact with light in different and anisotropic ways. The empirical method may provide reasonable results for localized portions of an image or where

land cover is uniform across an image, but over the full extent of an image of varying land cover, error may be introduced.

Physically based models try to capture this anisotropic behaviour by determining the BRV properties of each surface type through field data reflectance measurement of each surface at all possible view and illumination geometries. Jackson et al., (1990) describes this as a demanding task and as a result the BRV for a surface is usually approximated by measuring bi-directional reflectance factors for a limited set of illumination and viewing geometries. This is generally done using a spectroradiometer that records the reflectance characteristics when placed in a range of positions called a goniometer creating surface signatures that can be used to correct the imagery (Coburn and Peddle, 2006). However, the imagery must be well calibrated to reflectance (using atmospheric correction and sensor calibration algorithms), and the land cover types must be fairly well mapped in order to apply the BRV correction for each. For these reasons, empirical correction methods were adopted as the focus of this research.

2.3.2 The Impacts of BRV Corrections on Analysis and Mapping

The correction of BRV has been done in several studies to improve the accuracy of land cover classification. Although this study is focused on the improvement of biophysical models with the use of BRV, no studies to date have reported their findings in the literature, so the results from land cover classification will be reviewed.

Pickup et al. (1995b) corrected airborne multi-spectral video data for lens shading (vignetting) and the geometry between the sun-sensor (BRV). The

corrections were applied to normalise data across a frame so that there is sufficient spectral standardisation for digital classification. The classification results were tested by comparing the results to ground observations of standard vegetation measurements. The classification results after the image was corrected for BRV show a major improvement by reducing the errors of commission and omission by as much as thirteen fold.

Mikkola and Pellikka (2002) corrected BRV effects in colour infrared imagery. Classifying three geographically different locations both before and after the correction and assessing the classification accuracy validated the correction. The magnitude of the correction was found to vary in different areas due to differences in land surface type and solar zenith angles. The overall accuracy was strongly dependent on the scattering angle (explained in sec. 3.6.1), which is a function of the sun-sensor geometry. The areas that were in the forward-scatter zone appeared to receive the most substantial changes before and after the BRV correction was applied. The overall classification accuracy improved by 9.8%, 2.4% and 16.5% for the first, second and third locations respectively after the correction of the imagery for BRV effects.

The studies reviewed for the correction of BRV for land cover classification revealed that the overall accuracy of the classified land cover increased. However, the results showed that the improvements for individual land cover types may not have improved or stayed the same after the correction of the imagery. This describes a problem with the empirical correction of BRV because it is a function of the vegetation (i.e. three-dimensional properties, which scatter, emit and absorb light

differently) in relation to the solar position, sensor position and location on the extent of the image. Pickup et al. (1995b) found that the BRV correction reduced rather than removed the effects. It was found that the forward-scatter and backward-scatter areas of the image still displayed these properties. Mikkola and Pellikka (2002) found that the increase in classification was strongly dependent on the type of land cover. Despite the problems mentioned the results from both Pickup et al. (1995b) and Mikkola and Pellikka (2002) indicate that an empirical BRV correction can improve the information extracted from remotely sensed imagery.

2.4 Vignetting (Brightness Fall-off)

Brightness fall-off, hereafter termed vignetting, is due to the fact that light incident on the sensor is only directly incident at the centre of the frame, and decreases with incidence angle radially towards the edge of the sensor (Figure 4) (Scarath, 2003).

Figure 4. Decrease in image brightness from centre due to vignetting.

There are three main types of vignetting, which produce similar brightness problems, but have different causes. Natural and optical vignetting are innate to each lens design, while mechanical vignetting is due to the use of improper attachments to the lens (van Walree, 2006).

2.4.1 Natural Vignetting

Natural Vignetting, also known as cosine fall-off or shading, is mainly related to the angular dependence of irradiance on lens-target geometry that theoretically follows the $\cos^4 \theta$ law of illumination (Pellikka and King, *unpublished*, 2004). The $\cos^4 \theta$ law of illumination states that irradiance that passes through the lens and impinges on the sensor is not uniform; it decreases radially from the centre of the sensor as a function of $\cos^4$ of the view angle, θ (King, 1992). Three factors are responsible for $\cos^4 \theta$ fall-off (Lillesand and Kiefer, 1979; Slater, 1980; King, 2004; van Walree, 2006). 1) Elliptical change occurs in the entrance pupil reducing the effective area on the lens ($A_\theta = A \cos \theta$). The solid angle in which the radiation passes decreases from that of nadir by $\cos \theta$. 2) The distance from the camera lens to the focal plane, f_θ , increases as $1/\cos \theta$ for off axis points ($f_\theta = f / \cos \theta$). Since exposure varies inversely as the square of this distance, there is an exposure reduction of $\cos^2$ (Lillesand and Kiefer, 1979). 3) Radiation that is being sensed in an incremental area, dA , is spread over a larger area than at nadir, thus radiance decreases in proportion to $\cos \theta$ ($dA_\theta = dA \cos \theta$) (Figure 5).

Figure 5. The $\cos^4 \theta$ law of illumination (Adapted from Slater, 1980).

where

θ = the angle between the optical axis and the ray to the off-axis point;

E_θ = the exposure at the off-axis point;

E_o = the exposure that would have resulted if the point had been located at the optical axis.

The $\cos^4 \theta$ law of illumination is not necessarily a law, but rather a combination of cosine factors which may or may not be present in a given situation (van Walree, 2006). Modern lenses are constructed in ways that reduce fall-off to

levels significantly below the theoretical $\cos^4 \theta$ fall-off (i.e. they are typically in the range of $\cos^{1.5} \theta$ to $\cos^4 \theta$ (Lillesand and Kiefer, 1979).

2.4.2 Optical Vignetting

Optical vignetting is caused by a reduction of the cross-sectional area of an oblique beam traversing the lens in comparison to that of an equivalent axial beam (van Walree, 2006). It can occur when light entering the camera is diminished by the aperture (f-stop) size, which in turn relates to the amount of light absorbed by the lens walls. The aperture only allows direct light to contact the sensor at the image centre. This reduction of brightness is also known as the ‘cat’s eye effect’ (Edirisinghe, 1997). It becomes apparent when large apertures are used (Edirisinghe et al., 2001).

2.4.3 Mechanical Vignetting

Mechanical Vignetting is caused by attachments positioned on the camera that obstruct the field of view. This causes some peripheral darkening of the image due to the absorption by the lens barrel walls (Ray, 1988). The obstruction can be caused by a lens hood that may be too long or in the wrong aspect ratio (Edirisinghe, 1997).

2.4.4 Correction of Vignetting

There are several different methods to reduce the effects of vignetting. One of the simplest pre-imaging methods is to use an anti-vignetting filter designed for the specific camera lens. It is more opaque in the centre and gradually more transparent towards the image edges. This is a quick method for dealing with vignetting,

however, it may not provide the best results because it tends to reduce the overall contrast in the image and block weak signals from reaching the sensor (Pellikka and King, *unpublished*, 2004; Nguyen et al., 1996).

Vignetting can be corrected by using another method outlined in Lillesand and Kiefer (1979). This method normalizes the off-axis exposure measurements to its equivalent value at the principal point (Figure 5) using Equations 1 to 3 (Lillesand and Kiefer, 1979).

$$\theta = \tan^{-1}(r / f) \quad (1)$$

where

θ = viewing angle between the optical axis and the off-axis point;

f = the focal length of the camera lens;

r = the number of units from the frame centre.

The distance (r) is determined with:

$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2} \quad (2)$$

where

x_c = the centre column of the image;

y_c = the centre row of the image;

x, y = the locations of each pixel within the dimensions of the image.

Since the light fall-off is a systematic lens-related effect, the correction model can be developed using measurements of the distribution of pixel values across the image (Pellikka, 1998). The values to normalize the image are calculated with:

$$E_o = \frac{E_\theta}{\cos^n \theta} \quad (3)$$

where

E_θ = pixel value in the off-axis position;

E_o = the pixel value that would have resulted had the pixel been located at nadir;

$\cos^n$ = correction factor for different aperture settings (Lillesand and Kiefer, 1979; Pellikka, 1998).

Vignetting can also be corrected using a post-imaging method by creating image masks of the illumination properties of the camera. Masks are created for each spectral band because the illumination differs as a function of wavelength. To create a mask, a Lambertian panel is imaged using the same camera settings that are used at the time of image acquisition. The Lambertian panel can indicate where the illumination fall-off effects occur over the extent of the image. The values obtained on the panel are inverted to create a digital mask (Figure 6).

Figure 6. Example of brightness fall-off (left) and inverted mask (right).

This method relies strongly on the quality of the surface of the test target and the uniformity of the illumination on the lambertian panel. The method for creating a uniformly illuminated surface is not straightforward and the lambertian panel can be particularly expensive. The reduction of vignetting in Edirisinghe et al. (2001), which used a system of calibration panels for different f stops, corrected the loss of image brightness from the periphery of the image to the centre from 36 to 4 percent.

2.5 Effects of Topography

Several studies have shown the importance of correcting the radiance variations across an image caused by topography to improve the results of common applications in remote sensing (Cavayas, 1987; Dymond, 1992; Meyer et al., 1993; Gu et al., 1999).

2.5.1 Sun-Topography Interactions

Topographic illumination is related to the sun-topography geometry, which creates variations in brightness and causes areas of the same land cover to be brighter on slopes facing towards the sun and darker on slopes facing away from the sun (Figure 7). The sun facing slopes receive direct radiation (L_d), diffuse radiation (L_s), and scattered light from other surfaces (S) (Pellikka, 1998). Slopes not directly

facing the sun receive less to no direct radiation as well as radiation from environmental scattering or diffuse radiation. This creates a problem when making comparisons of areas representing similar attributes over the full extent of an image. Pons and Sole-Sugranes (1994) describe the difficulty associated with conducting land cover classification over areas that are influenced by topography because variation is found within similar land cover classes. This problem has led to the development of several methods for rectifying the inconsistencies in brightness by reducing the effects of the sun's position in relation to the topography.

Figure 7. The sun-exposed slopes receive diffuse (L_s), direct (L_d) and environmental scattered (S) radiation while slopes with aspects opposite to the sun receive diffuse, environmental scattering with a small amount of direct radiation depending on the slope gradient and wavelength (λ). The area in the shadow zone is also darker because it does not receive direct radiation (L_d).

2.5.2 Topographic Brightness Corrections

Methods for correcting topographic effects are generally grouped into two categories: those based on band ratio techniques and those requiring digital elevation models (DEM) (Riano et al., 2003). Band ratio techniques are more straightforward to apply because there are no ancillary data required and they are calculated by dividing the radiance value in one spectral channel by the corresponding radiance in another spectral channel or a normalized combination of channels. This technique has shown satisfactory results in areas that have a small amount of relief (Colby, 1991), but it has not been widely used since it has shown large variations that are strongly dependent on the sensor properties and geographic location being examined. As a result, this method will not be further discussed in this paper.

The second group of correction techniques is based on the relationship of the sun's position relative to the topographic variation. These corrections require information pertaining to the slope and aspect, which can be obtained from a Digital Elevation Model (DEM). Four slope-aspect correction algorithms are presented below.

2.5.3 Cosine Relationship

All four of the corrections to be discussed are based on the cosine relationship, which states that radiation over a surface is proportional to the cosine of the angle between the incident beam and the normal at the surface, termed the incidence angle (i) (Pons and Sole-Sugranes, 1994). $\cos(i)$ can vary from -1 to +1, for minimum to

maximum illumination, respectively (Riano et al., 2003) and is derived using the following equation:

$$\cos(i) = \cos \theta_s \cos \theta_n + \sin \theta_s \sin \theta_n \cos(\varphi_s - \varphi_n) \quad (4)$$

where

θ_n = surface normal zenith angle or slope of the terrain;

θ_s = solar zenith angle;

φ_s = solar azimuth angle;

φ_n = surface aspect (azimuth) of the slope angle (Figure 8) (Smith et al., 1980).

Figure 8. Imaging geometry over a sloping surface (Collins, 2003).

2.5.4 Cosine Correction

Recognizing the cosine relationship of the sun-topography geometry, a cosine correction method was developed (Meyer et al., 1993) as follows:

$$L_H(\lambda) = L_T(\lambda) \frac{\cos(\theta_s)}{\cos(i)} \quad (5)$$

where

$L_H(\lambda)$ = radiance observed for horizontal surface at a given wavelength λ ;

$L_T(\lambda)$ = radiance observed over inclined surface at a given wavelength λ ;

i = sun's incidence angle in relation to the surface normal.

Several authors have shown that this method tends to overcorrect the illumination variation (Meyer et al., 1993; Vincini and Frazzi, 2003; Soenen et al., 2005). Reeder (2002) found that pixels from forested locations orientated away from the sun, such as on northwest-facing slopes, are overcorrected and appear brighter than similarly forested pixels on southeast-facing slopes after the correction is performed. The cosine relationship is based on the assumption that the reflectance properties of the surface being sensed are isotropic.

However, the reflectance interaction over a surface is highly dependent upon the geometry of the features and is very seldom uniform. In reality, reflectance properties of different surfaces are complex and most tend to be anisotropic. As a result, generalizations are made to reduce the sophistication by assuming the surface to be Lambertian. The Lambertian assumption is that a surface is presumed to be a perfectly diffuse reflector, appearing equally bright from all viewing directions (Ekstrand, 1996). Slope-aspect corrections are usually divided into two groups Lambertian and non-Lambertian methods.

2.5.5 Minnaert Correction

The most common Non-Lambertian correction is the Minnaert correction, which is similar to the cosine correction, but a constant k and exitance angle (e) are applied:

$$L_H(\lambda) = L_T(\lambda) \left[\frac{\cos^k(\theta_s) \cos(e)}{\cos^k(i) \cos^k(e)} \right] \quad (6)$$

where

k = the Minnaert constant;

e = exitance angle (Meyer et al., 1993; Reeder, 2003).

The Minnaert constant is considered to be a measure of the extent to which a surface is Lambertian (Meyer et al., 1993). If $k = 1$, the surface behaves like a perfect Lambertian surface, if $k = 0$, the surface is considered to be a specular reflector (Riano et al., 2003). The exitance angle, in the case of a nadir view angle, is equivalent to the slope angle (Soenen et al., 2005). Several other methods are available that adjust the dependence of $\cos(i)$ or further adjust the effect of the Minnaert constant (k) (Ekstrand, 1996). Two such methods are the statistical-empirical and C-correction, both, which reduce the dependence on $\cos(i)$.

2.5.6 Statistical-Empirical Correction

The statistical-empirical correction evaluates the influence of the radiance over an inclined surface and a horizontal surface with the use of a regression function. In other words, the correction performs a regression between the angle of incidence (i) and the measured radiance (Soenen et al., 2005). The correction is achieved using the following equation:

$$L_H(\lambda) = L_T(\lambda) - \cos(i)m - b + \overline{L_T(\lambda)} \quad (7)$$

where

$\overline{L_T(\lambda)}$ = the average of $L_T(\lambda)$;

m = slope of regression line;

b = intercept of regression line (Meyer et al., 1993).

The objective of this approach is to remove the statistical correlation by rotating the data to remove the dependence of the $\cos(i)$ (Soenen et al., 2005).

2.5.7 C-Correction

The c-correction proposed by Teillet et al. (1982) is based on a linear relationship that exists between $L_H(\lambda)$ and $\cos(i)$ using the following equations

$$c = \frac{b}{m} \quad (8)$$

where m and b are as above.

$$L_H(\lambda) = L_T(\lambda) \left[\frac{\cos(\theta_s) + c}{\cos(i) + c} \right] \quad (9)$$

The (c) parameter serves to reduce the effect of the Lambertian correction and is found to produce more homogeneous brightness values on opposing slopes of similar characteristics (Reeder, 2002). Mathematically, the effect of c is similar to that of the Minnaert constant. It increases the denominator and weakens the over correction of faintly illuminated pixels as a consequence (Meyer et al., 1993).

The four topographic corrections previously defined, provide a basic understanding of how illumination differences caused by topography can be reduced. These corrections are the most common methods presented in the literature and have been tested in several studies, which will be summarized in the following section.

2.5.8 The Impacts of Topographic Corrections on Analysis and Mapping

A variety of studies have made use of topographic corrections to increase the reliability of information extracted from remotely sensed imagery. A literature analysis was conducted to assess the results of several case studies and determine which method provides the best results for use in this research.

Meyer et al. (1993) examined the influence of four topographic corrections (cosine, Minnaert, statistical-empirical and c-correction) for the classification of forest versus non-forest using Landsat TM data. The effectiveness of each correction was tested statistically and visually. The results indicated the cosine correction drastically over-corrected the imagery, especially in sections of the image that had a small incidence angle (i). They described this problem to be associated with the division of a very small number ($\cos(\theta_s)$) by a very small number ($\cos(i)$) as in Equation 5, which leads to disproportional brightening effects. The outcome of each correction was further investigated when visually comparing the illumination variance between the four correction methods. The cosine method demonstrated brightness flare-ups creating artefacts along mountain ridges, while the other three approaches were more acceptable. It was concluded that the best results for the reduction of topographic brightness variations were obtained using the c-correction.

The statistical-empirical and Minnaert corrections were deemed mediocre, while the cosine correction was considered ineffective.

Riano et al. (2003) conducted a similar study to evaluate the effectiveness of three topographic corrections to improve the mapping of vegetation types using Landsat Thematic Mapper (TM) imagery. Their work tested the *IL* weighted, Minnaert and c-corrections. The *IL* weighted considers the illumination conditions over the extent of an image and is believed to be an improvement from the cosine correction. Each correction method was evaluated by the standard deviation within each vegetation class before and after the corrections. This helped determine how the variability between each class was reduced to produce a more homogenous vegetation map. The results showed that the c-correction retained the spectral characteristics and provided the highest reduction in class variability. The results from this study support the findings from Meyer et al. (1993) and further define the c-correction as the best method.

McDonald et al. (2002) also found the c-correction to perform best for the improvement of land cover classification using Landsat TM data. The Minnaert correction performed well, but they concluded that the c-correction is easier to apply, provides a significant reduction in illumination variation and increases the separation of spectrally similar classes. Despite the improvement gained from the c-correction, McDonald et al. (2002), Meyer et al. (1993) and Riano et al. (2003) acknowledged that there is still a large need for further advancement of the sun-topography approach.

Throughout the literature, similar problems reappear regarding the simplicity of corrections based on the sun-topography relationship. The problem is associated with the fact that the surface is not simply bare, but consists of different land covers exhibiting different geometries that interact with light in an anisotropic manner. Gu and Gillespie (1998), recognizing this drawback, developed a topographic correction that uses a sun-canopy relationship instead of the traditional sun-topography method. Their approach evaluates the effects of not only the topography, but also the positioning of trees and the amount of shadow cast by them in the canopy. The sun-canopy correction was compared to the cosine correction, c-correction, and Minnaert by evaluating the determination coefficient (r^2) of the variance explained by the terrain correction model, the root mean square error of the fit, and the relative error of the predicted radiance on horizontal terrain following correction. It was found that the sun-canopy correction outperformed the other three. However, Soenen et al. (2005) expressed concerns that the sun-canopy method can overestimate radiance, consequently not characterizing diffuse radiance properly.

Recognizing this problem, Soenen et al. (2005) proposed a new correction method to improve the sun-canopy correction by introducing a moderator (c) to account for diffuse radiation, which is adapted from the c-correction. It was compared to five topographic corrections (cosine, Minnaert, statistical-empirical, c-correction and the sun-canopy) using a full range of terrain orientations and forest structures. The results showed that the sun-topography and sun-canopy corrections generated reasonable results, but overall the sun-canopy correction with (c) moderator was the most effective.

2.6 Summary of BRV, Vignetting and Topographic Corrections

The reduction of BRV in imagery is not a simple matter given the complexity of radiation interactions that need to be taken into account. There are several methods that correct the overall trend in brightness variation caused by BRV, but caution is required because local variations are often not corrected enough or are over corrected leading to possible loss of information.

Vignetting can cause a decrease in brightness from the image centre to the edge of the imagery. Steps can be taken to reduce the variation in brightness caused by vignetting creating a more uniformly illuminated image. Several methods are available to correct vignetting, but care needs to be exercised when using these methods to ensure that the changes to the imagery are acceptable.

The previously cited literature indicates that the c-correction for topographic correction generally provides the best results when simply using the sun-topography geometry. Results were further improved when information pertaining to the vegetative structure was introduced into the correction signifying that a sun-canopy correction should be used whenever possible, however it was deemed to be too complex to be implemented within the scope of this thesis research.

2.7 Net Image Brightness Correction

Brightness variations caused by topographic variation, BRV and light fall-off often interact, and as a result nadir corrections can be useful to reduce overall brightness variations across an image scene when information for these parameters is unknown. Net image brightness methods work in similar ways to the empirical

corrections described previously. The main idea is to determine the overall trend of brightness across an image and then reduce the differences by either inverting a polynomial fit or by simply adjusting the average column brightness from the image centre (nadir) to the image edge. To use this method the land cover sensed needs to be fairly uniform across the image, otherwise the fit will adjust for these differences, which could cause error. Band ratios can also be used to adjust the net image brightness variation, but as stated in Section 2.5.2, there are several problems with this method that make it an inadequate technique to normalize image brightness.

3.0 METHODS

3.1 Site Description

The study area is located in the Great Lakes - St. Lawrence forest in Southern Quebec, Canada (Figure 9). It is part of the Gatineau Park and is managed by the National Capital Commission (NCC). Covering approximately 10 by 50 km, the forest is comprised mostly of temperate hardwoods. The dominant overstory canopy consists primarily of mature sugar maple (*Acer saccharum*) with patches of American beech (*Fagus grandifolia*), trembling aspen (*Populus tremuloides*), American basswood (*Tilia americana*), and red oak (*Quercus rubra*). The forest understory is mainly sugar maple with a mix of white ash (*Fraxinus americana*), American Beech, ironwood (*Ostrya virginiana*) and white birch (*Betula papyifera*).

Gatineau Park is located on the Canadian Shield with rolling hills and elevations of up to 200m above mean sea level. The topography relates strongly to the distribution of tree species because of the range of slopes and aspects. Red oak is more abundant on warm southwesterly slopes, while beech and sugar maple are mainly located on flat areas and northerly slopes (Pellikka et al., 2000).

The study plots were located on two north-south transects in the southern portion of the park (Figure 10). They have been part of ongoing research on monitoring of forest structure and health following the ice storm of 1998 using field (King and Bemrose, 2005) and remote sensing data (Pellikka et al., 2000).

Figure 9. Study area.

Figure 10. Study plot locations.

This area provides a good setting to study forest health and structure dynamics because of the severe weather event that occurred in 1998. In January of 1998, approximately 100mm of freezing rain fell in only six days in eastern Canada and the

northeastern United States during a storm that is often considered ‘the storm of the century.’ It affected primarily eastern Ontario, Southern Quebec, New Brunswick and Nova Scotia in Canada and New York, Vermont, New Hampshire and Maine in the United States. It is estimated that the storm covered an area of 10 million hectares (Olthof et al., 2003).

As a result of this substantial accumulation of ice in such a short period, the forests throughout the affected areas experienced a great deal of damage (Figure 11). The degree of forest damage in a particular area was highly correlated to the level of ice accumulation in the region, as well as to the health and physical structure of individual trees.

Figure 11. Field picture from Gatineau Park displaying the damage caused by the ice storm, seven years later.

3.1.1 Previous Remote Sensing Research in Gatineau Park

Pelikka et al. (2000) and King et al. (2005) used colour infrared (CIR) photos and data collected in the field for the assessment of structural damage of the forest canopy caused by the 1998 ice storm. Several measures were taken in the field at the individual tree and canopy level to determine damage, including the number of broken stems, first order branches and second order branches, the number of fallen branches per plot and cross sectional area of coarse woody debris, a visual tree health index, effective leaf area index (LAI_e) and canopy closure. Image variables of texture and shadow fraction were derived after image brightness corrections for BRDF and light fall-off effects had been applied. Stepwise multiple regression of image spectral, textural and shadow fractions produced significant relations ($p < 0.05$) for forest structure measures of ELAI, canopy closure, basal area and the health score (Pelikka et al., 2000) and numbers of fallen branches per plot (King et al., 2005).

The methodology of this research follows similar methods to that of the work conducted by Pelikka et al. (2000), but additionally includes an understanding of how regression based relationships between image variables and field data change with the correction of brightness variation.

3.2 Field Data Collection

Field data were collected from the middle of July to the end of August during the summer of 2005 to correspond to full leaf-on conditions and minimize any temporal differences that may occur between field and image data. A total of 55 of the plots installed in 1998, each 20 m x 20 m (400 m²) in area, were used. The 20 m

x 20 m plot size was based on findings from a previous study conducted by Butson and King, (1999) on semi-variance and forest structure where the semivariogram range of various tree structural attributes was found to be up to 16 m. The location of each plot had been selected by a visual assessment of the forest stands that could be categorized as not damaged, slightly damaged, moderately damaged and highly damaged in 1998 (Pellikka et al., 2000a). The plots locations were also selected to be on a variety of slopes, aspects and elevations. The coordinates of four corners and centre of the plots had been collected using a differential Global Positioning System (GPS) with better than 1m accuracy. The GPS data were collected with the projection set to UTM Zone 18 with NAD83 as the datum.

For this research in 2005, within each plot, the diameter at breast height (DBH), stem density and health of the dominant trees were recorded. Criteria and methods for these measurements were selected to match those of Pellikka et al. (2000) to allow temporal comparison in other studies (e.g. King and Bemrose, 2005). A tree was deemed to be dominant if at least one-half its crown would be visible to a sensor at a range of view angles. To determine the level of damage sustained to each tree a rating system was used with five levels (Table 1 and Figure 12).

Table 1. Tree health rating scheme.

0	No indications of damage (No damage).
1	Small upper branches are broken or leaves are discoloured (Slight Damage).
2	Several large branches are broken or the stem is held in a bent position by other trees. Up to ½ the crown displays visible damage (Significant Damage).
3	Only a few live branches remain. Greater than ½ the crown is missing or dead (Severe Damage)
4	No living foliage (Dead).

(Pellikka et al., 2000)

Figure 12. Visual example of tree health rating scheme. *The numbers located to the left of the trees correspond to Table 1 Tree Damage Rating Scheme.

This rating system provides a universal description of the level of health of each tree found at every plot and can be easily cross calibrated amongst several observers. Although it is subjective, precision (standard deviation) amongst observers has been found in repeated randomized tests to be about 0.24 (Lévesque and King, 1999). The health score was assigned to each dominant tree in 2005 and the average health score was used in regression modelling against image variables as described in section 3.13.2. Hemispherical photography was also utilized to calculate effective leaf area index and percent canopy closure as described in Section 3.3.

3.3 Measures of Effective Leaf Area Index (ELAI) and Canopy Closure Using Hemispherical Photography

Hemispherical (fisheye) lenses, which have a 180° field of view, are often used with photographic or digital cameras to measure and analyze the structure of forest canopies (Frazier et al., 2000; Rich, 1990). The images are taken vertically beneath the forest canopy, producing a circular view of the canopy and sky (Figure 13). They are then analyzed by separating the image into binary representation of vegetation (black) and sky (white) using a threshold approach. Calculations are then

performed on the binary image to provide quantitative values for variables representing the properties of the forest canopy.

Hemispherical images were acquired from the middle of July to the end of August 2005 to coincide with image acquisition. They were taken with a Nikon Coolpix 8800 with a Nikon UR-E18 adapter ring and Nikon FC-E9 fisheye lens. The Nikon Coolpix 8800 has 8.0 million effective pixels producing an image size of 3264 x 2448 pixels at the highest resolution setting. The bottom of the camera was oriented to north when mounted on a tripod positioned 1.25 m above the ground and levelled. Understory vegetation that was directly (within arms' reach) obstructing the lens was held below the field of view (0 to $\pi/2$) during acquisition. Images were taken at five different locations within 31 of the 54 plots, at the centre and 3 m from centre in all four cardinal directions (Figure 14). The images were taken at dusk or during the day when uniform overcast conditions were present. The camera settings (f-stop and shutter speed) were determined by taking a reading of sky luminosity with a Minolta spot meter. It was important to acquire the photographs when the sunlight was either obstructed by cloud or at dusk to reduce scattering effects of light through the canopy, which would cause error in the amount of sky calculated from the images.

Figure 13. Example of hemispherical image.

Figure 14. Hemispherical photograph locations (black dots) within the 20m x 20m plot.

In order extract amounts of vegetation and sky from hemispherical photos, the distortion of the fisheye lens needed to be taken into account. Hemispherical

photographs produce a hemispheric projection on to a plane (Rich, 1990), while the exact nature of the projection varies according to the lens used (Jonckheere, 2005). Every lens invariably exhibits a (small) deviation from the theoretical projection (Jonckheere, 2005). Hemiview Canopy Analysis Software v2.1 (Delta-T Devices, 1999) does not have a lens coefficient for the Nikon Coolpix 8800 with UR-E18 adapter and FC-E9 fisheye, but McKeown (*pers. comm.*, 2006) explained that the distortion is similar to that of a Coolpix 5400 with UR-E10 adapter and a FC-E9 Fisheye. The coefficients are available in Hemiview and could be used for this camera set-up. The imagery was adjusted by using a second order polynomial coefficient for calibrating lens distortion. The numerical coefficients were: $a_0 = 0.6427$, $a_1 = 0.0346$ and $a_2 = -0.02449$, respectively.

The photographs were acquired in this study to calculate effective leaf area index (ELAI) and percent canopy closure (PCC). Results in Pellikka et al. (2000) indicated that significant relationships exist between these two measures and colour infrared photo spectral and spatial variables. To calculate both of these measures, the gap fraction is required. Gap fraction is defined as the proportion of visible sky within a given sky sector, where a sky sector is defined by a range of zenith and azimuth angles (Delta-T Devices, 1999). In hemispherical images, this is determined by counting the number of sky and vegetation pixels using the following formula:

$$GF(\theta, \alpha) = \frac{P_s}{P_s + P_{ns}} \quad (10)$$

where

$GF(\theta, \alpha)$ = the gap fraction for a range of zenith angles with mean angle θ and angular resolution α ;

P_s = the number of pixels classified as “sky pixels” in a region centred on (θ, α) ;

P_{ns} = the number of vegetation pixels within a region centered at (θ, α) (Jonckheere et al., 2005).

Gap fraction was measured in five 15° zenith angle rings (centred at 7.5° , 22.5° , 37.5° , 52.5° , and 67.5°) and three 120° azimuth sectors (centred at 0° , 120° , and 240°) (Figure 15). Gap fraction was not collected for zenith angles greater than 75° because in dense canopies gap fraction is often zero (Gardingen, 1999) and it is not well related to ELAI or overhead PCC.

Figure 15. Gap fraction zenith (blue) and azimuth (green) angles.

There are many methods available to either manually or automatically threshold hemispherical images into portions of canopy and sky. The threshold between canopy and sky is of great importance because it determines the gap fraction, which in turn is used for the calculation of both ELAI and PCC.

Manual thresholding has been found to be limited for separating sky from vegetation because it involves a visual assessment, which can lead to subjectivity and user biases (Jonckheere et al., 2004; Nobis and Hunziker, 2005). However, recent work completed by Lindsay (2005) found that the difference between cover measured using an automatic and manual thresholding technique was minimal, with a strong

correlation between the two methods ($r = 0.92-0.99$, $p < 0.01$ for a range of zenith angles). There are several advantages and disadvantages to both automatic and manual thresholding techniques. Comparisons have also been made (Jonckheere et al., 2005) between both methods, which indicate that there are several factors at the point of image acquisition such as the camera settings (shutter speed and f-stop), sky luminosity and type of vegetation that play an important role in determining the quality of the segmentation regardless of the method. Automatic methods may be required for large datasets, but for small datasets the manual method may provide a reasonable technique.

This research adapts a semi-automatic k-means unsupervised clustering method to threshold images that was used by Pasher (2005). Cluster creation is automatic and statistically controlled, but manual interpretation of clusters as either sky or vegetation is required. Pasher (2005) determined that eight clusters provided the best differentiation between vegetation and sky after testing several different cluster sizes from four to twelve. Since the camera and lens were different in this study, tests were conducted to determine the best number of clusters. One hundred and sixty images were processed in batch mode using the code given in Appendix 6.

ELAI was calculated in Hemiview Canopy Analysis Software v2.1 (Delta-T Devices, 1999) as half the total “effective” leaf area (m^2) per unit of ground area (m^2) (Frazer et al., 2001). The calculation of ELAI involves use of Beer’s Law, which can be expressed as follows:

$$G(\theta) = \exp(-K(\theta) \times ELAI) \quad (11)$$

where

G = gap fraction;

$K(\theta)$ = the extinction coefficient at angle (θ) ;

θ = viewing zenith angle (Delta-T Devices, 1999).

The extinction coefficient is determined by the leaf angle distribution in the canopy and the incidence angle of the radiation (Campbell, 2006). The calculation is defined as:

$$K(\theta) = \frac{\sqrt{x^2 + \tan^2 \theta}}{x + 1.744(x + 1.182)^{-0.733}} \quad (12)$$

where

x = the leaf angle distribution;

θ = the angle of incidence of the radiation (vertical is zero).

If the leaves were all vertical, x would have a value of 0. If the leaves were all horizontal, x would be infinite (Campbell, 2006). ELAI was calculated using the gap fraction and, as a result $K(\theta)$ was assumed. This assumption, and the fact that foliage distribution was assumed to be random (not clumped as typical in reality); cause 'effective' LAI to be always less than actual LAI. For the purposes of this study, comparing image correction impacts on forest structure and health modelling, ELAI was much simpler to generate.

ELAI was calculated only for the photos taken in the centre of the plot. The other four photos were located 7m from the plot boundary, which means the field of view was outside the plots at zenith angles greater than 30°. ELAI is often calculated for zenith angles reaching as far as 75° (Welles and Norman, 1991), but this was not appropriate for this study because the plots are only 20 m x 20 m with an average vertical distance of 20.75 m from the camera to the canopy. With a zenith angle of 75°, the field of view would have been approximately 77.4 m. To be more representative of plot canopy structure, ELAI was calculated for two ranges of zenith angles. The first (ELAI1) was from 0° to 45° using the first three rings (as in Cosmopoulos and King, 2004). ELAI2 was from 0° to 60° using the first four rings.

PCC is defined as the relative amount of sky that is visible from a point beneath the forest canopy (Frazer et al., 2000). Average PCC for each plot was calculated using Equation 13:

$$C(\theta, \alpha) = (100 - P_c) / N_p \quad (13)$$

where

P_c = the number of pixels classified as gap fraction in a region centred (θ, α) ;

N_p = the number of photos per plot.

PCC was calculated for the first zenith angle 0-15°, centred at 7.5°, based on Cosmopoulos and King (2004) who explain that the narrowest zenith angle represents a number of sample points penetrating the canopy directly above. PCC was recorded

for each photo within the plot and averaged to produce an overall plot value. Since the average tree height minus the tripod height is 20.75 m and the photo location spacing is 3 m apart, there was some overlap between footprints (Figure 16). The average of all five is thought to produce a more reliable estimate of PCC than a single plot measurement.

Figure 16. Hemispherical image overlap for 0-15° field of view of the five photo locations in each plot.

3.4 Biophysical Forest Metrics

Using the field methods described above, six forest metrics were recorded: (1) average DBH (*AvgDBH*), (2) stem density (*SD*), (3) basal area (*BA*) is a summary of the number and size of trees in a stand, and is calculated as the total cross-section area of stems at breast height per hectare of land, (4) average health (*AvgH*), (5) effective leaf area index (*ELAI1* and *ELAI2*), and (6) percent canopy cover (*PCC*). Average DBH, basal area, average health and stem density were measured for fifty-four plots while ELAI and PCC were measured for thirty-one plots. Results of these measurements are given in Section 4.1.

3.5 Image Acquisition

Aerial colour infrared (CIR) images of the study area were acquired between 13:36 and 14:27 EST on September 04, 2005 using a DuncanTech MS4100 digital multispectral camera. The images were sent to a laptop frame grabber (PCMCIA Framelink from IMPERX). Three spectral bands were captured in the green (500-600 nm), red (600-700 nm), and near infrared (750-850 nm) at 1920(Horizontal) x 1080(Vertical), 8-bit pixel format (Figure 17). A Nikkor lens with a 24 mm focal length was used, which gave a nominal ground pixel size of 80 cm and ground coverage of about 864 m(d_v) x 1536 m(d_h) when flying at approximately 2596 m(H') above ground level. The camera was set with an automatic trigger to capture images every 9.6 s to provide 60% forward overlap. The angle of view (AOV) in the vertical(θ_v) and horizontal(θ_h) directions is 9.5° and 16.5° , respectively. The camera system was positioned on a fixed camera mount, which was secured to the seat rails of the co-pilot's seat in a Cessna 172 aircraft (Figure 18). The door and camera mount were provided by Dr. Peter Poole (*pers. comm.*, 2005).

The weather conditions were mostly sunny with the exception of occasional small cumulus clouds. During the time of acquisition no clouds were located over the study sites. The camera exposure times were manually set for each spectral band after performing a test flight across the study area. Exposures were set to provide the widest dynamic range in histograms viewed in-flight, while avoiding saturated pixels.

Figure 17. Example of the Aerial CIR Imagery.

A

B

C

Figure 18. Modified Cessna door (A), camera mount (B), and camera system installation(C).

When evaluating the quality of the resulting imagery, unsystematic striping and image blur were found in the red spectral band (Figure 19). As a result, these data were omitted from the analysis because they would have introduced noise.

Figure 19. Example of unsystematic striping found in the red spectral band.

3.6 Image Processing

This section describes the image processing that was conducted to implement the brightness correction methods. These procedures are commonly referred to as “pre-processing” steps in the literature because they represent methods to prepare data for “processing” or analysis. The section describes the methods used to correct image brightness variation using BRV, topographic and net techniques, the steps taken to determine the effectiveness of each correction, and the methods used to extract spectral and spatial information from the imagery. Theory and concepts for the corrections are given in Chapter 2.

3.6.1 Correction Procedure for Image Brightness Variations Caused by BRV

In order to normalize the imagery for BRV effects, the empirical approach presented in Pellikka (1998) was adapted and implemented in MATLAB (Appendix 8). This approach corrects BRV by evaluating the angle between the lines joining the

pixel to the sensor and the pixel to the sun (termed the ‘scattering angle’). The method follows many of the steps presented in Royer et al. (1985) and Pickup et al. (1995a). The scatter correction angle is calculated using Equations 14 to 23. The geometry of the equations is presented in Figure 20. The imagery is then corrected using the scatter correction angle (Equation 23). This process was implemented for each spectral band of each of the twenty-six scenes.

Figure 20. Geometry for the calculation of the scatter correction angle (Adapted from Pellikka, 1998).

Before performing BRV correction, information related to the geometric position of the sun and sensor was defined. To determine where the sun was during the time of acquisition in relation to the sensor, the aircraft heading was first determined. During the acquisition of the imagery, the airplane was flying flight lines

that were approximately orientated from south to north. Images were acquired on the first line (transect 2) between 13:36 47 and 13:38 48. The approximate solar elevation angle during this time was 41.1° and the solar azimuth was 211.8° (National Research Council Canada, 2005). Images were acquired on the second flight line (transect 1) between 14:24 50 and 14:26 50. The approximate solar elevation angle during this time was 36.1° and the solar azimuth was 224.8° (Figure 21).

Figure 21. Sun position in the sky during flight lines 1 and 2.

The distance between each pixel and the frame nadir (r) was calculated with:

$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2} \quad (14)$$

where

x_c = the centre column of the image;

y_c = the centre row of the image;

x, y = the locations of each pixel within the dimensions of the image.

Figure 22 displays how each pixel in the image is assigned a value in relation to its distance from the image centre.

Figure 22. Distance between each pixel and nadir.

The view zenith angle from the pixel to the sensor was calculated with:

$$\theta_v = \arctan \frac{r}{H'} \quad (15)$$

where

θ_v = view zenith angle from pixel to sensor;

r = distance between each pixel and the frame nadir;

H' = flight altitude above the terrain expressed as the number of pixels.

The azimuth angle from each pixel to the sensor was calculated by:

$$\alpha_p = \arctan \left[\frac{ABS(x - x_c)}{ABS(y - y_c)} \right] \quad (16)$$

where

α_p = azimuth angle from pixel to sensor and ABS is the absolute value.

When the pixel is located in the upper right quadrant of the frame, 180° must be added to α_p , and when it is located in the lower right, it has to be subtracted from 360° (Pellikka, 1998). When it is located in the upper left of the frame, it has to be subtracted from 180° (Pellikka, 1998). Figure 23 displays the azimuth angle calculated from 0 to 360° for each pixel to the sensor.

Figure 23. Azimuth angle from each pixel to the sensor.

The distance of the axis between the pixel and the sensor (d) is defined by:

$$d = \frac{H'}{\cos \theta_v} \quad (17)$$

and the distance of the axis between the zenith and the sensor altitude (b) was calculated with:

$$b = H' \cdot \tan \theta_v \quad (18)$$

The hypotenuse representing the line between the pixel and sun(e) was defined by:

$$e = \frac{H'}{\cos \theta_s} \quad (19)$$

where

θ_s = the zenith angle of the sun.

The distance of the axis between the sun at the level of sensor altitude (c) was defined by:

$$c = H' \cdot \tan \theta_s \quad (20)$$

The difference between the azimuth angle of the sun and that of the sensor was obtained by subtracting α_s from α_p with:

$$\beta = \alpha_s - \alpha_p \left[-360^\circ, \text{if } \beta > \pm 180^\circ \right] \quad (21)$$

where β = the angle between the azimuth angle to the sun and the azimuth angle to the sensor;

α_s = the azimuth angle to the sun;

α_p = the azimuth angle to the sensor.

If the resulting β is over $\pm 180^\circ$, then 360° is subtracted from β . If β is negative, it was changed to positive because only the size of the angle matters (Pellikka, 1998).

The length of the axis between the sensor and sun in the sensor altitude (a) was defined by:

$$a = \sqrt{b^2 + c^2 - 2bc \cos \beta} \quad (22)$$

The scattering angle γ_c was then calculated as in Pellikka (1998) by using the variables defined in Equations 17, 19, and 22 presented in Figure 20:

$$\gamma_c = \arccos\left(\frac{d^2 + e^2 - a^2}{2de}\right) \quad (23)$$

Figure 24 displays an example of the calculated scattering angle for one image in the first flight line. The scattering angle decreases in brightness from 1.0 and, unlike the vignetting filter, the correction does not reduce the brightest pixels, but adjusts all other pixels to that level.

Figure 24. Scattering correction angle.

The scattering correction angle (Figure 24) was then used in Equation 24 to normalize brightness variation.

$$DN^* = \frac{DN}{(1 + f \cdot \cos^3 \gamma_c)} \quad (24)$$

where

DN^* = corrected DN of the pixel;

DN = original DN;

γ_c = scatter correction angle.

The DN of each pixel is divided by the cosine of its scattering angle to the third power multiplied by the quantification factor f added to one (Mikkola and Pellikka, 2002).

The $1 + \cos^3 \gamma_c$ term was developed from the fundamental equation of angular dependence of Rayleigh scattering defined as $1 + \cos^2 \gamma$. This equation was modified to include some Mie scattering characteristics due to the fact that Rayleigh is always accompanied to some degree by Mie scatter (Pellikka, 1998). The f factor is used to account for the varying scattering characteristics of the land surface (Mikkola and Pellikka, 2002). Pellikka, (1998) determined the f factor by testing various values from 0.0 to 1.0, calculating the equations and evaluating the mean DN's for reference sites before and after each test. The best result was determined when the reference sites had the smallest difference. Reference data were not collected for this study; as a result the f factor was determined by testing a range of values from 0.1 to 1.0. This was done to determine the consequences the f factor has on image brightness and to determine which f setting should be used for both the green and NIR band. A visual assessment revealed that a f factor of 1.0 reduces overall image brightness drastically. A f factor of 0.2 was determined to be appropriate for both the NIR and green band over areas of uniform forest cover. After the calculation was performed, the values of the images were scaled from real numbers into an 8-bit range from 0 to 255 DN.

3.6.2 Correction Procedure for Image Brightness Variations Caused by Topography

The correction of brightness variations caused by topography required both a digital elevation model (DEM) and a georeferenced mosaic. The elevation was needed to determine where the brightness changes caused by topography would

occur. Mosaics were created of each flight line and then georeferenced to align the imagery to the DEM.

3.6.2.1 Digital Elevation Model

In order to correct the imagery for brightness changes caused by topography, a point-based DEM was used to create a surface. The National Capital Commission (NCC) (1998) provided the DEM used in this study. The resolution of the DEM was 10 m x 10 m, which was substantially coarser than the imagery, but it was the only available source. The elevation points had been generated using photogrammetric techniques applied to digitized aerial photography of 25cm resolution. A surface from the DEM values was created using a spline interpolation (Figure 25). The spline estimates values using a mathematical function that minimizes overall surface curvature, which results in a smooth surface that passes exactly through the input points (Childs, 2004). There are two variations of the spline calculation, tension and regularized. A regularized spline incorporates the first derivative (slope), second derivative (rate of change in slope), and third derivative (rate of change in the second derivative) into its minimization calculations (Childs, 2004). The tension spline uses only the first and second derivatives, but it includes more points in the spline calculations, which usually creates smoother surfaces at the cost of increased computation time (Childs, 2004). A tension spline was used in this study to interpolate the surface.

Figure 25. Flight line mosaics and plots located on interpolated elevation surface.

The interpolated surface was evaluated using 42 data points that were collected using a differential GPS with sub-metre accuracy over a range of aspects and slopes to capture the variation of the DEM. The root mean square error (RMSE), mean average difference, maximum difference and minimum difference were calculated between the interpolated surface and the reference points. The RMSE is calculated using the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (I_i - R_i)^2}{n}} \quad (25)$$

where

I_i = the interpolated values;

R_i = the reference values;

n = the number of values.

Results are given in Section 4.2.2.

3.6.2.2 Mosaic Procedure

Image mosaics were created using the fourteen images for flight line 1 and twelve images for flight line 2. A minimum of 10 tie points (TPs) was selected between each image to ensure that they were aligned properly (the RMSE for each image match is given in Appendix 3). The images were tied to one another in the reverse order of acquisition to ensure that the backscatter side of each image was retained in the overlap region between each image. The backscatter zone appeared to have a stronger overall contrast than the forward scatter zone making forest structure more visible in the imagery. Seed and King (2003) also reported that backscattered image data are more robust in empirical modelling of ELAI than foreshattered data. Selection of the TPs was easily done because the images were acquired 9.6 s apart. Each image in the mosaic was stitched together using a 1st order polynomial model with a nearest-neighbour interpolation.

3.6.2.3 Image Georeferencing

After a mosaic was produced for each of the two flight lines, they were georeferenced to orthophotos provided by the NCC (2001). The orthophotos were used as a reference because the resolution was considerably finer at 0.25 cm. The imagery was georeferenced to UTM zone 18 projection with a NAD83 datum. A total of 22 TPs were used for the first line and 18 TPs for the second line (Appendix 5). Each mosaic was transformed using a 2nd order polynomial model with a nearest-neighbour interpolation. Results of this procedure are given in Section 4.2.1.

3.6.2.4 Topographic Correction

Topographic correction was initially performed using the cosine correction (Equation 5) followed by the C-correction (Equations 8 and 9). The first step involved locating the image mosaics in the appropriate location on the interpolated surface. The sun's relation to the normal (incident angle) was then calculated using the ANG algorithm in PCI Geomatica (Figure 26). ANG computes the angle between a point on the surface and the line connecting this point to the point light source (PCI Geomatics, 2004). ANG requires three parameters to be defined: the solar elevation, solar azimuth, and the distance the imagery is from the light source. Assuming a line is drawn connecting the point source to the top left pixel of the image, the azimuth angle is the azimuth of the line in degrees clockwise from north (top of the image); the elevation angle of the line is expressed as degrees from the horizontal; the distance is the length of this line in kilometres, i.e. the distance from a zero elevation point at the top left corner of the image (0, 0) to the point source (i.e. the distance in

km from the upper left pixel to the bottom left pixel) (PCI Geomatics, 2004). The solar elevation was 41.1° , the solar azimuth was 211.8° and the distance to the light source sensor was 5.5 km for the first flight line. The solar elevation was 36.1° , the solar azimuth was 224.8° and the distance to the light source was 5.5 km for the second flight line. These parameters provided the conditions for the calculation of the cosine correction. The C-correction uses an additional parameter (c) that is added to the cosine correction. The value of c was determined for each spectral band and for each flight line by regressing the incidence angle with areas of forest not influenced by topography of the uncorrected imagery. Both corrections were implemented in MATLAB (Appendix 9).

Figure 26. Incidence angle image for flight line 1 when the solar elevation is 41.4° , solar azimuth is 211.8° and the distance from light source is 5.5km. Incidence angle image for flight line 2 when the solar elevation is 36.1° , solar azimuth is 224.8° and the distance from light source is 5.5km.

3.6.3 Net Correction

Both topographic and BRV correction techniques remove certain artefacts of brightness, but some residual variation can still be present after the process. The residual variation can be mitigated through the use of a net correction technique, or in some studies a net correction procedure has been applied alone without conducting optical, BRV, or topographic corrections. This research evaluates the consequences

of applying a net correction in two scenarios: after the BRV brightness correction, and with no other prior brightness adjustments.

Two net correction techniques were tested in this research. The first was a Nadir Correction method adapted from Richter (2005) and programmed in MATLAB (Appendix 7). The second method used the Antenna Pattern Compensation (APC) algorithm found in PCI Geomatics.

The nadir correction technique reduces brightness variation from the image centre to image edge. It calculates column means at a 1° sampling interval starting at $\pm 0.5^\circ$ from nadir (Figure 27). The differences in brightness are then adjusted using the following equation:

$$b_{norm}(j) = b(j) \frac{\bar{b}_{nadir}}{\bar{b}_m} \quad (26)$$

where

b_{norm} = nadir normalized brightness;

$\bar{b}_{nadir}$ = average brightness for nadir region ($\pm 0.5^\circ$);

$\bar{b}_m$ = the brightness value of interval m (1°);

j = pixel.

Figure 27. Nadir correction calculation.

The $\bar{b}_{nadir}$ value is divided by the $\bar{b}_m$ value for the column interval in the image to adjust the brightness to that of the nadir portion of the image. The algorithm was also implemented using the rows of the image after correcting the columns to reduce brightness differences in the top and bottom of the image. This process was considered unsuitable because the image appeared to be overcorrected, which also resulted in a decrease in the dynamic range. An option to use an image mask was added to the process after several trials revealed that areas of low brightness (lakes) and areas of high brightness (pavement) cause extreme values in column means. The mask was created by manually digitizing areas of the image that were not forest (Figure 28).

This method requires the land cover to be fairly uniform over the extent of the image, but the images used in this study have several variations (e.g. water, roads and wetlands). There is no option to apply an image mask when running APC, which would allow the exclusion of the data variations. However, there is an option in older versions of the algorithm to enter a database input window size (DBIW), which calculates the polynomial coefficients for a specified square area of the image. This method was tested, but determined to be unsuitable because the DBIW was not large enough to capture the variations in brightness over the full extent of the image. An attempt was made to apply the coefficients from a DBIW in one image to other images along a flight line, but again this method did not correct the brightness variations present in the imagery.

Since there was no mask option and the DBIW did not work well, the method was implemented with no consideration to the differences in land cover present in the imagery. To determine which polynomial order to use, several were tested from 1 to 7. A visual assessment was performed after each order change. A 2nd order polynomial was determined to be best because higher orders appeared to increase noise, while an order of 1 appeared to do little to improve the brightness differences.

3.7 Evaluation of Correction Techniques

After performing the BRV and nadir correction methods, the overall effectiveness of each technique was tested by calculating the average value of 20 x 20 pixel areas located in the left, centre, and right of the overlap area between images. Averages were taken in the forescatter and backscatter areas of the original data and

then again after applying each of the correction techniques. This was done randomly for ten overlap areas between images along both flight lines. The differences were compared using the mean absolute difference and RMSE. The overall effectiveness of each correction was also evaluated through a visual assessment.

The topographic correction was evaluated by determining the amount of variation between the uncorrected and corrected imagery for uniform areas of forest located on slopes greater than 15° , with aspects facing the sun ($211^\circ \pm 10^\circ$) and aspects facing away from the sun ($31^\circ \pm 10^\circ$). Five samples of 15×15 pixel averages were taken in each aspect direction for flight line 1. The overall effectiveness was also evaluated using a visual assessment of the changes to image brightness occurring before and after the correction.

3.8 Spatial and Spectral Data Extraction

Image spectral and spatial data were extracted from the raw, BRV normalized, topographic normalized and net normalized data. Image variables were selected that have previously shown good relationships with forest structure and health measures (Pellikka et al., 1998; Olthof and King, 2000; Levesque and King, 2003; Cosmopoulos and King, 2004).

3.9 Spectral Extraction

Only the near infrared (NIR) and green band were used in modelling because of limitations with the image acquisition discussed in section 3.5. The spectral data were also transformed using a Green Normalized Difference Vegetation Index

(GNDVI, Gitelson et al., (1996)), who found that the use of the green band allowed for a more reliable estimate of pigment concentration when compared to the Normalized Difference Vegetation Index (NDVI), which uses the red spectral band instead. GNDVI is defined as:

$$GNDVI = \left[\frac{nir - green}{nir + green} \right] \quad (28)$$

3.10 Texture Extraction

Texture measures may be derived from the frequency distribution of digital numbers (DNs) or grey levels within a window sample (first order measures), or they may be derived using spatial associations of DNs (second order measures) (Olthof, 1999). Co-occurrence matrices can be used to calculate some second order measures. They tabulate the frequency of occurrences of all pairs of digital numbers for corresponding pairs of sample pixels separated by a given distance (δ) and angle (θ) within a sample window of specified size (Pellikka et al., 2000). This probability distribution for the co-occurrence matrix can be defined as:

$$\Pr(x) = (C_{ij} | (\delta, \theta)) \quad (29)$$

where

C_{ij} = the co-occurrence probability between grey levels i and j , which is defined as:

$$C_{ij} = \frac{P_{ij}}{\sum_{i,j=1}^G P_{ij}} \quad (30)$$

where

P_{ij} = the number of occurrences of grey levels i and j within the given window, given

a certain (ϕ, θ) pair;

G = the quantized number of grey levels.

The sum in the denominator thus represents the total number of grey level pairs (i, j) within the window (Clausi, 2002).

Eight statistics were calculated using the co-occurrence probabilities (Haralick et al., 1973; Haralick and Shanmugan, 1974; Clausi, 2002; Hall-Beyer, 2005) as given in Equations 31 to 38.

$$\text{Angular Second Moment} \sum_{i,j=0}^{G-1} P_{i,j}^2 \quad (31)$$

$$\text{Contrast} \sum_{i,j=0}^{G-1} P_{i,j} (i-j)^2 \quad (32)$$

$$\text{Correlation} \sum_{i,j=0}^{G-1} P_{i,j} \left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \right] \quad (33)$$

$$\text{Variance } \sigma_i^2 = \sum_{i,j=0}^{G-1} P_{i,j} (i - \mu_i)^2 \quad (34)$$

$$\text{Entropy } \sum_{i,j=0}^{G-1} P_{i,j} (-\ln P_{i,j}) \quad (35)$$

$$\text{Homogeneity } \sum_{i,j=0}^{G-1} \left(\frac{P_{i,j}}{1 + (i - j)^2} \right) \quad (36)$$

$$\text{Dissimilarity } \sum_{i,j=0}^{G-1} P_{i,j} |i - j| \quad (37)$$

$$\text{Mean } \mu_i = \sum_{i,j=0}^{G-1} i(P_{i,j}) \quad (38)$$

where

G = the number of grey levels;

i, j = grey level pair.

Angular Second Moment (ASM) is a measure of the uniformity of a set of pixels.

Contrast (CON) is a measure of the amount of local variation of the maximum and minimum values of a set of contiguous set of pixels. It detects sharp changes in grey

level such as at edges of objects. The squared term magnifies these changes in output Contrast values. Correlation (COR) is a measure of the grey-tone linear-dependencies in a set of pixels. High COR values (close to 1) imply a linear relationship between grey levels of pixel pairs. Variance (VAR) is a measure of heterogeneity and is strongly correlated to first order statistical variables such as standard deviation. VAR increases as the probability of grey level pairs increases and as the grey levels differ from the average of the set of sample pixels. Entropy (ENT) measures the disorder in a set of pixels; when a set of pixels is completely random (white noise), Entropy is at its highest. Homogeneity (HOM) measures uniformity as it assumes larger values for smaller grey tone differences in pairs of pixels. Dissimilarity (DIS) is similar to contrast, but without squaring the grey level difference. Mean is the average probability of grey level pair occurrences within the window (Haralick et al., 1973; Haralick and Shanmugam, 1974; Baraldi and Parmiggiani, 1995). In some studies, HOM is called inverse different moment, CON is called inertia and ASM is called energy or uniformity (Baraldi and Parmiggiani, 1995).

These eight texture measures were computed for both the NIR and green spectral bands using a 25 x 25 pixel window size. This window size was selected to correspond closely to the size of the plot (20 m x 20 m). It was also selected with consideration of a study conducted by Butson and King (2006) that compared the use of lacunarity and semivariance to determine the optimal window sample size for texture extraction. It was found that the semivariogram range was generally too small to capture the larger pattern scales that were detected by lacunarity. An optimal window size for 54 cm airborne imagery was in the range of 14-18 m as identified by

Figure 28. Mask over image values of roads, wetlands and water bodies.

The APC algorithm was originally designed for radar antenna pattern correction, but has been found to be suitable to correct brightness variations across optical imagery (Cosmopoulos and King, 2004). It calculates the mean of each column of an image and then fits a polynomial to the series of means across the image. The polynomial is then inverted to normalize the brightness values across the image (PCI Geomatics, 2004) and is derived using the following equation:

$$Output(x) = ((Input(x) - Min) / (P(x) - Min)) * Mean \quad (27)$$

Where

$Output(x)$ = output grey level at pixel position x ;

$Input(x)$ = input grey level at pixel position x ;

$P(x)$ = estimated mean grey level at pixel position x based on the polynomial function;

$Mean$ = mean input grey level of image;

Min = minimum input grey level of image (PCI Geomatics, 2004).

lacunarity. Recognizing the difference between the pixel size of the study conducted by Butson and King, (2006) and that of this study, a window size of 25 x 25 was assumed to be reasonable to capture the appropriate spatial variations at the forest canopy scale.

3.11 Extraction of Image Variables from Plot Sub-scenes

The image variables described above were extracted from plot sub-scenes by first loading the plot coordinates from the GPS data. Square vectors were then drawn by connecting the four corners of each plot (Figure 29). For the spectral variables, the average brightness extracted from the plot was recorded. The texture values for each plot were taken from the centre pixel of the plot, as the recorded texture for this pixel was derived from the surrounding 20 m x 20 m region. This process was conducted for the raw and normalized data sets.

Figure 29. Example points depicting the corners of a plot overlaid on the image data.

3.12 The Complete Data Set

The abbreviations and descriptions of all image and forest variables used in the analysis are presented in Table 2. The data set included six forest variables and 19 image variables. The field variables consisted of stem density, average health, basal area, effective leaf area index (ELAI) and percent canopy cover. The image variables were calculated for the raw, BRV normalized, topographic normalized, net normalized, and BRV with net normalized. They included three spectral and 16 texture measures.

Table 2. Biophysical forest metrics and image variables.

Image Variables	Biophysical Forest Metrics
<p><i>Spectral</i></p> <p>NIR Average NIR brightness</p> <p>Green Average Green brightness</p> <p>GNDVI $(\text{NIR} - \text{Green}) / (\text{NIR} + \text{Green})$</p> <p><i>Texture</i> (Calculated for NIR and Green band)</p> <p>CON25x25</p> <p>DISS25x25</p> <p>ENT25x25</p> <p>HOM25x25</p> <p>ASM25x25</p> <p>Mean25x25</p> <p>VAR25x25</p> <p>COR25x25</p>	<p><i>Forest Measurements</i></p> <p>Stem density (trees/plot)</p> <p>Average health (avg. tree health /plot)</p> <p>Basal area (m^2/plot)</p> <p>Average DBH (cm)</p> <p><i>Hemispherical Imagery Measurements</i></p> <p>ELAI1 Effective leaf area index (rings 1-3)</p> <p>ELAI2 Effective leaf area index (rings 1-4)</p> <p>PCC Percent canopy cover (ring 1)</p>

3.13 Statistical Analysis

The statistical analysis consisted of two main parts. First, the correlation between all predictor variables was checked. Second, multiple regression was used to develop biophysical models of forest health and structure with image variables as predictors.

3.13.1 Correlation Analysis of Image Predictor Variables

Before the development of the multiple regression models, each image variable was assessed for correlation with all other variables in a correlation matrix. Variables that were found to have a Pearson correlation coefficient above 0.85 were considered highly correlated and were discarded before the regression analysis. The 0.85 cut-off was used because variables with correlation coefficient higher than 0.85 were considered to only offer redundant information that would not lead to a better understanding of the independent variables. This correlation analysis was conducted only for the raw data before correction. It was assumed that similar variables would be correlated in the normalized data, and discarding of different variables for each data set would have led to inconsistent results.

The correlation of the predictor variables indicated that the texture measures Entropy and Dissimilarity for both the NIR and green were highly correlated with the other image variables (Table 3). These variables were dropped from the analysis because they could cause problems of multi-collinearity in the development of models using multiple regression.

Table 3. Correlation matrix for all image variables. The highlighted numbers in the matrix are correlated >0.85. (g = Green and n = NIR).

	NIR	Green	GNDVI	HOM n	CON n	DISS n	Mean n	VAR n	ENT n	ASM n	COR n	HOM g	CON g	DISS g	Mean g	VAR g	ENT g	ASM g	COR g
NIR	1.00																		
Green	0.80	1.00																	
GNDVI	-0.28	-0.79	1.00																
HOM n	-0.04	-0.03	-0.02	1.00															
CON n	0.03	-0.01	0.07	-0.91	1.00														
DISS n	0.03	0.00	0.05	-0.97	0.98	1.00													
Mean n	0.50	0.33	-0.03	-0.07	0.07	0.06	1.00												
VAR n	-0.08	-0.09	0.10	-0.66	0.80	0.76	-0.15	1.00											
ENT n	-0.02	-0.01	0.03	-0.90	0.92	0.93	-0.04	0.88	1.00										
ASM n	0.01	-0.04	0.05	0.86	-0.78	-0.83	0.05	-0.69	-0.92	1.00									
COR n	-0.18	-0.13	0.06	0.14	-0.05	-0.09	-0.34	0.54	0.19	-0.09	1.00								
HOM g	0.10	0.01	0.07	0.73	-0.63	-0.69	0.23	-0.40	-0.66	0.75	0.17	1.00							
CON g	-0.13	-0.06	0.00	-0.62	0.68	0.67	-0.28	0.55	0.66	-0.63	-0.01	-0.86	1.00						
DISS g	-0.13	-0.05	-0.03	-0.69	0.69	0.70	-0.29	0.52	0.69	-0.70	-0.07	-0.95	0.96	1.00					
Mean g	0.40	0.40	-0.24	0.00	-0.08	-0.05	0.80	-0.25	-0.08	-0.01	-0.30	0.09	-0.19	-0.17	1.00				
VAR g	-0.18	-0.06	-0.02	-0.51	0.61	0.58	-0.35	0.80	0.72	-0.63	0.50	-0.61	0.79	0.75	-0.19	1.00			
ENT g	-0.10	0.01	-0.09	-0.71	0.67	0.70	-0.22	0.59	0.77	-0.82	0.09	-0.90	0.88	0.92	-0.02	0.82	1.00		
ASM g	0.01	-0.07	0.12	0.68	-0.55	-0.62	0.07	-0.41	-0.68	0.94	0.05	0.85	-0.68	-0.76	-0.11	-0.57	-0.89	1.00	
COR g	-0.07	-0.01	-0.02	0.19	-0.11	-0.15	-0.11	0.39	0.08	0.02	0.82	0.39	-0.28	-0.32	0.00	0.35	-0.08	0.17	1.00

3.13.2 Development of Biophysical Models Using Multiple Regression Analysis

Multiple regression was used to explore the relationships between the forest metrics and images variables. Before conducting the analysis, the relations between individual image and field variables were assessed using scatter plots of each variable pair. The image variables that did not exhibit linearity and normality were transformed using the logarithm (base 10 logarithm) of the variable. Forward stepwise regression was employed as a means to determine the combination of image variables that best models each forest measure. The forward method first selects the independent (image) variable that has the highest significant correlation with the dependent (forest) variable. The partial correlation coefficients of the remaining independent variables are then calculated and the variable with the highest significant coefficient is introduced next in the regression (Levesque and King, 2003). The effect of adding each variable is assessed as it is entered, and variables that do not significantly add to the success of the model are excluded (Brace et al., 2006). The process of adding variables is repeated until there are no remaining independent variables that contribute significantly to the model. The F -to-enter (significance level to enter) a variable was set to 0.05 and the F -to-exit was set at 0.10.

As in other multivariate techniques, multi-collinearity may obscure the results of the regression analysis because it reduces the unique predictive power of the independent variables (Cosmopoulos, 2001). Multi-collinearity was not expected to be a problem because some x variables had been discarded if they were highly correlated with others (as described in 3.13.1). To verify that model multi-collinearity was low, the variance inflation factor (VIF) was calculated using the Equation 39:

$$VIF = 1/(1 - R^2) \quad (39)$$

where R^2 is the squared multiple correlation of two model variables.

It is a measure of the degree to which collinearity among the predictors degrades the precision of the estimate. A VIF value of 10 suggests a point at which collinearity can be expected to cause problems (Marquardt, 1970; Rawlings et al., 1998). A VIF value of 3.6 was determined to be the cut-off for this study to try and lessen the possibilities of collinearity between the predictor variables. The VIF value was determined based on the results of the Pearson correlation coefficient table where variables were discarded with $r \geq 0.85$.

Significant models ($p \leq 0.05$) were compared based on the model p-value, adjusted coefficient of determination (R^2), and standard error of estimate (SE). All models were checked for normality of residuals and multi-collinearity. Regressions were first implemented for the uncorrected data followed by each corrected dataset. The models produced before and after the data corrections were then compared for differences.

4.0 RESULTS

4.1 Field Data Collection

A summary of the forest measurements for the fifty-four plots is presented in Table 4 (values for each plot are given in Appendix 1). The data collected has reasonable ranges, which capture the variation in structural differences in the forest.

Table 4. Summary of forest measurements.

	Average Health (0-4)	Average DBH (cm)	Basal Area (m²/plot)	Stem Density (Trees/Plot)
Mean	1.3	27.3	20.2	19.2
Maximum	2.3	40.3	44.1	37.0
Minimum	0.6	16.5	6.9	6.0

Thresholding of the hemispherical digital photos in order to calculate gap fraction was fairly straightforward because the contrast between vegetation and sky was clearly defined (Figure 30).

Figure 30. Example of hemispherical image (left) and the corresponding classified canopy/sky image (right).

A summary of values of ELAI1, ELAI2 and PCC derived from the hemispherical photography for the thirty-two plots is given in Table 5. Individual plot values are given in Appendix 2.

Table 5. Summary of values for percent canopy cover (PCC), and effective leaf area index 1 and 2 (ELAI1 and ELAI2).

	PCC (%)	ELAI1 (No Units)	ELAI2 (No Units)
Mean	82.4	3.8	3.7
Maximum	95.4	6.3	5.6
Minimum	46.0	2.5	2.3

The values presented in Table 5 indicate considerable ranges that were deemed to be representative of observed canopy variations in the field and also suitable for regression modelling against image variables. There was only a slight difference in average effective leaf area calculated for the two different sets of rings, indicating that they are essentially the same ($R^2 = 0.97$).

4.2 Image and DEM Acquisition and Processing

When visually assessing the NIR and green bands for a scene that consisted of primarily forest cover, it was found that brightness was darker at the image centre and increased towards the image edge. This effect was stronger in the NIR band (Figure 31) than the green band (Figure 32).

Figure 31. Image brightness in near-infrared channel (after applying a 5 X 5 average filter).

Figure 32. Image brightness in green channel (after applying a 5 X 5 average filter).

This unbalanced brightness was not limited to one image, but was present in all images acquired. The difference in brightness over the horizontal FOV did not follow expected variations as described in Chapter 2 for optical and BRV effects. In fact, the bowl shape appeared to be the inverse of standard vignetting, and this effect occurred almost entirely in the horizontal image direction (Figures 33 and 34). The cause of this is unknown, but it is likely related to the improper factory calibration of the camera-lens system settings. The camera may have been set-up to compensate for the loss of brightness caused by vignetting, but overcompensation was applied. This calibration issue is currently being investigated and corrected (King, *pers. comm.*, 2006).

The average brightness in the vertical direction (Figures 35 and 36) is highest at the top of the image. This might be a result of BRV where the backward scatter area of the image is brighter and the forward scatter portion of the image is darker. This can also be seen in Figures 35 and 36, where a subtle variation in brightness can be seen from the bottom to the top of the image.

Figure 33. Brightness variation horizontally across the raw NIR band in a sample forest. Blue indicates the DN values extracted along the horizontal axis of the image and the red line indicates the overall trend in the DN values.

Figure 34. Brightness variation horizontally across the raw green band in a sample forest. Blue indicates the DN values extracted along the horizontal axis of the image and the red line indicates the overall trend in the DN values.

Figure 35. Brightness variation vertically across the raw NIR band in a sample forest. Blue indicates the DN values extracted along the vertical axis of the image and the red line indicates the overall trend in the DN values.

Figure 36. Brightness variation vertically across the raw green band in a sample forest. Blue indicates the DN values extracted along the vertical axis of the image and the red line indicates the overall trend in the DN values.

4.2.1 Image Mosaic and Georeferencing

The image mosaics for flight lines 1 and 2 can be seen in Appendix 4. The first flight line had an RMSE of 6.70 m (x) and 11.62 m (y). The second flight line had a RMSE of 5.73 m (x) and 9.49 m (y) for the tie points used in the transformation. The RMSE is high, but given that the attitude of the aircraft (yaw, pitch and roll) during the time of acquisition was unknown, this magnitude of error was expected.

4.2.2 Digital Elevation Model

The spline tension interpolation performed reasonably well with a mean difference of 5.97 m, RMSE of 7.52 m, maximum difference of 18.45 m and a

minimum difference of 0.18 m between the surface and the reference point elevations. Figure 37 displays the relationship between the reference points and the same points on the interpolated surface. The figure indicates that some generalization has occurred in the interpolated surface, but that is to be expected because of the coarse resolution of the DEM. The DEM was considered accurate enough to be used for the topographic correction because the relationship is strong between the reference points and interpolated surface points ($R^2 = 0.76$).

Figure 37. Comparison of interpolated surface and reference elevation.

4.3 Evaluation of Brightness Correction Techniques

4.3.1 APC, BRV and Net Correction

Qualitative Assessment

A quick visual evaluation was enough to determine that the APC correction approach did not work properly. In areas (columns) of the image where water was present (i.e. low DN), the neighbouring pixel values of forest cover were substantially overcorrected (Figure 38). If a mask could be applied to this algorithm as for the nadir correction method, perhaps it would perform better, however, as the APC code was proprietary, the whole algorithm would have had to be re-programmed. This was deemed to be beyond the scope of the study after the programmed nadir correction was found to perform adequately with a mask applied. The nadir correction method produced an overall uniformly illuminated image (Figures 39 and 40). Brightness from the centre to the edge appeared to have little variation.

Figure 38. NIR band image before correction (A) and after APC correction (B). Red arrow indicates columns that were overcorrected due to the presence of water.

The BRV correction produced an overall increase in image brightness while at the same time causing a strong flare-up in brightness near the edges of the image (Figures 39 and 40). This correction appears to be causing an additive effect to the inverse vignetting problem that was more visible in the NIR band than the green band. This effect was more evident on the left side of the image. The BRV correction is based on the scattering angle, which, for these data, considers the lower left corner to be the darkest (forward-scatter) shown in Figure 24. As a result, the BRV correction increases the pixel reflectance values where the values are already too high, due to inverse vignetting problem and due to bright southwest slopes in this portion of the imagery.

The process of first applying a BRV correction followed by the nadir correction to remove residual differences produced a fairly consistent level of brightness across the image for both the NIR and Green band (Figures 39 and 40). Overall, the image brightness appears to be slightly higher than the nadir correction alone for the NIR band.

Figure 39. Comparison of NIR raw imagery (A) to net corrected (B), BRV corrected (C) and BRV plus net corrected (D).

Figure 40. Comparison of Green raw imagery (A) to net corrected (B), BRV corrected (C) and BRV plus net corrected (D).

Quantitative Assessment

The average difference and RMSE between the fore and back scatter zones (the overlapping areas) of adjacent images for both the NIR and green band in the raw imagery compared to the net, BRV and BRV plus nadir corrected imagery indicated improvements in only the processes involving the nadir correction (Tables 6 and 7). The nadir correction performed best, reducing the RMSE by 2.2 and 1.3 DN for the NIR and green band, respectively. The BRV correction did not perform well, increasing the RMSE and average difference for the two bands. Brightness peaked at the horizontal edges of the images with the highest increase in brightness on the right side of the images for both bands. The BRV correction, in combination with the reverse vignetting effect, caused a jump in brightness. The BRV plus nadir correction decreased this effect, but the leftover residual from the high brightness produced by

the BRV is still present on the left side of the images with a difference of 10.0 and 7.5 DN for NIR and green bands, respectively.

Table 6. Comparison of NIR brightness before and after each correction for the fore and back scatter zones. All units are in DN.

	NIR raw	NIR net	NIR BRV	NIR BRV+net
Average Difference	6.3	5.2	8.8	6.2
Right difference	9.7	5.7	11.5	6.4
Centre difference	1.1	1.2	3.7	2.3
Left difference	8.2	8.7	11.2	10.0
RMSE	9.3	7.1	10.9	7.9

Table 7. Comparison of green brightness before and after each correction for the fore and back scatter zones. All units are in DN.

	Green raw	Green net	Green BRV	Green BRV+net
Average Difference	7.7	6.3	9.0	7.1
Right difference	12.4	8.1	13.6	8.6
Centre difference	4.6	4.2	6.3	5.2
Left difference	6.0	6.5	7.2	7.5
RMSE	9.2	7.9	10.1	8.6

4.3.2 Topographic Correction

Qualitative Assessment

The cosine correction, as expected, over-corrected the imagery causing some extremely bright patches (Figure 41). The C-correction appeared to perform reasonably well (Figures 41 and 42), but there were obviously residual variations related to the reverse vignetting effect. The left side of the image, which has most of its slopes facing towards the sun was not adjusted enough to reduce the brightness to a reasonable level.

Figure 41. The cosine algorithm over corrected on the slopes facing southwest (A), while the C-correction produced a more uniformly illuminated image (B).

Figure 42. Comparison of NIR raw image (A) to topographically corrected image using the C-correction (B).

Quantitative Assessment

The C-correction decreased brightness for both NIR and green bands for surfaces that were facing the sun and increased the brightness for surfaces facing away from the sun (Tables 8 and 9). The results indicate that the correction is working properly by adjusting the brightness for both the slopes facing and looking away from the sun.

Table 8. Differences between surfaces facing the sun on slopes greater than 15°. Topo= topographically corrected using C-correction. All units are in DN.

Aspect 211° ± 10°						
	NIR			Green		
	Raw	Topo	Diff.	Raw	Topo	Diff.
1	166.7	160.8	-5.9	156.1	150.6	-5.5
2	170.6	158.9	-11.7	130.9	121.9	-9
3	144.3	135	-9.3	113.4	106.1	-7.3
4	150.5	148.5	-2	130.8	129	-1.8
5	175.1	164.4	-10.7	141.1	132.5	-8.6
	Average Diff.		-7.92	Average Diff.		-6.44

Table 9. Differences between surfaces opposite the sun on slopes greater than 15°. Topo= topographically corrected using C-correction. All units are in DN.

Aspect 31° ± 10°						
NIR				Green		
	Raw	Topo	Diff.	Raw	Topo	Diff.
1	119.3	124.8	5.5	105.1	111.6	6.5
2	98.2	106.6	8.4	117.3	119.2	1.9
3	114.9	118.4	3.5	101.2	105.4	4.2
4	110.6	119.2	8.6	100.3	106.2	5.9
5	106.5	113.3	6.8	104.6	110.8	6.2
	Average Diff.		6.56	Average Diff.		4.94

4.4 Multiple Forward Stepwise Linear Regression Analysis

Scatter plots revealed that ELAI1 and ELAI2 had a curvilinear relationship with many of the predictor variables and did not produce any models. ELAI1 and ELAI2 were therefore log transformed (base 10 logarithm), which produced more linear relationships with the independent (image) variables.

Tables 10 through 15 present the results for the regression models from the raw and corrected image variables for each of the four field variables. Significant relationships were not found for average health, PCC and logELAI1 before and after each correction. Results presented in Pellikka et al. (2000) found relationships for ELAI, PCC and average health for the same data collected in 1998. It is thought that

variability at the plot level found after the damage caused by the ice storm is no longer present, which is why these variables did not produce significant models. A quick assessment of all tables revealed that many different predictor variables entered the regressions for each dependent variable after the various correction methods, although there were some consistently entered variables. The best models for average DBH and BA were produced with the BRV plus net corrected imagery (Tables 10 and 11). Stem density did not improve with any of the correction methods, thus the best relationship was produced using the raw imagery (Table 12). The best model for logELAI2 was produced with the BRV corrected data (Table 13). The best model for stem density had a lower R^2 and a higher standard error of approximately 30%.

Variance NIR texture was the variable most entered followed by the Mean green and Correlation NIR textures. Mean green texture was the best predictor variable for average DBH and BA. Correlation NIR was the strongest predictor variable for stem density. Contrast NIR produced the strongest relationship for predicting ELAI2 similar to the results found by Olthof and King (2000) and Cosmopoulos and King (2004). GNDVI was not the best predictor for any model, but was entered into models of DBH, BA and stem density, indicating that spectral information in the visible and NIR is related to these forest structural variables. This variable was entered primarily after the correction of the image variables for BRV. The variable inflation factor (VIF) threshold of 3.6 was never met for each predictor variable entered into all the models. The normal probability plots of the model residuals were additionally checked, but no plots indicated strong departures from normality with no systematic trend with the dependent variables.

The variables entering the models were primarily textures, followed in some cases by spectral variables that contributed less to the variance accounted for. The entered variables also appeared to be related to the changes caused by the image correction operations. The first variable for average DBH using the raw imagery was Variance texture. A better model was obtained using the BRV plus net corrected imagery but the Mean green texture became the first variable entered. Similar results can be seen for both basal area and stem density. It is not as strongly noticeable for basal area, but the major contributing variable from the raw data model to BRV plus net model changes from Correlation NIR to Mean green with the addition of the Homogeneity NIR texture (Tables 10 and 11). Stem density did not produce very strong models, however it did display similar changes in the variables entered relating to the type of corrections performed. Mean green texture was also entered as the first predictor of stem density for the BRV plus net corrected data. The model observed for stem density with the raw imagery had Correlation NIR as the first contributor (Table 12). The results from the combination of the corrections suggest that they reduce local variation textures, giving rise to more predictive power from the textures measuring uniformity.

Table 10. Comparison of regression results for average DBH for the raw imagery and the four correction methods. Highest adjusted R^2 highlighted in yellow.

Model	R^2	Adjusted R^2	R^2 Change	Predictor Significance	Overall Significance	SE
<i>Average DBH Raw</i>						
VAR_nir	.389	.352	.143	0.000	0.000	4.5
Mean_green			.179	0.002		
ASM_green			.067	0.023		
<i>Average DBH BRV</i>						
COR_nir	.336	.310	.140	0.000	0.000	4.7
GNDVI			.196	0.000		
<i>Average DBH Topographic</i>						
Mean_nir	.261	.232	.157	0.001	0.000	4.9
VAR_nir			.105	0.010		
<i>Average DBH Net</i>						
Mean_green	.408	.373	.192	0.018	0.000	4.5
VAR_nir			.124	0.000		
ASM_nir			.092	0.007		
<i>Average DBH BRV+Net</i>						
Mean_green	.416	.381	.194	0.018	0.000	4.4
VAR_nir			.117	0.000		
ASM_nir			.105	0.004		

Table 11. Comparison of regression results for basal area for the raw imagery and the four correction methods. Highest adjusted R^2 highlighted in yellow.

Model	R^2	Adjusted R^2	R^2 Change	Predictor Significance	Overall Significance	SE
<i>Basal Area Raw</i>						
COR_nir	.409	.385	.263	0.000	0.000	6.7
GNDVI			.146	0.001		
<i>Basal Area BRV</i>						
COR_nir	.407	.384	.267	0.000	0.000	6.7
GNDVI			.140	0.001		
<i>Basal Area Topographic</i>						
Mean_nir	.357	.319	.178	0.020	0.000	7.1
VAR_nir			.079	0.007		
COR_nir			.100	0.007		
<i>Basal Area Net</i>						
Mean_green	.418	.383	.206	0.020	0.000	6.7
VAR_nir			.103	0.000		
HOM_nir			.109	0.004		
<i>Basal Area BRV+Net</i>						
Mean_green	.436	.402	.204	0.033	0.000	6.6
VAR_nir			.101	0.000		
HOM_nir			.130	0.001		

Table 12. Comparison of regression results for stem density for the raw imagery and the four correction methods. Highest adjusted R^2 highlighted in yellow.

Model	R^2	Adjusted R^2	R^2 Change	Predictor Significance	Overall Significance	SE
<i>Stem Density Raw</i>						
COR_nir	.304	.277	.176	0.001	0.000	6.5
VAR_nir			.129	0.003		
<i>Stem Density BRV</i>						
COR_nir	.297	.269	.175	0.000	0.000	6.6
GNDVI			.122	0.004		
<i>Stem Density Topographic</i>						
Mean_nir	.306	.264	.156	0.012	0.000	6.6
VAR_nir			.085	0.002		
HOM_nir			.064	0.036		
<i>Stem Density Net</i>						
VAR_nir	.292	.264	.144	0.000	0.000	6.6
HOM_nir			.148	0.002		
<i>Stem Density BRV+Net</i>						
Mean_green	.239	.209	.139	0.011	0.000	6.8
VAR_nir			.100	0.012		

Table 13. Comparison of regression results for log effective leaf area index 2 for the raw imagery and the four correction methods. Highest adjusted R^2 highlighted in yellow.

Model	R^2	Adjusted R^2	R^2 Change	Predictor Significance	Overall Significance	SE
<i>Log Effective Leaf Area Index 2 (Rings 1-4) Raw</i>						
ASM_green	.355	.309	.127	0.001	0.002	0.0810 (1.2)
CON_nir			.228	0.004		
<i>Log Effective Leaf Area Index 2 (Rings 1-4) BRV</i>						
CON_nir	.516	.482	.344	0.000	0.000	.07014 (1.1)
HOM_green			.172	0.004		
<i>Log Effective Leaf Area Index 2 (Rings 1-4) Topographic</i>						
CON_nir	.328	.280	.192	0.001	0.004	0.08267 (1.2)
COR_green			.136	0.024		
<i>Log Effective Leaf Area Index 2 (Rings 1-4) Net</i>						
No Model						
<i>Log Effective Leaf Area Index 2 (Rings 1-4) BRV+Net</i>						
No Model						

5.0 DISCUSSION AND CONCLUSIONS

5.1 Significant Findings

Quantitative and visual assessment of the imagery produced by the correction algorithms indicated the corrections were performing reasonably well despite the underlying problems with the reverse vignetting found in the raw data. The simple nadir correction method was visually the most satisfying because it created a balance of overall brightness across the image. The reverse vignetting effect was diminished and the image brightness from the image centre was similar to the brightness on the edge.

This is the first known study to evaluate the effects of image corrections on regression-based empirical models of forest structure and health. Image corrections were programmed and implemented, showing visible and quantitative effects on brightness variations across the FOV. The improved imagery generally produced better regression models of forest structure variables, but the improvements were small or inconsistent between forest variables.

The regression models created using raw and corrected image data (all corrections) were not very strong in terms of variance accounted for, but those for DBH, BA and stem density and ELAI2 were significant and good enough to determine whether the corrections were improving the results. The BRV plus net corrected data produced the best results for the prediction of average DBH and basal

area. The BRV correction alone improved the model for logELAI2. The models for stem density did not improve using any of the corrected data.

5.2 Research Limitations

One of the main limitations in this study relates to the location of the field data collection (plots) in relation to the imagery. The plots had been located in a moderately straight transect line from south to north for another study (Pellikka et al., 2000). During the flight planning, it was thought best to ensure the plots were captured in the imagery along the vertical image axis of each flight line. This resulted in the plots being located in the imagery mostly around nadir. However the nadir area of each image is considered to be least affected by optical and BRV brightness distortions. As the image corrections had greatest impact towards the image edges where there were few plots and the nadir areas with most plots were not modified significantly, the biophysical models did not change much using the corrected data. It would have been advantageous in terms of evaluation of correction effects on the biophysical models to locate the plots over the full extent of view angles.

The imagery acquired had striping in the red spectral band and all bands had an unexpected inverse vignetting effect that was very strong and that did not follow light fall-off cosine law theory nor BRDF theory. The red band had to be omitted, but may have been quite useful in the development of models, as found for the prediction of ELAI and PCC by Pellikka et al. (2000). Pellikka (2001) also found in another study that PCC was only correlated with red, while only weak correlations were found for NIR and green. Other vegetation indices such as NDVI could have

been used if the red band was not omitted from the study. Wulder et al. (1998) found NDVI with the combination of textures to be a good estimate of LAI in hardwood forest stands. The inverse vignetting effect that caused a brightness flare-up towards the edge of the imagery created a level of uncertainty when correcting the data. It was difficult to comprehend whether the corrections were performing properly or over compensating for this problem. The corrections used in this research were designed to correct systematic brightness variations related to theoretically proven causes and not sensor calibration errors that were present. Since these data were acquired, the MS4100 camera has been calibrated better to remove the noise problem, reduce the inverse vignetting variations, and provide image masks of spatial brightness variations of a uniform target at various f-stops that can be inverted and multiplied by the airborne images in each band. Imagery acquired for another project in the summer of 2006 was of much better quality in all of these respects.

It was difficult to determine if the correction was over or under correcting without proper field validation information. This was evident for both the BRV and topographic correction methods. The BRV requires the setting of a quantification factor, which is determined by choosing reference areas that are: 1) flat to avoid the impact of slope and exposure on the reflectance characteristics; 2) large enough to capture the spectral variation in the land cover; 3) of similar land cover type (Pellikka and Mikkola, 2002). This information would have helped determine the proper setting of the quantification factor instead of making a subjective decision. Topographic correction could also have benefited from the collection of reference data in a similar fashion to evaluate the BRV, but instead of limiting the reference

data to only flat terrain, the data should be collected on a range of slopes and aspects. This would help establish how much the c factor in the C-correction was influencing the brightness.

5.3 Future Directions

The next step will be to apply the corrections used in this study in combination with the flat field correction recently provided by the camera company to the 2006 imagery that has been acquired following the improved camera data described above. This will help to determine if the corrections really are effective in reducing topographic, BRV and vignetting effects when starting with raw data of better quality than was available for this study. It would also be advantageous to collect data to test how models created from a range of view angles change with each correction.

Additionally, by recognizing how each correction reduces certain distortions in the imagery the research should be directed towards development of a processing chain could be developed as in Pellikka (1998) and Scarth (2003) that combines these corrections with atmospheric and noise reduction algorithms. This chain could then be implemented as an automated method directly after image acquisition. This would help alleviate the problems associated with the misinterpretation of results obtained from uncorrected imagery.

Alternatively, when evaluating the BRV and nadir correction techniques using the fore scatter and backscatter zones of the imagery, it was thought that the brightness differences due to BRV might be useful themselves in modelling. Tests

should be conducted to determine if measures such as the difference in brightness of a given forest pixels from one image to the next as a function of scattering angle could be a useful predictor of forest structure or health variables.

5.4 Overall Conclusions

Despite the poor image quality in this study, and the plot placement to the flight line azimuth the results of this research indicate that high-resolution image-based biophysical models of forest structure variables can improve after the correction of the data for image brightness variations caused by topography, BRV and vignetting. Algorithms to correct each of these effects that had been reported to perform well in the literature were programmed and applied to airborne digital camera imagery of 80 cm resolution. The corrections reduced brightness distortions to varying degrees so combinations were tested. A BRV correction followed by a net brightness correction was best, but residual brightness variations remained.

Regression models of forest structure variables were dominated by image texture predictor variables. Corrected imagery generally produced models of higher significance, greater variance accounted for and lower standard errors. Continued research is needed with better image data and forest plots spread throughout the possible image view angles to verify and improve on these techniques.

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APPENDIX 1. Biophysical Forest Metrics Values (PCC, ELAI1, and ELAI2).

<i>Plot ID</i>	<i>PCC (%)</i>	<i>ELAI1 (No Units)</i>	<i>ELAI2 (No Units)</i>
T1-02	93.6	3.3	3.2
T1-04	74.7	3.1	3.0
T1-07	84.6	3.1	3.1
T1-08	75.9	4.0	3.7
T1-09	89.6	3.1	3.0
T1-12	79.4	2.9	2.9
T1-13	79.5	2.5	2.3
T1-14	88.3	3.7	3.7
T1-15	79.7	4.5	4.4
T1-16	90.8	3.5	3.5
T1-20	46.0	3.0	3.2
T1-29	88.4	4.2	4.2
T1-30	71.1	6.3	5.6
T1-31	85.5	3.6	3.5
T1-34	71.3	3.5	3.4
T1-37	90.2	5.2	5.1
T2-04	54.1	4.2	4.0
T2-05	83.3	5.3	5.3
T2-07	88.8	3.3	3.3
T2-08	93.2	4.5	4.2
T2-10	85.1	2.9	3.0
T2-14	87.9	2.9	3.0
T2-15	94.4	3.7	3.6
T2-17	88.9	3.0	2.9
T2-18	89.0	2.9	2.8
T2-19	95.4	3.5	3.5
T2-21	71.1	5.0	4.5
T2-24	89.7	2.8	2.8
T2-25	80.6	5.0	4.8
T2-34	90.2	4.3	4.3
T2-35	72.2	5.8	5.4
Average	82.4	3.8	3.7
Maximum	95.4	6.3	5.6
Minimum	46.0	2.5	2.3

APPENDIX 2. Biophysical Forest Metrics Values (AvgH, AvgDBH, BA, and SD).

Plot ID	AvgH (0-4)	AvgDBH (cm)	BA ($m^2/plot$)	SD (Trees/plot)
T1-02	0.8	27.2	20.6	12.0
T1-04	1.7	28.2	21.2	12.0
T1-05	1.0	25.5	16.1	21.0
T1-06	2.0	28.1	19.1	19.0
T1-07	1.8	18.5	8.5	36.0
T1-08	1.8	16.5	6.9	37.0
T1-09	1.6	22.7	12.7	25.0
T1-11	1.3	22.4	12.7	29.0
T1-12	2.3	27.0	19.3	16.0
T1-13	1.5	40.3	40.2	10.0
T1-14	1.5	38.2	35.6	11.0
T1-15	1.5	33.1	28.5	11.0
T1-16	1.3	28.5	20.9	18.0
T1-17	1.1	31.4	24.4	15.0
T1-20	1.6	30.9	23.3	14.0
T1-22	1.7	24.5	15.4	18.0
T1-23	1.6	18.7	8.5	33.0
T1-25	1.8	22.5	13.0	28.0
T1-29	1.0	21.7	12.1	23.0
T1-30	0.6	22.2	12.2	21.0
T1-31	0.9	22.7	12.8	24.0
T1-34	1.1	29.9	22.2	25.0
T1-37	0.6	35.7	32.3	12.0
T1-38	1.0	27.8	18.8	15.0
T1-39	1.0	27.8	44.1	9.0
T2-02	1.2	34.1	30.3	6.0
T2-03	0.8	30.9	23.5	13.0
T2-04	1.1	31.0	26.4	10.0
T2-05	1.0	38.0	36.1	8.0
T2-07	1.4	29.5	23.0	17.0
T2-08	1.9	24.5	15.5	20.0
T2-10	0.8	33.5	27.6	12.0
T2-12	1.2	23.9	14.3	17.0
T2-14	1.0	27.4	18.2	23.0
T2-15	1.3	24.9	15.3	26.0
T2-16	1.2	24.5	14.8	22.0
T2-17	1.3	22.1	12.5	26.0
T2-18	1.2	22.1	12.2	25.0
T2-19	1.4	24.7	15.7	18.0
T2-20	1.5	19.7	10.2	25.0
T2-21	1.3	17.1	7.4	37.0
T2-22	2.1	28.3	20.4	22.0
T2-23	1.3	19.8	10.3	33.0

APPENDIX 2. (Continued).

T2-24	1.6	27.9	21.9	19.0
T2-25	1.4	24.4	14.9	25.0
T2-26	0.8	33.0	28.2	11.0
T2-27	0.6	31.3	24.8	15.0
T2-28	1.3	35.9	31.8	10.0
T2-32	0.8	32.5	26.1	13.0
T2-33	0.8	29.9	22.3	16.0
T2-34	1.3	23.2	14.8	25.0
T2-35	1.5	23.7	14.5	20.0
T2-36	0.9	33.1	26.8	13.0
T2-37	1.3	36.3	33.2	12.0
Average	1.3	27.3	20.2	19.2
Maximum	2.3	40.3	44.1	37.0
Minimum	0.6	16.5	6.9	6.0

APPENDIX 3. Tie Point RMSE for Flight Line Mosaics.

Flight line 1

Images	Tie Points	RMSE (Pixels)	
		X	Y
13 to 14	10	3.23	5.52
12 to 13	11	1.10	4.23
11 to 12	12	2.46	4.96
10 to 11	10	1.49	3.87
9 to 10	11	2.71	3.48
8 to 9	10	2.62	3.58
7 to 8	10	2.30	2.89
6 to 7	10	1.38	3.07
5 to 6	11	1.62	2.86
4 to 5	10	1.99	4.03
3 to 4	10	1.31	5.95
2 to 3	11	2.00	5.05
1 to 2	10	2.19	6.49
Average		2.03	4.31

Flight line 2

Images	Tie Points	RMSE (Pixels)	
		X	Y
11 to 12	12	0.71	2.21
10 to 11	11	2.48	3.68
9 to 10	11	1.28	2.88
8 to 9	11	1.20	2.39
7 to 8	10	2.86	4.51
6 to 7	10	0.98	3.48
5 to 6	10	2.20	2.62
4 to 5	10	2.19	1.35
3 to 4	10	3.77	3.15
2 to 3	10	2.82	3.23
1 to 2	10	2.01	3.36
Average		2.05	2.99

APPENDIX 4. Flight line Mosaics, Raw Imagery.

Flight line 1

Flight line 2

APPENDIX 5. Tie Points for Registering Mosaic to Orthophotos.

Flight line 1

Tie Points	Pixel (Col)	Line (Row)	UTM X	UTM Y
1	1824.125	6012.625	428707.162	5039808.135
2	2869.500	4556.500	429377.353	5040894.330
3	3003.500	3522.500	429405.688	5041622.216
4	2706.625	704.625	428991.008	5043709.830
5	2443.500	4568.500	429061.230	5040853.351
6	2397.125	6511.625	429160.034	5039509.246
7	2306.500	5675.500	429037.576	5040083.206
8	1905.500	6331.500	428769.007	5039594.021
9	2662.500	6135.500	429332.756	5039798.915
10	2313.500	4661.500	428971.296	5040785.992
11	2523.500	5626.500	429194.775	5040135.454
12	3046.500	4340.500	429497.100	5041060.294
13	2622.500	4907.500	429220.647	5040631.553
14	1655.500	5278.500	428525.817	5040315.760
15	2081.500	4349.500	428778.616	5040992.679
16	2966.500	864.500	429218.183	5043609.944
17	1394.500	3999.500	428243.203	5041195.780
18	1084.750	7072.250	428182.098	5038971.656
19	2788.875	6754.875	429467.779	5039379.139
20	2447.500	2274.500	428902.306	5042482.002
21	3076.500	915.500	429313.291	5043577.417
22	2954.500	3711.500	429389.673	5041483.400

Flight Line 2

Tie Points	Pixel (Col)	Line (Row)	UTM X	UTM Y
1	1503.500	358.500	432159.180	5041814.330
2	875.500	4893.500	432164.180	5038476.330
3	1880.500	4847.500	432915.180	5038544.330
4	2034.500	395.500	432604.180	5041830.330
5	2720.500	764.500	433203.180	5041593.330
6	1937.500	1801.500	432691.180	5040690.330
7	1104.500	5025.500	432363.180	5038384.330
8	1153.500	2581.500	432152.180	5040067.330
9	1531.500	5841.500	432734.180	5037888.330
10	1666.500	2676.500	432560.180	5040029.330
11	2628.500	3115.500	433340.180	5039788.330
12	1384.500	4388.500	432510.180	5038824.330
13	2504.500	3931.500	433314.180	5039187.330
14	1639.500	5288.500	432776.180	5038242.330
15	2819.500	1681.500	433367.180	5040854.330
16	1177.500	2743.500	432186.180	5039952.330
17	927.500	5488.500	432261.180	5038083.330
18	1570.500	2391.500	432472.180	5040224.330

APPENDIX 6. Batch Process for K-means Clustering of Hemispherical Images (clus.eas).

This script is written in the Engineering Analysis and Scientific Interface (EASI), which is part of the PCI Geomatica software. These command lines were written in a text file, called an EASI script (.eas) and then run in the command environment by first loading the script (load "C:\clus.eas") and then executed (run "clus.eas").

```
local mstring filelist
```

```
filelist = "C:\hemidata\hemiT1-02\batchC-DSCN0371.pix
```

```
.
```

```
.
```

```
.
```

```
filelist[159]= "C:\hemidata\hemiT2-35\batchW-DSCN0429.pix
```

```
local integer i,j
```

```
for j=1 to 159
```

```
file = filelist[j]
```

```
REM add 2 channels
```

```
for i =1 to 2
```

```
    pciop = "ADD"
```

```
    pcival = 2
```

```
    monitor = "OFF"
```

```
    r pcimod
```

```
endfor
```

```
REM run kmeans (isoclus) clustering to create 8 classes
```

```
    dbic = 1,2,3
```

```
    numclus = 8
```

```
    seedfile =
```

```
    maxiter = 20
```

```
    movethrs = 0.01
```

```
    dboc = 4
```

```
    mask =
```

```
    siggen = "NO"
```

```
    backval =
```

```
    nsam =
```

```
    report = "OFF"
```

```
    r kclus
```

```
endfor
```

```
stop
```


APPENDIX 7. Nadir Correction (nadir.m).

This script along with brv.m and topo.m were written in MATLAB. The scripts were implemented in MATLAB by setting the appropriate functions if required.

```
function datanew=nadir(datafirst)
datafirst=double(datafirst)
datanew=zeros(1080,1920);
centre=1908/2;
centre_right=(1908/2)+1;
pixel=0.8;
h=2596.06;

l=0;    %Length in metres
k=0;
angle=0.5;    %Value of angle
increment=angle;    %Increment of angle
first_angle=angle/2;
index=0;
sh=0;
for j=centre_right:1908
    sh=sh+1    %Index for first 0.5 degree
    k=k+1;    %Counter for number of pixels in each line (within angle)
    l=l+pixel;
    mean=0;    %Counter for total average meaning
    n=0;    %Counter for number of pixels for average

    if index==0 if (rad2deg(atan(l/h)))>=first_angle
        index=index+1;
        for ii=1:row
            for jj=(j-k):j
                if data(ii,jj)>0
                    mean=mean+data(ii,jj); %Calculate data for average for
                                           this group
                    n=n+1;
                end
            end
        end
        aver=mean/n;
        for ii=1:row    %loops for creating new data with average
                        meaning
            for jj=(j-k):j
                datanew(ii,jj)=aver;
            end
        end
        angle=angle+first_angle;
        k=0;
    end
end
```

```

                aver=0;
            end

        else if (rad2deg(atan(l/h)))>=angle
            for ii=1:row
                for jj=(j-k):j
                    if data(ii,jj)>0
                        mean=mean+data(ii,jj);
                        n=n+1;
                    end
                end
            end
            aver=mean/n;
            for ii=1:row
                for jj=(j-k):j
                    datanew(ii,jj)=aver;
                end
            end
            angle=angle+increment
            k=0;
            aver=0;
        end
    end
end

% % Calculate the same to the left side from centre
l=0;
k=0;
angle=0.5;    %Value of angle
increment=angle;    %Increment of angle
first_angle=angle/2;
index=0;
for j=1:centre_right-1

    k=k+1;
    l=l+pixel;
    mean=0;
    n=0;

    if index==0 if (rad2deg(atan(l/h)))>=first_angle
        index=index+1
        for ii=1:row
            for jj=(centre_right-j):(centre_right-j+k)
                if data(ii,jj)>0
                    mean=mean+data(ii,jj);

```

```

        n=n+1;
        end
    end
end
aver=mean/n;
for ii=1:row
    for jj=(centre_right-j):(centre_right-j+k)
        datanew(ii,jj)=aver;
    end
end
angle=angle+first_angle
k=0
aver=0;
end

else if (rad2deg(atan(l/h)))>=angle
    for ii=1:row
        for jj=(centre_right-j):(centre_right-j+k)
            if data(ii,jj)>0
                mean=mean+data(ii,jj);
                n=n+1;
            end
        end
    end
    aver=mean/n;
    for ii=1:row
        for jj=(centre_right-j):(centre_right-j+k)
            datanew(ii,jj)=aver;
        end
    end
    aver=0;
    angle=angle+increment
    k=0;
end
end
end
aver1=(datanew(1,953)+datanew(1,960))/2;
for i=1:1080
    for j=1:1908
        if datanew(i,j)==0 datanew(i,j)=0.001;
        end
        finalim(i,j)=data(i,j)*aver1/datanew(i,j);
    end
end
finalim=uint8(finalim);
imwrite(finalim,'0.5degree.tif');

```

APPENDIX 8. BRV Correction (brv.m).

```
clear all
data=imread('first.tif');%Read original image
data=double(data);%Convert data to double type
d=data(1:1080,1:1920,1);%Image dimensions to be processed

%1 Distance of the axis between the pixel and frame nadir point
S=size(d);
xm=S(1,1);
ym=S(1,2);
xc=xm/2;
yc=ym/2;
for x=1:xm
    for y=1:ym

        r(x,y)=sqrt((x-xc)^2+(y-yc)^2);

    end
end

%2 Zenith angle from the pixel to the sensor
h=2596/0.8;
angle1=atan((r(:,)/h));

%3 Azimuth angle from pixel to sensor
angle2=zeros(xm,ym);
for x=1:xm
    for y=1:ym
        if x==xc angle2(x,y)=atan(abs((y-yc)/(eps)));
        else
            angle2(x,y)=atan(abs((y-yc)/(x-xc)));
            ass(x,y)=atan(abs((y-yc)/(x-xc)));
        end
        if (y-yc)<=0
            if (x-xc)<=0 angle2(x,y)=-angle2(x,y)+(2*pi);
            elseif (x-xc)>=0 angle2(x,y)=pi+angle2(x,y);
            end
        elseif (y-yc)>0
            if (x-xc)<0 angle2(x,y)=angle2(x,y);
            elseif (x-xc)>0 angle2(x,y)=(pi)-angle2(x,y);
            end
        end
    end
end

end
end
```

```

%4 Distance between pixel and sensor
dist=cos(angle1).\h;
distt=uint8(dist);
q=cos(angle1);

%5 Distance between zenith and sensor
b=h*tan(angle1);

%6 Distance between pixel and sun's ray
anglesun=deg2rad(41.1);
e=h/anglesun;

%7 Distance of the axis between the solar zenith
c=h*tan(anglesun);

%8 Angle between the azimuth angle of the sun and that of the sensor
as=deg2rad(211.8);
B=as-angle2;
for i=1:xm
    for j=1:ym
        if abs(B(i,j))>(pi) B(i,j)=B(i,j)-2*pi;
        end
        if B(i,j)<0 B(i,j)=-B(i,j);
        end
    end
end

%9 Length between the sensor and sun in the sensor altitude
a=sqrt(b.^2+c^2-2*c*b.*cos(B));

%10 Scattering angle
Yc=acos((((dist.^2)+(e^2)-(a.^2))./(2*dist.*e));

%11 Correction of original image
f=[0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1]; % Bracketing of f factor from 0 to 1
n=1;% normalization factor (which actually serves no point, but was presented in the
    % original equation. This should be an additional step to scale the image from
    % 0-255, 8-bit
for i=1:11
    DN(:,i)=(n*d)./(1+f(i)*((cos(abs(Yc))).^3));
end

```

APPENDIX 9. Topographic Correction (Topo.m).

```
C=3;
Q=deg2rad(50);
L=imread('greenline1.tif'); %Read uncorrected image data
L=single(L);
I=imread('iline1.tif'); %Read image incidence angle (i)
I=single(I);
a=size(L);

d=1;
k=1;
kk=1;
dk=8;
for ii=1:a(1)
    for i=1:a(2)

        Ln(ii,i)=L(ii,i)*(cos(Q)+C)/(cos(deg2rad(I(ii,i)))+C); %C correction

    end

end

Ln=uint8(Ln); %Change image format to 8-bit
imwrite(Ln, 'Green1.tif');
```