INFORMATION TO USERS

This manuscript has been reproduced from the microfilm master. UMI films the text directly from the original or copy submitted. Thus, some thesis and dissertation copies are in typewriter face, while others may be from any type of computer printer.

The quality of this reproduction is dependent upon the quality of the copy submitted. Broken or indistinct print, colored or poor quality illustrations and photographs, print bleedthrough, substandard margins, and improper alignment can adversely affect reproduction.

In the unlikely event that the author did not send UMI a complete manuscript and there are missing pages, these will be noted. Also, if unauthorized copyright material had to be removed, a note will indicate the deletion.

Oversize materials (e.g., maps, drawings, charts) are reproduced by sectioning the original, beginning at the upper left-hand corner and continuing from left to right in equal sections with small overlaps.

Photographs included in the original manuscript have been reproduced xerographically in this copy. Higher quality 6" x 9" black and white photographic prints are available for any photographs or illustrations appearing in this copy for an additional charge. Contact UMI directly to order.

Bell & Howell Information and Learning
300 North Zeeb Road, Ann Arbor, MI 48106-1346 USA
800-521-0600

UMI[®]

TEMPORAL ANALYSIS OF FOREST CHANGE AT AN ABANDONED MINE SITE
USING HIGH-RESOLUTION REMOTE SENSING

by

Patricia (Panayota) Cosmopoulos, B.Sc. (Hons)

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

Master of Science

Department of Earth Sciences

Carleton University

Ottawa, Ontario

December, 2000

© Copyright

2000, Patricia (Panayota) Cosmopoulos

National Library
of Canada

Acquisitions and
Bibliographic Services

395 Wellington Street
Ottawa ON K1A 0N4
Canada

Bibliothèque nationale
du Canada

Acquisitions et
services bibliographiques

395, rue Wellington
Ottawa ON K1A 0N4
Canada

Your file *Votre référence*

Our file *Notre référence*

The author has granted a non-exclusive licence allowing the National Library of Canada to reproduce, loan, distribute or sell copies of this thesis in microform, paper or electronic formats.

The author retains ownership of the copyright in this thesis. Neither the thesis nor substantial extracts from it may be printed or otherwise reproduced without the author's permission.

L'auteur a accordé une licence non exclusive permettant à la Bibliothèque nationale du Canada de reproduire, prêter, distribuer ou vendre des copies de cette thèse sous la forme de microfiche/film, de reproduction sur papier ou sur format électronique.

L'auteur conserve la propriété du droit d'auteur qui protège cette thèse. Ni la thèse ni des extraits substantiels de celle-ci ne doivent être imprimés ou autrement reproduits sans son autorisation.

0-612-57786-4

Canada

The undersigned recommend to
the Faculty of Graduate Studies
acceptance of this thesis

**"TEMPORAL ANALYSIS OF FOREST CHANGE AT AN ABANDONED MINE SITE
USING HIGH-RESOLUTION REMOTE SENSING"**

submitted by Patricia (Panayota) Cosmopoulos
in partial fulfillment of the requirements for
the degree of Master of Science

A handwritten signature in black ink, appearing to be 'C. R. D. King', written over a horizontal line.

Chair, Department of Earth Sciences

A handwritten signature in black ink, appearing to be 'Dang King', written over a horizontal line.

Thesis Supervisor

Carleton University

December 2000

ABSTRACT

Research was carried out at an abandoned mine site, near Timmins, Ontario, to assess forest structure changes related to stress caused by acid mine tailings contamination using high-resolution multispectral airborne digital camera imagery. Significant changes were detected in the plot-based field data between 1997 and 1999 using paired t-tests, while the spatial distribution of forest structure measures was highly correlated with distance from the tailings. Canonical correlation analysis of the 1997 forest structure and image variables revealed a significant relationship between the two variable sets ($R = 0.727$). The integrated set of forest structure variables that comprised the first canonical variate was used as a forest health index. An image-based forest structure health model was then developed using stepwise regression. Image texture, texture variation, and mean brightness, as well as sunlit crown fraction were included in the image model, which was capable of predicting 66% of the variation found in the forest health index. The image model was used to estimate the forest health index for the 1997 and the 1999 sample plots, and the difference of the two sets of indices was used to interpolate a forest change map. This research has demonstrated that forests adjacent to large non-remediated mine tailings may be highly stressed, resulting in significant structural changes over short time periods. The image-predicted forest change map showed potential in detecting forest changes, including overstory degradation and understory vegetation.

ACKNOWLEDGEMENTS

First and foremost I would like to thank my supervisor, Dr Doug King, for taking me on as his student, offering his encouragement, and for passing on his research enthusiasm for forestry and remote sensing. Furthermore, his support and advice during the completion of my thesis were invaluable.

This research was funded by the National Science and Engineering Research Council (NSERC) and the National Geographic Society. Field equipment was provided by the Department of Geography and the LICOR instrument was supplied by the Canadian Centre of Remote Sensing (CCRS). The aircraft and personnel for image acquisition were provided by AIRTEC, of Timmins, Ontario.

A special thanks to Chris Butson for his assistance in the collection of the field and image data, and for supporting me whenever he could. I sincerely thank Ian Olthof for his contribution to the development of the methodology used in this thesis and also Evan Seed, Peter Pulsifer, and Josée Lévesque for helping me out in the lab and for being there to talk over ideas and research interests. I would also like to thank Sharon Carr and Sheila Thayer for their support and help.

Finally, I would like to thank my brother Yanni for supporting me in my decisions and encouraging me along the way, also for giving me a place to stay for the past three years and for making this all possible. And finally a special thanks to Andrew for being my sounding board and more during the last year.

TABLE OF CONTENTS

ABSTRACT.....	iii
ACKNOWLEDGEMENTS.....	iv
TABLE OF CONTENTS	v
LIST OF TABLES	viii
LIST OF FIGURES.....	ix
1. INTRODUCTION	1
2. ACID MINE CONTAMINATION AND FOREST STRESS ASSESSMENT USING REMOTE SENSING.....	6
2.1. Acid mine contamination.	6
2.1. Forest health assessment and monitoring.....	11
2.3. Remote sensing for the evaluation of forest structure condition.	13
3. STUDY AREA.....	17
3.1. Mine history.	17
3.2. Geology.....	18
3.3. Geography.....	21
3.4. Mine site conditions.....	27
3.6. Previous research at the Kam-Kotia mine.....	34
4. METHODS	39
4.1. Field data acquisition.	39
4.2. Analysis of forest structure change (1997–1999) and spatial pattern.	47
4.3. Image acquisition and processing.....	49

4.4. Extraction of image parameters from plot subscenes.	58
4.5. The complete data set.	61
4.6. Statistical analysis to determine an integrated forest health index and image model of forest health.....	62
4.7 Temporal analysis of forest health.....	71
5. RESULTS.....	75
5.1. Preparation of data prior to analysis.	75
5.2. 1997-1999 forest structure change analysis.	77
5.3. Spatial distribution of forest structure.	78
5.4. Image processing results.	83
5.5. Multivariate relations between image and forest structure variables.	96
5.6. Temporal analysis of forest health.....	106
6. DISCUSSION.....	116
6.1. Evaluation of the multivariate analysis results based on previous literature.	116
6.2. Evaluation of forest change detection using an image-based model.	120
6.3. Sources of error, limitations in the study. and recommendations for future research.	121
7. CONCLUSIONS.....	125
8. REFERENCES	127
9. APPENDICES	137
APPENDIX 1: Image and field plot measurements from 1997 and 1999.....	137

APPENDIX 2: Principal component analyses	141
APPENDIX 3: Canonical correlation script and final report.....	145
APPENDIX 4: Stepwise regression report.	147

LIST OF TABLES

Table 4.1. Forest structure and image variables for 36 field plots and image subscenes.....	61
Table 5.1. Detection of outlier plot values and estimated z values for the 1997 and 1999 data.....	76
Table 5.2. Paired t-tests for 1997 and 1999 forest structure variables.....	77
Table 5.3. Results of principal component analysis of 1997 data.....	96
Table 5.4. First canonical variate pair of forest structure and image variates, 1997 data.....	99
Table 5.5. Stepwise regression results of the forest health index (forest structure canonical variate) against image variables. 1997 data.....	102
Table 5.6. Unstandardized coefficients and their standard errors for the best-fit regression model.....	103
Table 5.7. Image-predicted and (actual) forest change scores.....	107

LIST OF FIGURES

Figure 3.1. General geology of the Superior Province (Modified from Card and Ciesielski, 1986).	19
Figure 3.2. Study area at the Kam-Kotia mine site.	22
Figure 3.3. Elevation contour map showing a shallow NE gradient (Walsworth, 1998).	25
Figure 3.4. Photographs of the mine tailings and study area.	29
Figure 3.5. Forest types in the study area (Olthof, 1999).	32
Figure 4.1. Transects and field plot locations at the study site.	40
Figure 4.2. Original digital frame camera imagery from the 1999 data: 1. Near infrared, 2. Red, 3. Green, and 4. Blue band. Pixel spacing is 50cm.	50
Figure 5.1. Scatterplots of stem density (live, dead, and blowdown) with distance from the tailings' edge for the 1997 and 1999 data.	80
Figure 5.2. Scatterplots of basal area (live, dead, and blowdown) with distance from the tailings' edge for the 1997 and 1999 data.	81
Figure 5.3. Scatterplots of canopy closure and effective leaf area index (LAI _e) in relation to the distance from the tailings' edge for the 1997 and 1999 data.	82
Figure 5.4. Example of radiometric corrections on a 1999 image frame.	84
Figure 5.5. 1999 mosaic: a. uncorrected image, and b. corrected image.	86
Figure 5.6. 1997 mosaic (Nir band) of the study area. Pixel spacing is 50cm.	88
Figure 5.7. 1999 image mosaic of the study area. Pixel spacing is 50cm.	90

Figure 5.8. Example of histogram adjustment correction for a 1997 subscene (A10): a) 1999 image subscene, b) 1997 image subscene, and c) 1997 corrected image subscene.	92
Figure 5.9. Extraction of radiometric shadow components (S1, S23, and S4) using unsupervised classification.....	95
Figure 5.10. Normal probability plot of residuals for best-fit model of the forest health index from image variables.....	104
Figure 5.11. Residual plot from the best-fit multiple regression model.....	105
Figure 5.12. Dendrogram of the image-predicted change in forest health index...	110
Figure 5.13. Dendrogram of the actual change in the forest health index.	111
Figure 5.14. Image-predicted forest change map (1999-1997).....	112
Figure 5.15. Forest change (actual) map (1999-1997).	114

1. INTRODUCTION

Mining has been an important industry in Ontario for more than one hundred years. During this time a large number of mineral deposits were mined out or became uneconomic. Many of these were abandoned leaving a legacy of open shafts, unattended tailings, and derelict sites.

The Canadian mining industry produces more than 500 million tonnes of solid waste per year (Tapper *et al.*, 1991). Mine waste is visible on the landscape in various forms: waste rock dumps, tailings and tailing ponds, as well as mine site clearings. At active mine sites, the contaminants are managed by the mine operators, while most abandoned mine sites belonging to the province generate untreated acidic and metallic effluents. The cost of remediation is too high to be borne by the province and in many cases the mine management companies have dissolved. When acid runoff generated from tailings or waste rock is left uncollected, it can pose a great environmental hazard to the surrounding environment and communities. It contaminates groundwater and local water resources, damaging human health, plants, wildlife, and aquatic habitats (Filion and Ferguson, 1989).

The level of mine site development varies considerably throughout the province of Ontario. Local geology has greatly influenced the development of mining exploration. The largest number of developed mine sites is within the Precambrian Canadian Shield (Thurston *et al.*, 1991). In addition, many mines operated in Canada during the Second World War to provide strategic materials. Production of gold and other precious metals in Canada was essential for the purchase of war materials. For example, the Federal

Government operated the Kam-Kotia base metal mine near Timmins, Ontario, as a source of copper. However, the goal of wartime mining was to maximize production, and thus little was done in mine reclamation or to ensure physical and chemical stability of mine wastes. With the signing of the "Lend and Lease Act" in 1941 and the entry of the United States into the war, a number of mining ventures in Canada were closed down without rehabilitation, as mineral resources and other war material were provided by the United States.

The development of mineral exploration has also been influenced by the contemporaneous mining laws and technological capabilities. In the late 1800's, it was a requirement of the Mining Act that mineral deposits should be discovered before any claim could be made in a given area. Consequently, a huge number of exploratory open pits and trenches were generated to locate mineralized zones. After abandonment, they posed a significant hazard to human health. Public safety problems associated with surface cave-ins, mine tailing sites, open mine shafts, and toxic wastes created a demand for stricter environmental laws (Slater, 1995).

Ontario's Mining Act was first implemented in 1906 and underwent frequent amendments for administrative purposes until about 1970. It was not until 1991 that new rehabilitation requirements came into force (Cowan and Robertson, 1999). The principal thrust of these changes was to require proponents of advanced exploration and mine projects to provide mine closure plans supported by financial assurance (RSO 1990, Ch. M. 14). Additional changes to the legislation were introduced in 1996. These amendments provided for surrender of rehabilitated mining lands to the Crown upon closure (Doran and McIntosh, 1995). To date, proponents of mining projects are being

handed greater responsibilities in providing for mine rehabilitation in Ontario. Mining legislation has greatly evolved in the past few years and may effectively reduce or even prevent future mine hazards. Nevertheless, abandoned mines continue to pose a serious threat to the environment (Mackasey, 1989; 1993).

It is estimated that there are more than 100,000 inactive mines in Canada and the United States (Singhroy, 1995). In Ontario alone, there are more than 6,000 mine sites that have been abandoned in the past one hundred years (Vance *et al.*, 1995; Mitchell and Mackasey, 1997). In some cases, the consequences of mine contamination on the environment can be irreversible due to high acidity and treatment of tailings and acid runoff can cost millions of dollars. The estimated collective liability in Canada from sulphide-rich mine wastes is between two and five billion dollars (Feasby *et al.*, 1997). Therefore, there is a great need to monitor these abandoned mine sites to prevent further contamination of the surrounding environment.

Ground-based forest surveys have been used in the past to monitor environmental changes, although these are often difficult to do in remote and inaccessible locations. In recent years remote sensing has been considered as an alternative to ground-based surveys, as it allows for larger area analysis compared to that provided by field inventories.

Most image studies have been used to detect contamination of the water resources (Anderson and Satterwhite, 1995; Anderson and Robbins, 1998) and to investigate possible deterioration of the vegetation found in affected lakes and rivers (Courtin *et al.*, 1993). Only a few studies (eg. Mikkola 1996; Mueller *et al.*, 1997) have been conducted to detect vegetation changes that are located downstream and downwind from mine sites.

and tailings, such as the Kam-Kotia study area. However, most of these studies have been concerned primarily with the detection of vegetation stress or abundance using image spectral variations. While the present study includes this approach in an attempt to detect forest structural changes induced by long-term mine contamination, it also uses analysis of spatial and image properties in low-cost high-resolution imagery.

The goal of this research was to examine the feasibility of employing an image-based forest health index for monitoring the effects of mine contamination on forest health. This is based on the premise that forest health may suffer from toxicity associated with acid mine drainage (AMD) and windblown tailings, mechanical wind stress, and microclimatic changes resulting from a large open tailings surface. Such forest stress could manifest itself as changes in forest structure and spectral reflectance that can be detected by image spectral, textural, and structural measures. The following research objectives were set:

1. Assess whether significant forest structural changes have taken place between 1997 and 1999,
2. Analyze the spatial distribution of forest structure with distance from the tailings' edge to determine if gradients or other patterns exist that would improve our understanding of the effect of the tailings on forest deterioration.
3. Conduct a multivariate correlation analysis between image variables and forest structure variables to determine an integrated set of forest structure variables that have the potential as a forest health index to be monitored by remote sensing.

4. Develop an image-based model of the forest health index using plot data from 1997 and apply the model to the 1999 image data.
5. Conduct a temporal analysis of image-predicted forest change for this period and identify issues that need to be addressed to advance this methodology towards operational implementation.

In order to address these objectives, this thesis is organized into seven chapters. The next chapter presents background information related to this study including the environmental impacts of acid mine contamination and the use of remote sensing to monitor forest stress. Chapter 3 describes the study area, including mine history, geology, and a geographical perspective accompanied by specific mine site conditions as well as previous research conducted in the area. The methods of image and field data acquisition, processing and analysis are described in Chapter 4. Results are presented in Chapter 5 and include: temporal and spatial analysis of the 1997 and 1999 field data; image processing results; multivariate analysis of field-image data relations to determine an appropriate forest health index; the development of an image-based model of the forest health index and temporal analysis of forest change. Chapter 6 presents significant findings of this research in the context of previous work, the limitations and sources of error encountered in this study, as well as future research directions. Concluding remarks are presented in Chapter 7.

2. ACID MINE CONTAMINATION AND FOREST STRESS ASSESSMENT

USING REMOTE SENSING.

This chapter provides background information on three underlying concepts involved in this research: 1. acid mine contamination; 2. forest health assessment and monitoring; and 3. remote sensing for the evaluation of forest structure condition. The latter discusses the use of image spectral, textural, and structural measures for forest stress assessment.

2.1. Acid mine contamination.

Heavy metals and their compounds may be released to the environment as solutions, colloids or suspended particles in aqueous effluents, or as gases and aerosols or dusts from smelter stacks, ore stock piles and tailings. The metals continue to move until trapped in sediments or biota. Two distribution processes of acid mine contamination have been recognized, namely acid mine drainage and atmospheric dispersal (Thornton, 1983).

Acid mine drainage

Acid mine drainage (AMD) is indeed the single largest environmental problem facing the metal mining industry and is therefore a public concern (Tapper *et al.*, 1991; Feasby, 1993; Tremblay and Weatherell, 1998). Field observations and research have shown that once sulphide minerals start to react and produce acid runoff, it has been very difficult, if not impossible, to stop. Furthermore, AMD poses a future problem as it has

also been reported many years after mines have ceased operations (Weatherell *et al.*, 1997).

Most Canadian base metal and uranium mines contain sulphide minerals either in the ore or in the surrounding waste rock. When these sulphide minerals, mainly pyrite and pyrrhotite, are exposed to oxygen and water (Equations 1-4) they produce sulphuric acid commonly known as AMD (Gray, 1997).

From these reactions it is clear that pyrite can remain in its reduced state in undisturbed strata when the conditions are anaerobic as long as there is no exposure to oxygen or water. Although there are many cases where acid streams occur naturally, most are a result of mining activities. Furthermore, the milling of the ore may increase the rate and the susceptibility of iron-bearing phases to oxidation processes (Pratt *et al.*, 1996). As the reactions proceed, temperature and acidity increase, resulting in an increased rate of reaction. In a low pH environment ($2 < \text{pH} < 4$), the bacteria *Thiobacillus* and ferric iron catalyze the reactions and the reaction rate can be 20 to 100 times faster than normal rates (Anderson and Robins, 1998). In acidic waters ($\text{pH} < 4$), AMD can also dissolve heavy metals such as lead, zinc, copper, arsenic, selenium, mercury, and cadmium that are found in the waste rock and tailings. Rainfall and snowmelt flush the toxic solution

(AMD) from the waste site to the downstream environment (Filion and Ferguson, 1989). As the acid runoff is transported via groundwater and surface runoff, the extent of the contamination depends on hydraulic conductivity as well as the buffering capacities of the surrounding environment. Over many areas, naturally occurring limestone deposits (CaCO_3) can reduce soil acidity (Brady, 1990).

AMD affects the environment in numerous interactive ways. These effects can be categorized as chemical, physical, biological, and ecological. It is recognized as a multi-factor pollutant which may produce increased soil and water acidity, salinization, metal toxicity, and changes in sedimentation and water processes. Environmental recovery is suppressed due to species elimination, the toxic nature of sediments, and bioaccumulation of metals in flora and fauna (Gray, 1997).

Atmospheric dispersal

When contaminants are released in the air, they are carried by the wind and eventually fall to the ground. The pattern of contamination depends on the nature of the emitting source, the size and density of the particles, and wind strength and direction.

Area sources such as dry tailings or smelters may also contribute significant quantities of dusts to the immediate environment. Ore smelting and refining have long been recognized as a cause of air pollution (Thornton, 1983). Direct damage to vegetation is usually due to emission of sulphur gases. At Sudbury, Ontario, Gorham and Gordon (1960) observed that vegetation was severely blighted within 3km of the smelter and damage could be observed up to 8km. According to Mikkola (1996) sulphur dioxide and heavy metal emissions from two smelters Pechenganikel and Severonikel on the Kola

Peninsula, Russia have caused complete destruction of flora and fauna in the nearby areas. Forest destruction in the area is evident by premature browning of the forest trees or even tree defoliation.

Effects of acid mine contamination on forests

The impact of acid mine contamination on forest ecosystems is a complex process. Mine tailings present a serious problem as they may have concentrations of heavy metals that are toxic to plants. High soil acidity and metal content may cause stunted plant growth, localized absence of certain species, and reduced vegetation cover. In forests the cumulative effect of acid mine contamination may also cause structural changes related to increased tree die-back, crown thinning, and canopy openness.

However, not all metals are toxic to plants and some are actually required in small quantities for plant growth and maintenance. Also, many metals are found in soils in non-toxic amounts as part of the weathering of the parent bedrock. The availability of soil nutrients to plants can depend on numerous factors such as pH, soil type, buffering capacity, and capability to bind metals. For example, the availability of nitrogen, sulfur, and molybdenum is somewhat restricted by low pH (<5), whereas the availability of phosphorus is best at intermediate pH levels (pH=6-8). A pH range of 6-7 seems to promote the best availability of plant nutrients if they are sufficiently present in the soils. Likewise, toxic levels of elements such as iron, manganese, and aluminum are established at low pH (Brady, 1990). Ultimately soil pH also influences the presence of bacteria and other microorganisms that are essential in soil biological processes, as they

affect the redistribution of soil metals by oxidation and reduction or by metal binding (Thornton, 1983).

Some researchers have attempted to link metal toxicity in plants to growth rate, tree die-back, reduction in chlorophyll concentrations (chlorosis), and changes in plant parameters such as plant architecture and phenology. Based on this research, certain grasses such as Redtop (*Agrostis gigantea*), Tufted Hairgrass (*Deschampsia caespitosa*) and small trees such as Dwarf Birch (*Betula pumila*) as well as White Birch (*Betula papyrifera*) seem to be more resilient to acid soils and possess some metal tolerance (Brady, 1990; Winterhalder, 1992). Hence, some studies of remediation and prevention of acid mine drainage have proposed the use of vegetative covers in order to reduce the acidity of mine tailings (Kalin *et al.*, 1989; Winterhalder, 1995). However, as the Boreal forests of Ontario are situated primarily on the acid sensitive soils of the Canadian Shield, a low amount of contamination can significantly affect soil health and vegetation productivity (Hall, 1995).

Most studies concerning the effects of heavy metal pollution on the environment have been directly related to human health. Accordingly, there are numerous studies on acid mine contamination of water resources (Kalin, *et al.*, 1989; Whitehead and Jeffrey, 1995; He, *et al.*, 1997; Goser, 1999). Likewise, studies on the effects of heavy metals on plants are limited mostly to agriculture crop species (Thornton, 1983). Milton *et al.* (1989) conducted laboratory experiments, which investigated the sensitivity of plants to excesses or deficiencies in soil elements and heavy metal pollution. Some of the symptoms of toxicity from soil metals were plant dwarfism, chlorosis, and early

senescence. On the other hand, the response of forest ecosystems to acid mine drainage is not yet fully understood, as there has been inadequate research on this topic.

2.1. Forest health assessment and monitoring.

Assessment and monitoring of forest health is essential for the development of environmental policy and for management of environmental resources. Effects of direct pollution on forests were first recognized a hundred years ago. More recently, the health of forests was thought to be declining due to chronic exposure to air pollution and/or acidic deposition (Feretti, 1997).

In 1993 research priorities were set by the forest research advisory council of Canada (FRACC) in order to develop methods for sustainable management of the diversity and resilience of forest ecosystems, and to improve forest health (FRACC, 1994). According to the Society of American Foresters (SAF) forest health can be defined as: *“a condition wherein a forest has the capacity across the landscape for renewal, for recovery from a wide range of disturbances, and for retention of its ecological resiliency, while meeting current and future needs of people for desired levels of values, uses, products, and services”* (More, 1996). Likewise, Murtha (1978) defined forest damage as impairment of the biological ability of tree growth and reproduction or both.

The effects of natural and human-caused stresses on forest ecosystems have been identified as one of the top priorities in forest research in Ontario (FRACC, 1994). The duration of these stresses may result in different levels of forest damage. Immediate signs of forest deterioration may be manifested as leaf discolouration or even leaf

shedding in cases of severe, suddenly applied stress. As stress factors are prolonged, breakage of defoliated branches may also occur, accompanied by a decrease in leaf size resulting in overall increased crown transparency. Continuing crown damage will eventually result in tree die-back and mortality leading to changes in the overall canopy architecture (Olthof, 1999). Therefore, evaluation of forest damage is complex and depends on the scale of the assessment, which can range from the individual leaf to the entire stand.

Forests are generally sensitive to biotic and abiotic stresses and continuous monitoring would allow for any deterioration of forest condition to be identified, provided that appropriate indicators were used. As there is no single measurement that can be used to assess forest conditions it is important to select suitable indicators. Trees are the most obvious components of a forest ecosystem and are commonly used as indicators of forest health (Everham *et al.*, 1996; Ferretti, 1997). Structural parameters of trees reflect their condition, and thus, have been used to quantify forest health. For example, Hall (1995) used tree mortality rates and crown condition to evaluate damage from air pollution in different forest ecozones. Everham (1996) pointed out that forest damage from catastrophic wind could be quantified using a combination of indicators, such as changes in forest volume or mass, as well as stem and canopy damage. Ferretti (1997) assessed forest vigour using stem density, standing volume, and tree diameter at breast height (DBH) as indicators. Therefore, previous studies have demonstrated that forest structure can be used successfully to assess forest health in a variety of different circumstances. It provides a simple and objective method that can be used for long-term forest change detection. For example, stem damage is commonly reported as percent of

downed trees, perhaps caused by wind. Canopy damage can be directly quantified from estimates of structural loss or indirectly from changes in light levels. Tree mortality can be measured as the percent of dead, defoliated or snapped standing trees (Everham, 1996).

2.3. Remote sensing for the evaluation of forest structure condition.

Monitoring vegetation changes by comparing images acquired in the same area at different times is one of the major applications of remote sensing (Singh, 1989). Multispectral remote sensing techniques have been used successfully in the past to monitor revegetation success at rehabilitated mine sites (Gagnon *et al.*, 1985; Singhroy, 1995; Glasser *et al.*, 1999; Lévesque *et al.*, 1999).

Forest structural loss is related to forest damage (i.e. tree die-back and mortality) and represents a visual expression of environmental stress. Remote sensing for stress detection is accomplished through analysis of forest damage symptoms which permits only inference of stress until positively correlated with ground reference data (Murtha, 1983). Most research on forest conditions has concentrated on spectral image analysis. Recently, image texture and structure have been introduced in forest structure analysis but rarely in the context of forest damage assessment.

Image spectral measures

Forest stress may be measured by changes in the spectral reflectance of canopy foliage (Murtha, 1978; 1983; Courtin *et al.*, 1993). This is demonstrated as changes in spectral reflectance across either some part or all of the visible and near-infrared (Nir)

portion of the electromagnetic spectrum, or as a shift towards shorter wavelengths of the steep gradient of reflectance between the Red and Nir known as the “red-edge” (Mueller *et al.*, 1997; Hagner and Rigina, 1998).

Vegetation indices have been used in remote sensing for monitoring temporal changes associated with vegetation (Lyon *et al.*, 1998). These indices are often derived from band ratios. Ratios including the Nir and Red bands have been used successfully in the past as an indicator of the fraction of vegetation cover (Purevdorj *et al.*, 1998; Lawrence and Ripple, 1998; Gitelson and Kaufman, 1998; Todd and Hoffer, 1998), leaf area index (LAI) and above-ground biomass (Lawrence and Ripple, 1998).

Image texture

While spectral information has proven adequate to detect certain types of forest damage mostly related to leaf discolouration (Singhroy, 1995), the inclusion of spatial information from high-resolution digital imagery can also provide additional information on forest structural changes (Wulder *et al.*, 1997).

Image texture has been defined as the spatial variation in tones and refers to the visual impression of coarseness or smoothness caused by the variability or uniformity of the image tones or colour (Avery and Berlin, 1992). It describes the relationship between elements of surface cover and is therefore related to forest structural information (Wulder *et al.*, 1997). Wulder *et al.* (1998) concluded that empirical relationships between spectral data and LAI are improved with the addition of texture measures.

Texture may be measured by a variety of statistics that characterize the relationships between neighbouring pixels. It is typically derived for a local image area

using a moving window. As the window passes through the image, a texture measure is derived directly from the window values and is used to replace the central pixel value, thus creating a texture image. Some of these texture measures consider the statistical distribution of the digital numbers within the window and are known as first-order measures. For example, the standard deviation can be derived directly from the image data.

Second-order texture measures can also be calculated using a derivative of the original data, such as the grey-level co-occurrence matrix (GLCM). This is a two-dimensional histogram of grey levels of pairs of pixels. It contains the relative frequencies of the spatial association of the pixel values within a window that occur at a specified distance and direction (Haralick, 1979). For example, "Contrast", the relative change of pixel values over short distances and "Homogeneity", the overall uniformity of pixel values are commonly used second-order texture measures which are derived from the GLCM. The selection of an optimum window size for the calculation of image texture is one of the main difficulties in texture analysis. The semivariogram range, the distance at which spatial independence is reached, has been used in previous studies to determine the appropriate window size for textural analysis (Franklin *et al.*, 1996) but most often experimentation with various window sizes is conducted.

Image structure

Whereas texture refers to spatial variability around a point, the image scene can also be viewed as a series of discrete objects (trees) which are capable of selectively absorbing or reflecting radiation at different wavelengths and also casting shadows

depending on their structure (Rosema *et al.*, 1992). The proportions of directly illuminated crown, diffusely illuminated crown, shadow, and background have come to be termed “radiometric components”.

In addition to spectral and textural analysis, the “radiometric components” of high-resolution imagery have been successfully studied for the potential of estimating forest structure measures (Hall *et al.*, 1995; Hall *et al.*, 1996; Peddle *et al.*, 1999; Pellikka *et al.*, 2000). Image structure analysis has been conducted using geometric-optical reflectance and spectral mixture modeling to estimate canopy biophysical variables (Hall *et al.*, 1995; Hall *et al.*, 1996; Peddle *et al.*, 1999). These studies have demonstrated that there is a strong relationship between scene shadow components and canopy biophysical variables such as leaf area index (LAI), biomass and above ground net primary productivity (NPP). More recently, Pellikka *et al.* (2000) used image spectral, textural and shadow fraction measures to predict individual forest structure measures. This study determined significant relations between the image measures and various forest parameters including LAI, percent vegetation cover and a forest structure damage score.

3. STUDY AREA.

The study area is located near Kamiskotia Lake, 40 kilometres northwest of Timmins, in northern Ontario. It is adjacent to the abandoned zinc and copper deposit of the Kam-Kotia Mine. Three tailings areas covering about 350 ha are located to the south, north, and northeast of the mine near the edge of the study area (Figure 3.2).

3.1. Mine history.

Initial exploration at the Kam-Kotia mine/mill complex started in 1926 and was terminated temporarily two years later in 1928. It was reopened in 1943 under the management of Hollinger Mines Ltd., in order to support the war effort. It was not until 1950 that Kam-Kotia Mines Ltd. was officially formed and underground operations were initiated (Walsworth, 1998).

Approximately six million metric tonnes of ore were mined and 200,000 tonnes of waste rock containing large amounts of massive pyrite were deposited on the site from 1942 to 1972 (Ferguson, 1993). The ore was rich in chalcopyrite, sphalerite, pyrrhotite, and pyrite and was mined primarily for its copper and zinc content (Winterhalder, 1992). During the years of operation, mine waste was discharged near the mill to the south and in the swampy area to the north of the mine site. In order to retain the huge amount of mine waste, impoundment walls and rock-berms were constructed between 1967 and 1969. During these two years the mine waste was deposited in the abandoned mine pit (Walsworth, 1998). These containment measures proved to be a temporary solution as the impoundment wall was built from mine waste with no additional lining imposed

upon previous tailings to prevent leakage. Subsequently, the unimpounded tailings to the south spread all the way to the Little Kamiskotia River posing a great hazard to the Kamiskotia community (Figure 3.2). The Kam-Kotia mine/mill complex was closed in 1972, leaving approximately 350 ha of sulphide-rich and acid-generating tailings. The mine remained private property until 1974 when the affected land reverted to the Crown without any remediation (Winterhalder, 1992).

In 1992, an exploratory License of Occupation was issued under the authority of Mining Act to Falconbridge Ltd., giving that company the right to explore for minerals on and near the mine site (Ferguson, 1993). The site is currently maintained by the province and is monitored annually by the Ontario Ministry of the Environment to determine the long-term environmental impacts.

3.2. Geology.

The Kamiskotia deposit is part of the Kamiskotia assemblage and is one of the many volcanic massive sulphide deposits (VMS) found in the Abitibi subprovince of the Canadian Shield (Figure 3.1). The Abitibi greenstone belt is unique in the Canadian Shield in that it has a high ratio of supracrustal to intrusive rocks, is the largest greenstone belt in the world, and contains a diverse spectrum of richly mineralized deposits (Thurston *et al.*, 1991). Subsequently, mining activities in the Abitibi subprovince have been intense during the last hundred years (Gagnon, 1985).

The greenschist facies of the Kamiskotia assemblage consist of the synvolcanic tholeiitic Kamiskotia Gabbroic complex (2707 ± 2 Ma), overlain by the younger Kamiskotia volcanic Complex (2705 ± 2 Ma) (Barrie and Davis, 1990). This assemblage

Figure 3.1. General geology of the Superior Province (Modified from Card and Ciesielski, 1986).

is bounded by: the north-northwest-striking Mattagami fault to the east, a metavolcanic assemblage to the north, and the Carscallen assemblage to the west and south.

Four volcanogenic copper-zinc ($\pm$ gold $\pm$ silver) mines (Kam-Kotia, Jameland, Canadian Jamieson and Genex) and several deposits occur within the Kamiskotia Volcanic Complex. The host rocks are predominantly mafic metavolcanic rocks and the deposits consist of several smaller masses of sulphide. The sulphide minerals in the deposits are pyrite, pyrrhotite, chalcopyrite, sphalerite, and minor magnetite; as well, traces of galena have been reported from the Kam-Kotia mine (Thurston *et al.*, 1991).

3.3. Geography.

The study area is situated in the province's Clay Belt Region and soils are glacial and post-glacial sand and silt (Legasy *et al.*, 1995). Topographically, most of the area surrounding the mine site is relatively flat and is characterized by poor drainage, forming swamps and meandering streams. Analysis of the Ontario Ministry of Natural Resources Base Map (1:10,000) revealed a gentle topographic slope of 1° from the tailings' edge to the north of the study site (Lévesque and King, 1999).

The entrance of the mine is situated on top of a hill consisting of Archean metavolcanics. Surrounding the mine are the three tailings areas; the unimpounded tailings to the south extending to the near edge of the Kamiskotia Lake; impounded tailings area to the north; and northeast unimpounded tailings area. The study area is adjacent to the northeast unimpounded tailings, which cover an area of 130 ha. The water flow is assumed to follow the elevation gradient from the north impounded tailings

Figure 3.2. Study area at the Kam-Kotia mine site.

towards the study site in the northeast. An elevation contour map constructed by N. Walsworth (1998) shows a shallow NE gradient with an average slope of 0.3-0.4 degrees (Figure 3.3). The central bog area (spruce swamp) is fairly flat and suffers from poor drainage, whereas the forest surrounding the swamp is situated on sandy soils and has higher slopes and better drainage. Outflow drainage from the northeast unimpounded tailings is collected in the northwest and north central seep, which eventually drain into the Kamiskotia River. These two creeks effectively delimit a forested area (study area) approximately 1.4km (east – west) by 800m (north – south) (Figure 3.2).

The north impounded tailings area is confined by a 7m high dam (impoundment wall), which runs from the mine site north of the pit for about 300m (Figure 3.2). At the end of the dam, towards the northwest of the impounded tailings, there is an esker of glacial sand, which forms a natural ridge around the tailings.

Figure 3.3. Elevation contour map showing a shallow NE gradient (Walsworth, 1998).

3.4. Mine site conditions.

The mine tailing areas contain pyrite, pyrrhotite, chlorite minerals, quartz, and lesser amounts of Cu and Zn sulphides. Surface tailings are highly acidic and measured pH ranges between 2 and 4 (Fortin *et al.*, 1996). An oxide-rich crust is formed on the surface of the tailings in dry areas. There are visible signs of oxidation as the colour of the tailings is bright orange (Figure 3.4.d).

Dry tailings are known to pose an area source for atmospheric dispersal of contaminants and contribute significant quantities of “fugitive dust” to the immediate environment (Thornton, 1983). In this case, fine grain-size air pollutants mainly from the impounded tailings, are easily transported to the adjacent forest by strong winds and deposited on tree leaves and the ground (Figure 3.4.b).

The north impounded tailings form a consistently deep layer of approximately 5.8 m, whereas the thickness of the tailings in the northeastern unimpounded area is highly variable and decreases toward the tailings' edge (Winterhalder, 1992). Surface oxidation takes place above the average water table (30–60cm depth) and varies from 5 to 20cm (Fortin *et al.*, 1996).

Dried out bark and stumps are scattered throughout the tailings area as remnants of forest destruction (Figure 3.4.e). The density of dead trees present on the tailings increases progressively toward the forested study area. In addition, the majority of the tree trunks found on the tailings still have branches indicating that high numbers of dead trees near the tailings edge are due to more recent forest die-back. However, within the tailings area there is also some vegetation located on slightly elevated islands, composed of sand, creating a buffering zone. Some debris mats, composed of deteriorated tree

elements, are also seen on the tailings area. These function as a 'refuge' for some shrubs and plants with shallow root systems.

Signs of forest damage are visible in the study area and include: 1. Uprooted and snapped trees (Figure 3.4.c) presumably a result of strong winds that develop over the open tailings' surface (Figure 3.4.b), 2. Undersized crowns, 3. Chlorosis (leaf discoloration), 4. Dead branches, 5. Low amounts of foliage, and 6. High crown and canopy openness. Canopy thinning is particularly obvious near the tailings, possibly due to windblown deposition of contaminants. Dead and fallen tree counts indicate that greater wind stress is present within 200 m from the tailings than beyond (Olthof, 1999). The pH of the water draining from the tailings in the north west and central seep (Figure 3.2) is between 1.4–2.0 and soil pH has been measured at between 4.2–6.8. All trees along the path of these red-coloured creeks are heavily damaged (Figure 3.4.f). Surface horizon soil analyses have demonstrated a decreasing gradient of metal content with increasing distance from the tailings in the forest. Also, soil analysis revealed that aluminum and iron content is significantly higher than acceptable toxic levels (Lévesque and King, 1999; Olthof, 1999).

Figure 3.4. Photographs of the mine tailings and study area.

a) Meandering stream on NE unimpounded tailings

b) Wind storm on the North impounded tailings

c) Snapped tree along transect A

d) NE unimpounded tailings

e) dead trees and stumps on NE tailings

f) Beaver dam located at the NW Seep

3.5. Forest at the study area.

The forest of the study area is a typical of a mixed-wood boreal forest of Ontario. The overstory canopy consists principally of mature trembling aspen (*Populus tremuloides*), balsam poplar (*Populus balsamifera*) and some white birch (*Betula papyrifera*), whereas jack pine (*Pinus banksiana*) is found in drier areas. The tree height generally varies from 10m to 30m. A conifer understory of balsam fir (*Abies balsamifera*), white spruce (*Picea glauca*) and black spruce (*Picea mariana*) is present in some of the more mature areas. Black spruce is present mostly in wet areas, while a mixture of both white and black spruce is found in areas of medium wetness. Figure 3.5 shows the broad forest types according to field data at the study area with four distinct divisions, labeled A-D. Section 'A', which is located at the northwest part of the site, consists mainly of trembling aspen (Ta) and balsam poplar (Bpo). Adjacent to the tailings' edge, at the southwest part of the study site, is section 'B'. The forest cover here has few jack pine (Pj), as well as black and white spruce (Bs, Ws). The central bog area, section 'C', is located in a depression area and as a result is characterized by poor drainage. It is a relatively wet swampy area with sparse forest cover, which consists of black spruce and balsam poplar. On the other hand, the understory vegetation in this section is quite dense and is mainly composed of balsam fir (Bf). Section 'D' is characterized by high canopy between 25 and 30m, consisting mainly of trembling aspen accompanied by some balsam poplar and white spruce (Olthof, 1999).

Figure 3.5. Forest types in the study area (Olthof, 1999).

3.6. Previous research at the Kam-Kotia mine.

After the Kam-Kotia mine was abandoned in 1974, a number of environmental studies were conducted in an attempt to temporally and spatially characterize the extent of the environmental degradation due to acid mine contamination. Most of these studies were based on field site assessments. In recent years, remote sensing in collaboration with ground surveys has been employed in order to develop the means to monitor long-term forest structural changes adjacent to the mine tailings.

3.6.1. Environmental studies.

Acid mine drainage from the site has caused significant impairment to the local environment. Due to government concerns of public safety several environmental studies were undertaken between 1980 and 1992 by the Ontario Ministry of Northern Development and Mines in collaboration with the Ontario Ministry of Natural Resources (O.M.N.R.) and Falconbridge Limited. These studies included surface drainage and receiving water sampling, groundwater sampling, soil sampling, sediment and tailings sampling. Moreover, annual monitoring of the groundwater quality has been conducted since 1980 to determine seasonal and long-term changes in water chemistry. The main purpose of these studies was to identify the nature and extent of the environmental impact of mine contamination resulting from past mining activities at the site (Ferguson, 1993).

Walsworth (1998) provided a summary of two environmental studies undertaken between 1982-1984 at the Kam-Kotia mine site, namely studies by Kilborn Ltd. (1983) and GTC Geologic Testing Consultants (1984). The purpose of these studies was to provide remediation alternatives and controls based on environmental assessment. The

first study indicated that the initial damage in the southern tailings area was a result of a spill from an outflow pipe and of leachate from sulphide-rich waste rock piles. Kilborn Ltd. proposed the construction of a seepage ditch along the western side of the tailings area to re-direct the tailings seepage away from the nearby Kamiskotia community.

The second study by GTC used computer modelling to predict acid generation rates at the Kam-Kotia site. The results of this study showed that sulphate discharge in the Kam-Kotia River would increase to 500% in the next 30 years. The remediation proposed by GTC was to confine all water leaving the unimpounded tailings, thus creating local ponds which would decrease acid generation rates.

In 1990 a long-term revegetation project was undertaken by Laurentian University (Winterhalder, 1992; 1995). The goal of this study was to conduct small scale trials of different low-cost revegetation methods. The preliminary revegetation field trials investigated the effectiveness of covers such as gravel, loam, and peat at different depths and combinations, as well as revegetation of metal tolerant plant species. The initial results of this study showed that a combination of revegetation methods would be the best approach including a cover of loam or gravel or both. Metal tolerant plants from the Sudbury area also showed some promise in the early stages of this project. However, these efforts, along with previously proposed remediation measures, remained at the experimental stage, as they required further capital to implement on the site.

In 1994, a study of the tailings composition was carried out by Fortin *et al.*, (1996) at the Kam-Kotia mine site to determine the role of iron-oxidizing bacteria (*Thiobacillus*) in Fe cycling. This study showed that *Thiobacillus* and other sulphate-reducing bacteria (SRB) are closely involved in Fe cycling in acidic and oxic mine

conditions. Tailing samples recovered from the site were highly oxidized and acidic ($2 < \text{pH} < 4$). The chemical and microbial oxidation of iron sulphides observed in the Kam-Kotia tailings was extensive, resulting in near depletion of pyrite at certain depths, while the lower portion of the tailings profile seemed to be characterized by melanterite ($\text{FeSO}_4 \cdot 7\text{H}_2\text{O}$) precipitation, an iron sulphate mineral found in abandoned tailings with high pyrite content.

3.6.2. Remote sensing research.

In previous image studies Mussakowski and Chan (1993) proposed the use of a drainage model in order to explain acid mine contamination at the Kam-Kotia mine site. This model was developed using digitized O.M.N.R. airphotos of the site dating back to 1946. According to this study the catastrophic spread of the tailings associated with forest die-back in the tailings area is evident during the years of mine operation. On the other hand landscape changes become more subtle after the closure of the mine in the early 1970's (Walsworth, 1998).

In an attempt to assess forest damage induced by acid mine contamination at the Kam-Kotia study area, a long-term research project was designed by D. King in 1992. The overall goal of this project was to develop forest health monitoring methods using spectral, textural and structural image measures extracted from high-resolution airborne digital camera imagery (Seed and King, 1997).

Walsworth (1998) conducted temporal modelling of forest change (1960-1990) using O.M.N.R. photography and cellular automata techniques to predict tree canopy dynamics in relation to distance from the tailings. This study derived canopy transition

probabilities for mortality and growth that were based on spatial characteristics in a local neighbourhood around each tree. Significant temporal trends toward canopy opening and deciduous growth were established in the 200m of forest next to the tailings while further away the trend was towards successional replacement of deciduous forest by coniferous. This indicated that the area near the tailings is very dynamic and undergoing change that does not follow normal successional trends.

Seed and King (1997) developed empirical models of canopy structure based on linear combinations of image shadow fractions. Significant correlations were found between forest structure measures, such as leaf area index, canopy closure, and basal area, with the image shadow fractions extracted from airborne digital camera imagery using thresholding techniques. The sensitivity of this model was attributed to three shadow fractions (deep, transitional, and diffuse), that provided surrogate information on the spatial distribution of canopy structure.

Lévesque and King (1996; 1999), investigated the relation of semivariogram parameters in 0.25–1m resolution airborne digital camera imagery with forest structure and health at the study site. The 0.5 m pixel resolution semivariogram range was significantly correlated with forest canopy measures such as crown size, tree height, and canopy closure. The semivariogram range from 0.25m resolution imagery was highly related to individual tree crown closure.

The principal limitation of the studies of Seed and King (1997) and Lévesque and King (1999) is that forest variables were only analyzed individually. During these studies it became evident that forest structural health would best be represented by a set of forest parameters, each describing an aspect of the damage. Subsequent work has therefore

used multivariate analyses of forest structure and damage parameters. Olthof and King (2000) developed an initial forest health index using a combination of forest parameters and an image model of the forest health index using image spectral and textural measures extracted from 0.5m pixel resolution digital camera imagery. Canonical correlation analysis was conducted to evaluate the relationship between multiple image variables and forest structure variables. Stepwise regression was employed to determine the contribution of selected individual image variables to the variance of the forest structure canonical variate (forest health index). Accordingly, the significant image variables were linearly combined for the formulation of the model, which was used to spatially characterize the variation of forest health in the study area.

The methodology of this research is an extension of that presented by Olthof and King (2000) but additionally includes: 1. Improved image acquisition and processing techniques, 2. Temporal analysis of ground-measured and image-predicted forest change, and 3. Incorporation of a new technique for image shadow fraction generation.

4. METHODS

This chapter describes the research methods in five general groups: 1. field data acquisition, including a description of the field plot location and the sampling methods used to conduct the forest survey; 2. comparison of the 1997 and 1999 forest measures; 3. airborne image acquisition and image processing prior to analysis; 4. the multivariate statistical analysis techniques employed for the development of an image-based forest health index using the 1997 data; 5. application of the image-based health index to the 1999 image data and validation using the 1999 field data; and 6. temporal analysis of forest health at the site using airborne imagery and field information from 1997 and 1999.

4.1. Field data acquisition.

The 1997 field and image data used in this research were acquired by Olthof (1999), while 1999 data were acquired as part of this thesis research. Field measurements were made in 44 plots located along six parallel transects, labeled A-F from east to west (Figure 4.1). These plots are a systematic subset of 84 plots that had been installed during previous research in 1997. This plot subset was deemed appropriate for continued spatial and statistical analysis while reducing the amount of field work required. The plots are 10m in radius (314 m²). The beginning of each transect is located at tailings' edge and the transect lengths range from 350m to 850m. The first plot is located 10m from the tailings' edge the second at a 50m distance from the first; the rest are located at 100m intervals up to 500m and beyond that at an interval of 200m.

Figure 4.1. Transects and field plot locations at the study site.

The sampling scheme was spatially biased, including more plots in the area near the tailings' edge, because previous studies (Lévesque and King, 1999; Walsworth and King, 1999; Olthof and King, 2000) had showed greater forest damage closer to the tailings' edge. This approach was considered appropriate to ensure that adequate representation of the forest variability was provided. Geographic coordinates for each plot and a variety of other locations were obtained using GPS techniques as described in 4.1.3.

4.1.1. Vegetation sampling.

In vegetation sampling, all standing trees above 2m in height were recorded; species were identified and diameter at breast height (DBH) was measured. Severe tree inclination was also noted if the tree was leaning on other trees causing damage, or if it was considered that it could not be seen from above due to its angle. The status of the standing trees was assessed visually, in order to distinguish between live (presence of foliage) and dead trees.

After all standing trees in a plot were recorded, all fallen trees were counted and species were identified. Care was taken to record only the fallen trees where the root system or main trunk was located within the plot. However, it was not always possible to identify the species of fallen trees, especially if the trunk had started to deteriorate. The perceived cause of death was noted in order to distinguish between snapped and uprooted blowdown trees. This was considered an important factor of forest health, since previous research showed that the number of fallen trees is related to the soil type and the presence of strong blowing winds (Everham, 1996; Olthof, 1999). It was not possible, however, to determine if a fallen tree had been dead before falling or not. The percent cover of the

shrub layer was recorded only in cases where it was extremely high, and therefore would interfere with the estimation of leaf area index (Seed, 1998; Olthof, 1999).

Plot basal area was estimated for all standing and fallen trees. Basal area is a measure of stem density and tree size and is an indirect measure of stand biomass (Seed, 1998). Basal area was derived for each tree from the diameter at breast height (DBH) using Equation 5 (Avery, 1975).

$$\text{Basal Area} = (\pi D^2) / 4 \quad (5)$$

where: $\pi = 3.14$ and $D = \text{DBH of a tree in centimeters}$. It was summed over all trees in the plot to provide the total plot basal area (m^2/plot).

4.1.2. Measures of leaf area index (LAI) and canopy closure using Li-Cor LAI-2000 PCA.

Leaf area index (LAI) is a commonly used parameter for quantifying forest structure and can be defined as the dimensionless index that represents the projected one-sided leaf surface area per unit ground surface area (Deblonde *et al.*, 1994; Eschenbach and Kappen, 1996). Another measure of forest structure is canopy closure, which is the percent of a forest area occupied by the vertical projections of tree crowns (Avery, 1975).

The determination of LAI and canopy closure as measures of forest structure are significant in forestry and can be used to monitor changes in forest productivity and forest health. For example, as the forest canopy becomes more open, there is less leaf coverage, which is represented by low LAI values and canopy closure. For large areas, reflected spectral radiances that are remotely sensed from airborne and spaceborne

platforms have been used to derive LAI (Chen and Cihlar, 1995). In this study, LAI was employed as a measure of forest structure because previous research had shown that it is significantly related to image measures (Olthof and King 1997; Seed and King, 1997; Olthof and King, 2000).

LAI can be measured either directly or indirectly. Direct measurements of LAI are labour intensive and destructive in nature, as they imply felling trees in the stands being studied. Consequently, an indirect method with an optical instrument was used for the measurements. An LAI-2000 Plant Canopy Analyzer (PCA) was used to measure the forest canopy cover and LAI from visible light penetration through to the forest floor. It estimates the total gap fraction, which is the percent of sky seen from underneath the canopy, at different angles (LAI-2000, Li-Cor, Inc., 1991). The LAI-2000 PCA provides continuous measurements of LAI that can be repeated frequently over a large area in a non-destructive fashion.

According to Eschenbach and Kappen (1996), optical techniques using light interception, such as the LAI-2000 PCA, actually measure the plant area index (PAI) as they include other tree elements apart from leaves, such as branches, stems and cones. Also, these methods often assume a random distribution of leaves in the canopy instead of clustering which occurs in nature leading to underestimation of actual LAI. Hence, this instrument provides a measurement of effective LAI (LAI_e) in a relative rather than an absolute sense.

The LAI-2000 PCA uses hemispherical optics and a ringed detector that simultaneously measure diffuse radiation in five distinct angular bands, centered at 7° , 22° , 38° , 52° , and 68° about the zenith. The narrowest view angle 0° – 15° (7° zenith

angle midpoint) represents a number of sample points penetrating the canopy directly above and therefore is used to estimate canopy closure, while the first three rings give the best estimate for LAI_c (LAI-2000, Li-Cor, Inc., 1991). Recent research (Frazer *et al.*, 2000) showed that rings 1–4 can also provide accurate estimates of LAI_c. The fifth ring (60°–74° view angle) was purposely omitted from these calculations, as it includes leaf area contributed by the understory vegetation cover due to the wide field of view (0°–74°) (Seed, 1998; Frazer *et al.*, 2000). In this case, the damage of the overstory canopy was of greater importance as it could be detected in the imagery, while the understory vegetation would not be visible from above.

The Li-Cor measurements were taken in late August in 1997 and 1999 to coincide with the time of the image acquisition, and were taken at dusk or at dawn under uniform diffuse sky conditions to avoid any interference from sunlit crown, the clouds or the sun. A view cap limiting the azimuth field of view was also used to ensure that only diffuse light was striking the sensor and that if the operator's shadow appeared, it would not influence the measurements. Care was also taken to ensure that both sensor heads were directed towards geographic North during the measurements. A test designed by Welles and Norman (1991) determined that a 45 degree cap should be used to reduce the measured errors caused by linear averaging of different gap fractions, such as dense foliage and a large gap. Two calibrated instruments both outfitted with such caps, were used for all measurements. One LAI-2000 unit was placed in a large open area to record the open sky, which is equivalent to above-canopy radiation, and a second unit was carried along the transects to take below-canopy readings at the plot centres. To

minimize the contribution of the understory vegetation, the instruments were leveled at a 2m height above the ground.

Canopy closure and leaf area index values are derived indirectly using LAI-2000 measurements (Welles and Norman, 1991). Two LAI_c values were derived for each plot by dividing the below and the above canopy readings using the LAI-2000 software provided with the instrument. Specifically, the first LAI value was estimated using rings 1–3, and the second from rings 1–4. Canopy closure was estimated for each plot using Equation 6 (Chen and Cihlar, 1996).

$$\text{Canopy Closure} = (1 - G(7^\circ)) * 100 \quad (6)$$

where: $G(7^\circ)$ = gap fraction estimated for the first sensor ring centered at 7° (zenith angle midpoint).

4.1.3. GPS locations.

Prior to the image acquisition in 1999, ten targets were placed along the perimeter of the study area to mark the ends of each transect. White shower curtains 1m² in size were used as targets because they were distinctly visible in contrast to the surrounding tailings and vegetation in multispectral airborne imagery. Care was taken to place the targets at locations easily seen from above to ensure that they would be located in the imagery.

The positions of these targets and the plot centres were recorded using a portable Trimble GPS (Pathfinder Pro XR/XRS) unit, as it provided real-time differential

correction and up to 0.40m accuracy. The Navstar GPS satellite system, which is a constellation of orbiting satellites, was used to provide the data for differential correction.

Location measurements were taken in late October after leaf-fall to avoid interference of the GPS signal from deciduous forest foliage. Approximately 10 to 30 readings were recorded at each sample station, which were then averaged automatically to provide a more accurate location estimate. At some plots it was not possible to get a reading due to thick coniferous vegetation or high trunk and branch density. For these, the location on the transect closest to the plot was sampled and the distance and bearing to the plot centre noted. The GPS coordinates were processed using the "pathfinder office" package included in the Pro XRS, and the Universal Transverse Mercator (UTM) projection was used as the output format.

4.2. Analysis of forest structure change (1997–1999) and spatial pattern.

Before embarking on an image model of forest health and temporal analysis, it was necessary to ensure that real forest structural changes had occurred in the 1997-1999 period. The two forest structure data sets were compared using student t-tests. Typically, this type of test is used to assess the difference between two independent sample means. For example, it can be used to compare populations that have been exposed to two different treatments. In this case forest structure measures were sampled at two different dates from the same study plot locations. This type of test has been used successfully in the past to detect forest change in a common scene (Murtha, 1983).

The t-statistic is defined as the ratio of the difference between the means of two groups to their standard error. The standard error is the difference between the means of

the two groups to be expected due to sampling error, shown in Equation 7 (Hair *et al.*, 1998).

$$t_{\text{statistic}} = (\mu_1 - \mu_2) / SE_{\mu_1\mu_2} \quad (7)$$

where: μ_1 = mean of group 1, μ_2 = mean of group 2, and $SE_{\mu_1\mu_2}$ = is the standard error of the difference in group means.

By forming the ratio of the actual difference in group means to the difference expected due to sampling error it is possible to quantify the difference between the two groups which is due to sampling error. A two-tailed test is performed. If the absolute value of the estimated t-statistic is greater than an estimated critical value (t-critical), then the null hypothesis of no difference ($H_0: \mu_1 - \mu_2 = 0$) is rejected (Davis, 1986). In other words, the two groups are significantly different.

The spatial pattern of all forest structure measures was also evaluated in relation to distance from the tailings' edge and compared between the two dates. The purpose of this comparison was to determine if any gradients or other patterns exist that may associate forest deterioration with proximity to the tailings. In addition, this approach may also reveal whether changes have occurred in the underlying processes that control forest structure at the study site.

4.3. Image acquisition and processing.

4.3.1. Image data.

A multispectral digital sensor (AMDFCS) incorporating a Kodak Megaplug 1.4 black-and-white, 1300X1000 pixel format camera was used for the image acquisition. The camera is entirely computer controlled with a rotating filter wheel placed in front of a 28mm focal length lens providing a total view angle of 18.2 X 14.3 degrees. It provides 8-bit data in up to eight user-selectable spectral bands of $\geq 10\text{nm}$ bandwidth within the range of 450nm to 900nm (King, 1995).

Imagery from 1997 and 1999 was used in this study. The first set of images were acquired August 18, 1997 and the second set August 19, 1999. Imagery from three different altitudes was obtained for both dates providing ground pixel spacings of 0.25m, 0.50m and 0.80m. The 0.50m pixel imagery was considered appropriate as it provided enough detail for the forest structure analysis (Olthof, 1999). Due to camera acquisition rate constraints (6.7 frames/s; 10 Mbytes/s) only four spectral bands could be obtained with enough overlap at this resolution. They were: Blue (430–470 nm), Green (545–555 nm), Red (665–675 nm), and Near-infrared (895–905 nm) band (Figure 4.2.). Four flight lines were flown in order to provide full coverage of the study area and to obtain adequate overlap between the image frames.

4.3.2. Band-to-band alignment

The sequential image acquisition of the camera-filter wheel assembly combined with an aircraft speed of about 40m/s resulted in offsets of approximately 6.7m (13–14 image rows) between spectral bands. These offsets were corrected by aligning three of

the four bands in each multispectral set to the fourth (reference band), using a minimum of four ground control points (GCP). A first-order transformation (Equations 8 and 9) and least-squares linear model were used to rectify the images to the reference frame (Lillesand and Kiefer, 1994).

$$x' = f_1^n(x, y) \quad (8)$$

$$y' = f_2^n(x, y) \quad (9)$$

where: (x', y') = uncorrected image coordinates (column, row), (x, y) = corrected (map) coordinates, and f_1^n, f_2^n = transformation functions of the n^{th} -order.

Figure 4.2. Original digital frame camera imagery from the 1999 data: 1. Near infrared, 2. Red, 3. Green, and 4. Blue band. Pixel spacing is 50cm.

Nearest-neighbour interpolation was performed in the resampling stage. In this procedure, the brightness values closest to the x' , y' location in the uncorrected image are extracted and relocated to the appropriate x , y coordinate location in the rectified output image (Richards and Xiuping, 1999). The model fit of the correction was estimated using the root-mean-square (RMS) error of the control points used in the correction, shown in Equation 10 (Jensen, 1996).

$$\text{RMS} = \left\{ \frac{\sum \{ (X' - X)^2 + (Y' - Y)^2 \}}{N-1} \right\}^{1/2} \quad (10)$$

where: (X', Y') = estimated coordinates in the original image, and (X, Y) = original row and column of the GCP in the rectified image.

In the final step of this process, the spectral bands are subset according to the smallest frame in the data set. Therefore, the resulting multispectral image was slightly smaller than the original one, which was 1300X1000 pixels in size.

4.3.3. Brightness correction

Remotely-sensed imagery that relies on the sun for terrain illumination and optical components for image formation suffers from spatial brightness variations due to sun angle and view angle. There are many techniques for correction of these effects that are based either on physical models of the terrain reflectance and optical characteristics, or on the brightness variations themselves. The latter group are applicable only to a given set of imagery but are advantageous for research in that they are simple and efficient to apply. One such correction technique involves determination of the mean of

each column of an image and fitting a polynomial to the set of means crossing the image. The polynomial is then inverted to normalize the brightness values across the image (PCI, Inc., 1994). In the 1999 images of this study, brightness variations were most evident in the N–S direction due to sun angle effects and the camera shutter, which opens and closes from one side of the entrance aperture. Closer visual inspection of the image sets revealed minor brightness variations in the E–W direction as well, probably due to lens vignetting; for this reason the correction was applied twice, once in the EW, and a second time in the NS direction. Specifically, the correction was applied first in the horizontal direction of the frame and then the image was rotated 90 degrees and corrected again in the vertical direction. The final corrected image was returned to its original position by rotating it 270 degrees.

The correction was applied using a second-order polynomial. In the PCI software, this correction was implemented using an algorithm designed for antenna pattern correction in radar imagery according to Equation 11.

$$\text{OUTPUT}(X) = [(\text{INPUT}(X) - \text{Min}) / (P(X) - \text{Min})] * \text{Mean} \quad (11)$$

where: $\text{OUTPUT}(X)$ = corrected output grey level at pixel position X ; $\text{INPUT}(X)$ = uncorrected input grey level at pixel position x ; Min = minimum input grey level of image; Mean = mean input grey level of image; and $P(X)$ = estimated mean grey level at pixel position x based on polynomial function.

Typically, this type of correction is effective when applied to images with uniform land cover (PCI, Inc., 1994). Nevertheless, it can accommodate non-uniform

land cover if a homogeneous portion is specified instead of the entire image. The corrections are calculated for the selected sub-area and then applied to the whole image.

Several tests were conducted for each spectral band to investigate the effects of the correction on mean image brightness and texture by comparing the uncorrected and corrected images. Visual assessments of the corrected images and their corresponding spectral plots were also used to determine the validity of this correction. Furthermore, the 1997 image data was not corrected as view angle effects were not noticeable in the imagery (as shown later in Figure 5.6). This was a result of two factors: 1. The camera was oriented E-W so the differential exposure due to the shutter mechanism was not added to bi-directional reflectance effects as in the 1999 data, and 2. The overall exposure level of all bands was much lower in this data (i.e. the images were a lot darker).

4.3.4. Mosaic procedure.

A mosaic consists of a number of multispectral image frames (scenes) joined in a seamless composite. Mosaics were assembled for both the 1997 and 1999 data, using a total of ten scenes to provide full coverage of the study site. All bands of each scene were registered simultaneously to the mosaic, as they had been previously perfectly aligned to each other. A multispectral mosaic of the whole study site was produced using a minimum of four ground control points (GCPs). Care was taken to select well-defined GCPs for the image registration to ensure that accurate polynomial models were generated. Nearest-neighbour interpolation was employed for the resampling process.

As there were still some residual spatial brightness variations (the above corrections were not perfect), colour matching was performed in the final stage of the

image registration in order to make the seams of the mosaic less noticeable. In this process the histograms of the overlap area between the two contiguous images that are being joined are matched. According to this procedure the image being registered is considered the uncorrected, and the mosaic image represents the reference or corrected data set. First, the histograms of both images, the reference and the uncorrected, are matched and then a “lookup table” (LUT) is generated to store the corrections. In the final step, the LUT is applied to all values in the uncorrected image in order to create a colour-balanced image.

4.3.5. Image georeferencing.

Once the 1999 mosaic of the study site was completed it was georeferenced to a standard cartographic projection and scale for the study area. The UTM coordinate system (Zone 17, Row U) was used for the corrections. First the 1999 mosaic was rotated by 90 degrees to coincide with geographic North to ease the correction. A total of eight GCPs were selected and a second-order transformation was used to warp the 1999 mosaic to the UTM grid. This transformation was considered appropriate for the correction, as it provided a more accurate fit and lower RMS than a first-order transformation.

Next, the 1997 mosaic was aligned to the georeferenced 1999 mosaic. Sixteen control points and a second-order transformation were used to tie down the 1997 mosaic to the 1999 grid. Both mosaics were resampled using nearest-neighbor interpolation. The RMS error at all stages of the georeferencing process was less than half a pixel.

4.3.6. Extraction of image subscenes.

Once the 1997 and 1999 mosaics were georeferenced and overlaid, all image subscenes corresponding to the field plots were extracted. Although the field plots were 10m radius in size it was not possible to extract circular sets of pixels from the image. In addition, several image measures such as texture have been designed for square scenes and cannot be applied to circular images. Hence, square subscenes were extracted, which corresponded to slightly bigger field plots, as they included data that extended to the corners of the square outside the plot range. As the image resolution was 50cm the subscenes were 40 by 40 pixels in size. Initially, the coordinates of the plot centre were used to locate the image subscenes in both mosaics. This was not possible in some cases due to imperfections present in the 1997 mosaic. However, care was taken to ensure that the scene centre was perfectly aligned for both image dates. In the next step, the upper right and lower left corner were calculated by adding and subtracting 20 pixels (or 10m) from the plot centre accordingly. Finally, the multispectral subscenes were extracted simultaneously from the two image dates. A total of thirty-six out of forty-four plots were extracted from the imagery, where data were available for both 1997 and 1999 image data.

4.3.7. Relative radiometric normalization of the image subscenes.

Images acquired on different dates must be subjected to brightness normalization as the atmosphere and imaging parameters may have changed. In fully calibrated sensors and with atmospheric correction, absolute comparisons can be made between images

acquired on various dates. However, the procedures for these calibrations are costly and tedious and do not lend themselves well to operational implementation of remote sensing.

Instead, relative radiometric correction of remote sensing data can be used where the intensities of one image are normalized to another (the reference image) (Hall *et al.*, 1991; Jensen 1996). This method does not require sensor calibration or information on the atmospheric conditions and therefore corrects the images from a common scene in a relative, rather than an absolute sense. There are several techniques to conduct relative radiometric calibration. Available relative methods include: 1. the Gaussian method, where the image histogram is used to determine an appropriate threshold value between areas of “change” and areas of “no change”, the radiometric corrections are then conducted on the areas of “no change” (Singh, 1989); 2. deterministic normalization method, which is used to calculate a path radiance correction for a constant (near zero) reflectance target (Eckhardt *et al.*, 1990); 3. linear regression using normalization targets (constant reflectors) present in both the reference scene and the scene being normalized (Hall *et al.*, 1991; Heo and Fitzhugh, 2000); 4. histogram matching, which matches the image histograms from the same area for two different dates (Chavez and MacKinnon, 1994);. 5. histogram adjustment of a multispectral image scene, where the spectral bands are corrected according to a reference band of the same scene using a subtractive bias (Jensen, 1996).

The radiometric correction technique used in this study was similar to the histogram adjustment method. The purpose of this correction was to reduce the brightness differences between the two image dates, without changing the overall shape of their histograms. Visual inspection of band histograms revealed that the exposure of

the 1997 image was much lower than the 1999 image resulting in lower brightness and small brightness range. Therefore the 1999 subscene bands were selected as reference for the correction of the corresponding 1997 scenes. By performing a linear contrast stretch, the 1997 histograms were fit to the corresponding reference (1999) histogram range. This approach was considered appropriate because it would provide images with the same histogram ranges, and thus reduce the brightness differences.

Furthermore, due to the low radiometric quality of the 1997 image and relatively narrow histogram ranges, this method can be viewed as equivalent to histogram linear contrast stretching (Equations 12 and 13).

$$F(X) = [A * (X - ISTR_1)^n] + OSTR_1 \quad (12)$$

$$A = [(OSTR_1 - OSTR_2) / (ISTR_2 - ISTR_1)]^n \quad (13)$$

where: X = input grey-level value, $F(X)$ = output grey-level value, A = scaling factor, n = power exponent (linear expo=1), $ISTR_1$ = minimum input grey-level value, $ISTR_2$ = maximum input grey-level value, $OSTR_1$ = minimum output grey-level value, and $OSTR_2$ = maximum output grey-level value.

New values were derived for each input brightness value according to the new output range. A lookup table (LUT) was then generated to tabulate the corrections, which were applied to the uncorrected image to perform the linear stretch. The results of this correction were evaluated visually, by comparing the corrected 1997 to the corresponding 1999 image subscenes. The image histograms were closely examined to

determine if any errors had occurred, such as changes in the overall distribution of the corrected histograms. It must be noted, however, that histogram adjustment of the 1997 data to match the range of the 1999 was based on the assumption that there was no overall change in brightness due to other factors.

4.4. Extraction of image parameters from plot subscenes.

Once all image subscenes for both dates were radiometrically corrected, image parameters that have previously demonstrated good relationships with forest structure measures (Seed and King, 1997; Olthof and King, 2000) were extracted. These parameters were included in the analysis and consisted of: 1. shadow fractions, and sunlit crown proportions using image clustering, 2. vegetation index (NDVI), 3. image texture, and 4. mean brightness in each band.

4.4.1. Image subscene classification for the extraction of shadow and sunlit crown fractions.

Multispectral classification is one of the most frequently used methods of information extraction from remote sensing imagery. The overall objective of image classification is to automatically categorize all pixels into distinct spectral classes. Unsupervised clustering was used in this case to provide an unbiased and consistent method for the classification of the subscenes of both image dates. Clustering was conducted to derive information on the shadow components and sunlit crown proportions present in each scene.

Classification was conducted using the ISOCLUS method, which is a widely used iterative clustering algorithm that requires relatively little input from the operator (Jensen, 1996). The strength of this method is the sensitive control of the spectral homogeneity of the clusters (Latifovic *et al.*, 1999). First, the number of classes is specified and then, the clustering algorithm examines the data statistically and automatically creates clusters. In the first iteration, each pixel is assigned to the cluster whose mean is closest in Euclidean distance (Jensen, 1996). Once the initial clusters are formed the means are re-calculated and pixels are re-assigned to other closer means if necessary. When the means do not move more than a specified threshold, the process stops, and produces a classification map and a statistical report with proportions of each class, as well as the mean spectral brightness of the clusters.

The results of the unsupervised classification were evaluated visually by comparing the original with the classified images in order to identify which land cover classes were represented by the classified spectral classes. In the final step of this procedure a classification report is generated from which the shadow fractions and the sunlit canopy proportions are derived.

4.4.2. Vegetation index transforms.

Vegetation indices provide a quantitative measure indicating the vigor of vegetation and show better sensitivity than individual spectral bands for green vegetation detection (Bannari *et al.*, 1995; Vogelmann, 1990). Likewise, vegetation indices, such as the normalized difference vegetation index (NDVI) (Equation 14) may also be viewed as a surrogate for vegetation scene content (Wulder *et al.*, 1997).

$$\text{NDVI} = (\text{Nir} - \text{Red}) / (\text{Nir} + \text{Red}) \quad (14)$$

where: Nir = subscene mean brightness for the near-infrared band, and Red = subscene mean brightness for the red band.

It was calculated for the 1997 and 1999 image subscenes and used in subsequent analysis.

4.4.3. Texture analysis.

Image texture was quantified using the co-occurrence matrix measure “Contrast”. A co-occurrence matrix tabulates the frequency of occurrence of all pairs of digital numbers (DNs) for corresponding pairs of sample pixels separated by a given distance and angle within a sample window of specified size (Pellikka *et al.*, 2000). “Contrast” is the sum, for all sample pairs in the window, of probabilities of each sample pair of DN times the square of their difference (PCI, Inc., 1994). When adjacent DN are similar “Contrast” texture is low. “Contrast” increases quadratically as the difference between adjacent DN increases, because of the inclusion of the squared difference of the DN in its calculation.

The mean and standard deviation of “Contrast” texture were selected for the texture analysis based on previous tests conducted using the 1997 imagery at the study site (Olthof and King, 1997). These measures were derived for each of the Red (Tex2, Texv2) and Green (Tex3, Texv3) bands of the image subscenes. These bands were selected for the extraction of texture measures as they had better radiometric quality (sharper) than the Nir and Blue bands. A sampling distance of 1 was applied in all

directions around the centre pixel (omni-directional) and a 3X3 window was implemented for the calculation to maximize information of local texture.

4.5. The complete data set.

The abbreviations and description of all forest and image variables used in the analysis are presented in Table 4.1. The data set included eight forest structure variables and twelve image variables. The forest structure variables consisted of measures of stem density, basal area, effective leaf area index (LAI), and canopy closure. Furthermore, stem density and basal area were estimated for live, standing dead, and blown down trees in each plot. The image variables included spectral measures, radiometric fractions, and texture measures.

IMAGE VARIABLES		FOREST STRUCTURE VARIABLES	
<i>Spectral</i>		<i>Stem density</i>	
Nir	Average Nir brightness	Lstem	Live stem density (trees/plot)
Red	Average Red brightness	Dstem	Dead stem density (trees/plot)
Green	Average Green brightness	Bdstem	Blowdown stem density (trees/plot)
Blue	Average Blue brightness		
NDVI	(Nir-Red) / (Nir+Red)	<i>Basal area</i>	
<i>Radiometric fractions</i>		Lbasal	Live basal area (m ² /plot)
S1	Deep shadow	Dbasal	Dead basal area (m ² /plot)
S23	Transitional shadow	Bdbasal	Blowdown basal area (m ² /plot)
S4	Sunlit crown	<i>Li-Cor measurements</i>	
<i>Contrast texture*</i>			
Tex2	Average texture (Red band)	Lai3	Effective leaf area (rings 1-3)
Tex3	Average texture (Green band)	Lai4	Effective leaf area (rings 1-4)
Texv2	Texture variation (Red band)	Canopy	Canopy closure (ring 1)
Texv3	Texture variation (Green band)		

* Contrast texture was extracted using a 3X3 window and a sampling distance of 1 in all directions (omni-directional)

Table 4.1. Forest structure and image variables for 36 field plots and image subscenes.

4.6. Statistical analysis to determine an integrated forest health index and image model of forest health.

The statistical analysis consisted of two multivariate techniques: 1. canonical correlation analysis between image and forest variables, and 2. Multiple regression of image and forest structure. These represent complex procedures that are subject to certain assumptions as well as rigorous interpretation, and therefore are described in detail in this section.

4.6.1. Canonical correlation analysis between image and forest variables.

The objective of the canonical correlation analysis (CCA) was to investigate the relationships between forest health parameters and image parameters to develop an forest-health index that is associated with multiple image variables. Such an analysis was initially conducted for the 1997 data by Olthof and King (2000). However, certain data problems limited its success, so an improved data set and methodology was developed for this research.

The goal of canonical correlation is to describe the number and nature of mutually independent relationships existing between two variable sets (Stevens, 1996). CCA can be viewed as a logical extension of multiple regression analysis. Whereas multiple regression predicts a single variable from a set of multiple independent variables, canonical correlation simultaneously predicts multiple dependent variables from multiple independent variables. Similar to principal component analysis, the underlying principle of CCA is to develop linear components (canonical variates) of the two sets of variables to maximize the correlation between them (Equation 15) (Hair *et al.*, 1998).

$$Y_1 + Y_2 + Y_3 + \dots + Y_n = X_1 + X_2 + X_3 + \dots + X_n \quad (15)$$

where: Y_i ($i=1,2,\dots,n$) represent the dependent variables and X_i ($i=1,2,\dots,n$) represent the independent variables.

Canonical variates are computed in descending order of magnitude. In the first step, the pair of canonical variates (canonical functions) that provides the highest correlation possible between the two variable sets is derived. Successive pairs of canonical functions are computed based upon the residual variance, which has not been explained by the previous variate pairs. Thus, each of the variate pairs for the same data set is orthogonal and independent of all other canonical functions. The number of canonical functions that can be derived for a data set equals the number of variables in the smaller of the two variates (Thompson, 1984). However, not all canonical functions may be statistically significant at a specified level (eg. $p \leq 0.05$).

Canonical correlation has been used in the past for temporal analysis and to detect relations between sets of multiple variables. For example, Neilsen *et al.* (1998) used canonical correlation in order to detect changes in multispectral bi-temporal image data. The basis of this approach was to relate image change to the differences between the variable sets of the canonical correlation. Korobov and Railyan (1993) and Jakubauskas (1996) used CCA to examine the relationships between image spectral and plant measurements.

Required statistical assumptions

Canonical correlation is constrained to identify linear relationships. Therefore, if the canonical variates relate in a nonlinear manner, the relationship will not be captured by canonical analysis. In addition, values that lie outside the distribution can also have an undue influence on the canonical correlation just as they have on other statistical analyses (Tabachnick and Fidell, 1996; Stevens, 1996; Hair *et al.*, 1998). The impact of these outliers should be minimized prior to the canonical analysis in order to enhance the canonical results (Olthof, 1999). In this case, a separate search for univariate outliers was conducted for all the individual variables of the 1997 and 1999 data sets. For small sample sizes (below 80 observations), cases falling outside 2.5 standard deviations may be designated as outliers (Hair *et al.*, 1998). These offending values were also assessed visually to determine their position in relation to the distribution and were corrected only in the case that they were the cause of non-normality. However, due to the small sample size (36 observations) deletion of the outlying cases was not deemed appropriate. Instead, a technique proposed by Tabachnick and Fidell (1996) was used to reduce the influence of these problematic values. According to this approach, the outlying cases are assigned a value on the offending variable that was one unit larger or smaller than the next most extreme case in the distribution.

Similar to other multivariate techniques, normality is desirable because it standardizes the distribution and allows for higher correlation among the variables. CCA can also accommodate non-normal variables if the correlation between the variables does not decrease. However, multivariate normality is required to perform the statistical significance test for each canonical function. Multivariate normality is hard to assess

because it requires that all variables and all their linear combinations be normally distributed. As an alternative, transformation of the offending variables is suggested in order to ensure linearity and normality (Tabachnick and Fidell, 1996; Hair *et al.*, 1998). Initially, a visual examination of the variable distribution may reveal whether it differs from normal. Statistically, there are two components of normality, “skewness” and “kurtosis”. The first has to do with the symmetry of the distribution; a skewed variable is one whose mean does not lie at the centre of the distribution. On the other hand, “kurtosis” can be defined as the peakness of the distribution; a non-normal distribution may be either too peaked or too flat. Significance tests of both “skewness” and “kurtosis” were conducted by comparing the obtained z value to the null hypothesis (Equation 16 and 17) (Tabachnick and Fidell, 1996).

$$Z = S_s / (6/N)^{1/2} \quad (16)$$

$$Z = S_k / (24/N)^{1/2} \quad (17)$$

where: S_s = “skewness”, S_k = “kurtosis” and N = sample size

According to Hair *et al.* (1998) for small sample sizes a z score greater than the value of 2.5, shows that the distribution differs substantially from normal, and thus requires transformation. The variables were transformed by taking the log (base 10 logarithm) of the offending variables, as this method performed best for the correction of the data to achieve normality. This correction was used to ensure the univariate normality and linearity of the variables.

The issue of sample size is often encountered in canonical correlation analysis. Very small sample sizes will not represent the correlations well, and meaningful relationships may not be observed. Consequently, it is important to ensure a minimum of 10 observations per variable to avoid “overfitting” the data (Tabachnick and Fidell, 1996; Hair *et al.*, 1998). However it is also important to note that very large sample sizes will have the tendency of indicating statistical significance in all instances.

High correlation between the variables in each set, otherwise known as multicollinearity, reduces the ability of this technique to isolate the impact of any single variable, making the interpretation less reliable. As principal components (PC) are orthogonal they were used instead of the original variables in order to reduce effects of multicollinearity and reduce the number of variables in relation to the number of observations Stevens (1996) in the analysis.

Principal component analysis of the variable sets

Prior to CCA a principal component analysis (PCA) was employed to reduce the dimensionality of the 1997 data sets (image and forest structure) and to provide orthogonal variables. PCA attempts to identify underlying dimensions, or principal components (PCs), that explain the pattern of correlations within a set of observed variables, with a minimum loss of information. Linear combinations of the original variables are derived, and often a small number of these account for most of the variance in the original data set.

PCA first seeks a linear combination that accounts for the maximum variance in the set of variables. Then, the next linear combination, orthogonal to the first, accounting

for the second largest variance in the set, is derived. Each successive principal component accounts for the maximum residual variance and is orthogonal to all other components.

Several criteria are commonly used for the selection of meaningful principal components. For sample sizes with less than 50 observations it is suggested that each PC should account for the variance of at least a single variable in order to be retained for the interpretation. A PC that represents an eigenvalue of one accounts for the same amount of variance found in a single variable. Thus, only the PCs having an eigenvalue of greater than 1 are considered significant (Kaiser, 1960; Stevens, 1996; Hair *et al.*, 1998). Secondly, the variables included in the PCA are well represented when their communalities are high, usually greater than 0.70. Communality is the amount of variance in a data set accounted for by a set of principal components. Accordingly, the selected principal components should account for most of the variance of the data, more than 75%.

Interpretation of the components is conducted using the variable loadings, which are the correlations between the variables and the PCs that are statistically significant. The statistical significance of the loadings is related to sample size. For small sample sizes (<50) the estimated critical value (loading) was equal to 0.75. This threshold was derived from a two-tailed test for significance ($\alpha=0.01$) (Stevens, 1996). Hence, only variables with loadings higher than 0.75 were considered statistically significant and were used in the interpretation. Variables that did not contribute highly (above 0.75) on any of the principal components were interpreted according to their highest loading.

Although principal components are useful in summarizing most of the variance found in the data with a smaller number of components, often components are not easily interpreted. Rotation of the principal components has been proposed by several researchers (Tabachnick and Fidell, 1996; and Stevens, 1996; Hair *et al.*, 1998) to improve the interpretability of the solution without changing its underlying mathematical properties. An orthogonal rotation method developed by Kaiser (1960) known as "varimax rotation", was used because it produces new orthogonal components that are more interpretable than the original ones. Specifically, the goal of the "varimax rotation" is to simplify the principal components, by maximizing the variance of the loadings within the principal components, across variables. Therefore, the spread in the loadings increases, as loadings that are high become even higher after rotation and loadings that are low become lower. Interpretation becomes easier as it becomes obvious which variables demonstrate the highest correlation with the principal components. However, "varimax" also tends to redistribute the amount of variance among the principal components so that they become more equal in importance.

Interpretation of canonical variates: relations of image and forest structure variable sets

As with most statistical techniques, establishing significance is the most common approach in evaluating a solution. The canonical correlation coefficients are considered statistically significant beyond a certain level, typically 0.05 or above. Below this, the independent functions are deemed insignificant and are excluded from the interpretation. As canonical variates (CV) are reported in descending order of importance, usually only the first few pairs of variates are analyzed.

Once significance is established the canonical correlation between the significant variate pairs is examined. The correlation coefficient is indicative of the magnitude of the relationship between the variable sets and the squared canonical correlation is the shared variance between a pair of variates. According to Tabachnick and Fidell (1996), most researchers do not accept canonical correlation values lower than 0.30, as they represent only 10% shared variance between the variate pairs.

4.6.2. Development of an image-based forest health model using multiple regression.

The set of forest structure principal components that formed the most significant canonical variate was selected as an integrated index of forest health that could be modelled by airborne imagery. It was included as the dependent variable in a multiple regression analysis in order to derive an image-based forest health model. The original image variables, which were previously included in the principal component analysis, were selected as the independent variables in the regression analysis. In this case, the image canonical variate, composed of image principal components, was replaced by the original image variables in order to simplify the interpretation of the regression and to quantify the relationship between each image variable and the forest health index.

A forward stepwise estimation method was used for the selection of the variables in the regression model. First, a correlation matrix for the independent image variables is constructed. The variables are evaluated depending on the magnitude of their correlation with the dependent variable (forest canonical variate). In the first step the predictor with the highest simple correlation is added to the regression. In subsequent steps,

independent variables that demonstrate smaller correlations are included in the regression. The independent variables enter the regression as long as their partial correlations are statistically significant. For example, variables may be dropped if their predictive power becomes insignificant when another independent variable is added to the model. The process is terminated when no new statistically significant information can enter the model equation. Initially, the independent variables were entered in the model at a statistical significance value of 0.05 and removed from the regression at an F probability of 0.10. However, due to the lower statistical significance of some of the image variables, the entrance probability had to be increased from 0.05 to 0.059, in order to allow more than one variable to enter the regression analysis, and thus obtain a more representative model.

As in other multivariate techniques, multicollinearity may obscure the results of the regression analysis because it reduces the unique predictive power of the independent variables. The variance inflation factor (VIF) was used to assess the collinearity between the predictors. It measures the degree to which each independent variable is explained by other independent variables (Equation 18).

$$\text{VIF} = 1/(1-R^2) \quad (18)$$

where: VIF= variable inflation ratio, and R^2 = is the squared multiple correlation

A VIF value of 5.3 or above was used as a cutoff threshold, which corresponds to correlations (r) of more than 0.90 among the independent variables (Tabachnick and Fidell, 1996; Hair *et al.*, 1998).

Significance tests were conducted on the different models derived from the stepwise regression to determine the goodness of fit. Hence, the selection of the best-fit model was based on the following criteria: 1. the highest adjusted coefficient of determination (adjusted R^2); 2. the lowest standard error of estimate (SE); and 3. using as few variables as required. The coefficient of determination measures the proportion of the variance of the dependent variable explained by the predictor variables. Hair *et al.* (1998) suggests the use of the adjusted R^2 , because it takes into account both the number of independent variables included in the regression equation and the sample size. Moreover, the simple coefficient of determination will always rise when new independent variables are added in the model, whereas the adjusted R^2 may decrease if the added independent variables have little explanatory power or if the degrees of freedom become too small. Thus, adjusted R^2 was considered a more reliable measure than the simple R^2 for the determination of the best-fit model.

Normal probability plots of the residuals were also constructed and examined for any departures from normality. As a final evaluation, a graph of the standardized residuals versus the predicted values was generated in order to determine the validity of the selected best-fit model, and to check for any departures from linearity or any trends in the residuals.

4.7 Temporal analysis of forest health.

Once the best-fit regression model was selected for the 1997 plot data it was applied to the 1999 image data in order to derive the image-predicted forest health index for each plot. The difference of the two scores (1999-1997) was used as a measure of

image-predicted forest change. In the same way, the 1997 forest structure variate was applied to the 1999 forest structure data for each plot and the difference of the two scores (1997, 1999) was used as a measure of actual forest change.

Forest change maps (1999-1997) were interpolated for the entire study area using the image-predicted and the actual change data for the thirty-six plots. The spatial analyst extension of the ArcView geographic information system (GIS) was used for the map interpolation. The maps were interpolated using an inverse distance weighted algorithm (IDW). This interpolator assumes that each point has a local influence that diminishes with distance. It weights the point that is closer to the processing cell more than those farther away. A specified number of points within a radius can be used to determine the output value for each location (Bohnam-Carter, 1994).

A value was interpolated for each cell in a specified grid using four neighbouring points. Specifically, the values of these four points were weighted according to their distance from the cell being analyzed and then they were averaged. This process is repeated until each map-cell (pixel) is given a value, creating a continuous map (ArcView GIS, 1997).

Classification of forest change

A hierarchical cluster analysis was conducted in order to identify the underlying plot groupings in the image-predicted forest change score. This approach was useful as it revealed information on the structure of these scores. The selection of the optimum number of clusters was based on both the Euclidean distance between the clusters and similarity measures generated for each class member.

A linkage or clustering criterion is a quantity that determines whether a partitioning of the samples is necessary. Linkage can be classified further as: 1. between-cluster linkage, which quantifies comparisons between the clusters; and 2. within-cluster linkage, which quantifies all samples within a single cluster. A within-cluster linkage (Ward's method) was used in this case as it mimics the biological hypothesis that samples from common environments are similar (Fishbein and Patterson, 1992). Initially, this agglomerative hierarchical algorithm considers each object or observation as an individual cluster. In subsequent steps, the clusters closest in Euclidean distance are joined to form a new aggregate cluster. This process continues until all observations are joined to form one large cluster (Fraley, 1999). In this cluster analysis the classification of objects is based on the following criteria: 1. the distance between two clusters is the sum of the squares between the two clusters summed over all variables; 2. the within-cluster sum of squares is minimized over all partitions obtainable by combining two clusters; and 3. clusters with small numbers of observations are combined. This method is presented as dendrograms relating pairs of clusters to a parent cluster.

Interpretation of forest changes and validation

Forest changes were interpreted on a plot-by-plot basis. For example, when plots had a negative value in the change data (1999–1997) this was interpreted as a decrease of the forest health score. Moreover, the magnitude of change was also examined in order to determine areas that presented greater decrease or increase in forest health than others. Plots that showed significant decrease in forest health were compared visually to determine whether significant changes were evident from comparison of common image

subscenes of the two dates. All areas representing a different change class value were also evaluated in terms of their proximity to the tailings and tree species composition.

The actual forest change score was used for the validation of the image-predicted forest change score. Their difference was derived in order to determine in which plots the image-predicted score deviated from the actual forest change score. Furthermore, the two forest change maps (image-predicted and actual) were compared visually to assess the accuracy of the classification.

5. RESULTS

This chapter presents a comparison of the 1997 and 1999 forest structure data using paired t-tests, and an examination of their spatial distributions in relation to distance from the tailings' edge. The 1997 and 1999 image data were corrected for radiometric and geometric errors. Image processing results were used to create a mosaic of the entire study site and were evaluated based on the effectiveness of the corrections. The multivariate relations of the image and forest structure variable sets were evaluated using canonical correlation analysis to develop a forest health index as a linear combination of forest structure variables. Next, stepwise regression was employed to formulate an image-based model to predict the forest health index. Finally, a temporal analysis was of the forest health index and the image model was conducted.

5.1. Preparation of data prior to analysis.

In preparing the data for statistical analysis, a maximum of two outliers were corrected for each variable (Table 5.1) and three forest structure variables were log-transformed to achieve linearity and normality: live stem (Lstem_1), dead stem (Dstem_1), and dead basal area (Dbasal_1). None of the image variables for 1997 and 1999 required any transformation. An examination of the histograms and the z values for "skewness" and "kurtosis" was conducted after the transformation and it was determined that the variables had been corrected and their histograms were close to the normal distribution.

Variable set	Variables	Outlier ^a	Z_{sk} ^b	Z_{ku} ^c
Forest Variables 1997	Lstem	F10, F60	2.85	1.42
	Dstem	D10	3.71	2.24
	Bdstem	F10	2.25	0.31
	Lbasal	C310	0.95	-0.14
	Dbasal	A710	3.15	0.82
	Bdbasal	A10, F10	2.11	0.87
	Lai3		1.17	0.37
	Lai4		0.36	-0.31
	Canopy		-0.38	-1.07
Image Variables 1997	Nir	C210	1.59	0.45
	Red		1.87	0.46
	Green		0.67	-1.20
	Blue		-0.51	0.27
	NDVI	A10	0.45	0.28
	S1		0.87	-0.36
	S23		0.31	-1.40
	S4		0.47	0.52
	Tex2		1.16	-0.79
	Texv2		1.63	-0.05
	Tex3		1.51	-0.39
	Texv3	F10	2.18	1.04
Forest Variables 1999	Lstem	F10	2.89	0.89
	Dstem	D10	6.4	10.23
	Bdstem	D10	2.50	1.78
	Lbasal		1.38	-0.33
	Dbasal	A710	3.07	0.91
	Bdbasal	F60	2.28	0.89
	Lai3		-0.15	-1.04
	Lai4		-0.23	-1.06
	Canopy		-1.73	0.13
Image Variables 1999	Nir	B410	2.41	1.36
	Red		1.98	0.72
	Green	F210	1.66	0.65
	Blue	A10	0.79	0.64
	NDVI	A10	-0.78	1.29
	S1		-0.56	-0.87
	S23		-0.33	-0.15
	S4	F210	1.92	0.49
	Tex2	D210	1.54	0.44
	Texv2	D310	1.48	0.76
	Tex3	D310	1.24	0.21
	Texv3	D310	1.76	2.19

^a values greater than 2.5 standard deviations

^b Z_{sk} is the statistic value (z) for "skewness" (S_s) calculated from equation 16 (section 4.6.1.).

^c Z_{ku} is the statistic value (z) for "kurtosis" (S_k) calculated from equation 17

Table 5.1. Detection of outlier plot values and estimated z values for the 1997 and 1999 data.

5.2. 1997-1999 forest structure change analysis.

A paired t-test (two-tailed) was conducted between the 1999 and 1997 forest structure data. The goal of this test was to determine if individual forest structure variables had changed significantly between 1997 and 1999 and whether this change was greater than the sampling error (standard error of mean). It was a necessary initial step before embarking on image modelling. Student's t-values and their significance for these differences are presented in Table 5.2.

		Paired Differences				t	Sig. (2-tailed)	
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference			
					Lower			Upper
Pair 1	bdbasal	-6.3E-02	.164438	2.7E-02	-.118693	-.0074	-2.301	.027
Pair 2	bdstem	-5.06	10.74	1.79	-8.69	-1.42	-2.823	.008
Pair 3	canopy	-14.1354	19.4426	3.2404	-20.7138	-7.5569	-4.362	.000
Pair 4	dbasal	3.2E-02	9.48E-02	1.6E-02	-.4E-04	6.E-02	2.006	.053
Pair 5	dstem	5.56E-02	4.18	.70	-1.36	1.47	.080	.937
Pair 6	lai3	-.3618	.9495	.1583	-.6831	-.0405	-2.286	.028
Pair 7	lai4	-.2852	.7425	.1237	-.5364	-.0340	-2.305	.027
Pair 8	lbasal	9.1E-02	.114886	1.9E-02	5.2E-02	.129638	4.740	.000
Pair 9	lstem	-5.39	12.67	2.11	-9.68	-1.10	-2.552	.015

Table 5.2. Paired t-tests for 1997 and 1999 forest structure variables.

The absolute t-value from the variable pairs (1999, 1997) from Table 5.2 ranges from 0.80 to 4.740. These values are compared to a t-critical value of 1.668 computed for the variable pair at a 0.05 significance level (Davis, 1986). Eight of nine differences are significant indicating that significant changes have occurred in the forest structure between 1997 and 1999. Canopy closure and live basal area differences are the most significant. This provides evidence that the Kam-Kotia study site is indeed a dynamic

environment. However, no significant changes were detected for the dead stem variable pair in the same period of time; the overall number of standing dead trees in most plots is similar for both dates. This indicates that mortality by contamination or natural causes is not as important in this two year period as blowdown.

5.3. Spatial distribution of forest structure.

All forest structure variables collected from the study site field plots in 1997 and 1999 were examined in relation to their proximity to the tailings' edge. These field plot measurements are presented in Appendix 1. The results of the spatial analysis showed that overall live, dead, and blowdown stem density all decrease with distance from the tailings (Figure 5.1). A strong increase of live stems and slight increase of blowdown are observed between 1997 and 1999. The most significant changes were observed for plots adjacent to the tailings' edge at a 10m distance. For example, live stem counts increased from 118 to 168 at plot F10 and blowdown increased from 17 to 74 at plot D10 between 1997 and 1999. The increase in live stem density from 1997 to 1999, could be due to the increased number of blowdown trees. Moreover, the blowdown trees created gaps in the forest canopy allowing for new trees to grow. However, similar to the t-test results there is no evident change in the trend of dead stem density with distance between 1997 and 1999.

In some plots there is a slight decrease in Bdstem, which was attributed to stem deterioration of the fallen trees. Blowdown trees included in the 1997 survey were a result of accumulated forest deterioration over the last twenty years. Therefore, it is

possible, especially in the wetter areas, that some of the blowdown trees had greatly deteriorated and as result were not included in the 1999 measures.

Live basal area (Lbasal) increases with distance from the tailings (Figure 5.2). Lower Lbasal is observed near the tailings possibly due to the presence of smaller trees. In addition, blowdown basal area (Bdbasal) decreased with distance from the tailings in the 1999 data. Blowdown is greatest closer to the tailings edge, where trees are unprotected from the strong winds developing over the open tailings area.

According to Figure 5.3 both canopy closure (Canopy) and effective LAI (Lai3, Lai4) increase with distance from the tailings, while their slopes decrease considerably from 1997 to 1999. Both, LAI and Canopy values have increased considerably closer to the tailings due to the new vegetation growth. Slope differences between LAI and Canopy from 1997 to 1999 indicate that understory vegetation has increased. Slope changes for Lai4 are greater than those observed for Lai3. As Lai4 uses a wider sampling angle (52°), the change in slope might better represent this increase in understory vegetation cover.

Figure 5.1. Scatterplots of stem density (live, dead, and blowdown) with distance from the tailings' edge for the 1997 and 1999 data.

* significant at > 0.05 level

** significant at > 0.001 level

Figure 5.2. Scatterplots of basal area (live, dead, and blowdown) with distance from the tailings' edge for the 1997 and 1999 data.

* significant at > 0.05 level

** significant at > 0.001 level

Figure 5.3. Scatterplots of canopy closure and effective leaf area index (LAI_e) in relation to the distance from the tailings' edge for the 1997 and 1999 data.

5.4. Image processing results.

Image processing was conducted in order to correct the 1997 and 1999 images from radiometric distortions. The algorithm was applied in two directions (NS and EW) to correct for brightness differences in the 1999 image frames. Figure 5.4. shows an example of an image frame (Nir band) from the 1999 data set before and after correction. The 1999 mosaic was constructed from the corrected datasets and was compared visually with an uncorrected mosaic (Figure 5.5. a, b). Three bands (Nir, Red and Green) are used to display the two mosaics in order to show the effect of the correction. Figure 5.5.b demonstrates the usefulness of the correction, as there are no brightness differences in the corrected mosaic.

The final georeferenced mosaics for 1997 and 1999 are shown in Figures 5.6. and 5.7. Image gaps (black areas) are present in the 1997 mosaic due to insufficient image overlap. The image subscenes were extracted from the mosaics simultaneously. Due to brightness differences between the mosaics a relative radiometric correction using histogram adjustment was applied to the 1997 plot subscenes. Figure 5.8 shows the correction of the 1997 image subscene (plot A10) using the 1999 image scene as reference. The minimum and maximum brightness values of the image histograms are matched for both images in order to stretch the 1997 to the 1999 min-max range. Visual inspection of the corrected subscene shows that it has brighter tones (sharper), while the 1997 and 1999 mean brightness values are still different.

Figure 5.4. Example of radiometric corrections on a 1999 image frame.

Brightness Correction of a 1999 image

b) Corrected image

a) Uncorrected image

Figure 5.5. 1999 mosaic: a. uncorrected image, and b. corrected image.

(b)

(a)

Figure 5.6. 1997 mosaic (Nir band) of the study area. Pixel spacing is 50cm.

1997 Mosaic Image:

Figure 5.7. 1999 image mosaic of the study area. Pixel spacing is 50cm.

1999 Mosaic image:

**Figure 5.8. Example of histogram adjustment correction for a 1997 subscene (A10):
a) 1999 image subscene, b) 1997 image subscene, and c) 1997 corrected image
subscene.**

a) A10 image subscene (1999)

min =58
max =176
mean=121

b) A10 image subscene (1997)

min =69
max =120
mean =85

c) 1997 corrected A10 subscene

min =58
max =176
mean =108

Unsupervised classification was performed in order to extract the radiometric components from the image subscenes for both dates. An example of the unsupervised classification is shown in Figure 5.9. for subscene A10 (1999). Three radiometric components were extracted: deep shadow (S1), transitional shadow (S23), and sunlit crown (S4). The darker tones of the image subscene are classified as deep shadow, the medium tones as transitional shadow, and the bright tones as sunlit crown. Visual inspection of the image classification revealed that the two shadow fractions, S1 and S23, contain information related to the dark regions of shadow between crowns and the smaller more heterogeneous areas of within-crown shadowing respectively. The sunlit crown fraction represented the illuminated portion of the tree crown. The radiometric fractions were estimated from the pixel count for each component in relation to the total pixels of the image subscene. For plot A10 transitional shadow represents the highest fraction (61%). Sunlit crown covers 22% of the image subscene, while only 16% is classified as deep shadow fraction.

a) Subscene A10 (1997 data set)

b) classified image subscene

S1 =Dark Shadow (26.50%)
S23 =Transitional shadow (59.44%)
S4 =Sunlit Crown (14.06 %)

Figure 5.9 Extraction of radiometric shadow components (S1, S23, and S4) using unsupervised classification

5.5. Multivariate relations between image and forest structure variables.

5.5.1. Principal component analyses.

Principal component analyses (PCA) were carried out for the two variable sets (forest structure and image) of the 1997 data. The results of these analyses are summarized in Table 5.3. The detailed PCA reports including the correlation matrices and the rotated factor matrices are included in Appendix 2. The image plot data used in the PCA for 1997 and 1999 are presented in Appendix 1.

Variable set	Component	Significant variables	Interpretation	Eigenvalue	Cumulative variance (%)
Forest structure	STR1	Lai3, Lai4, Canopy, (Lbasal)	Canopy closure (live tree volume)	3.739	41.546
	STR2	Bdstem, Bdbasal (Lstem_l)	Blowdown density & volume (the log transform of live stem density)	2.101	64.893
	STR3	Dbasal_l, Dstem_l	Dead stem, volume, & density (log-transform)	1.484	81.379
Image	IM1	-NDVI, Red, (Blue)	Spectral information	4.697	39.146
	IM2	S23, (-S1), Tex2, & (Texv2)	Transitional shadow, image (red) texture	2.132	56.914
	IM3	Tex3, Texv3, (Green)	Image (Green) texture and texture variation	1.531	69.674
	IM4	Nir, S4	Spectral information & sunlit crown fraction	1.310	80.587

* - sign shows inverse relationship

** variables in parenthesis had high loadings but were less significant (loading <0.75).

Table 5.3. Results of principal component analysis of 1997 data.

Forest structure components

The forest structure set, which included nine variables, was reduced to three components accounting for 81.3% of the total variance of the original variables. The loadings acquired from the rotated factor matrix (Appendix 2) were used for the interpretation of the components. These loadings represent the Pearson correlation coefficients between the variables and the components. Significant variables, with loadings greater than 0.75, were selected for the interpretation of each principal component. This threshold value was derived from a two-tailed significance test for 36 degrees of freedom ($P=0.01$) and was employed in order to ensure that the variables used in the interpretation contributed significant information to the components.

The first component of the forest structure set explains the variance in effective leaf area index and canopy closure. This component represents the highest percent of variance (41.5%) of the PCA and was also highly correlated with live basal area ($R=0.679$). Consequently, as the volume of live trees increases there is an increase in canopy closure and tree crown size.

The second component accounts for 23.3% of the total variance found in the original variables and is explained by blowdown stem density (Bdstem) and basal area (Bdbasal). Therefore, an increase in blowdown tree size and volume is accompanied by an increase in the number of blowdown stems. This also indicates that blowdown is more common in trees of greater stem size. Furthermore, the second component also related well ($R=0.580$) to the log of live stem density (Lstem_l). As the number of blowdown stems increases the forest canopy becomes more open and new trees start growing in the openings.

The third component explains 16.7% of the total variance of the original variables and is related to tree die-back (Dstem_1, Dbasal_1). Specifically, as the number of dead stems increases, there is an increase in dead stem size.

Image components

Principal component analysis reduced the set of image variables from 12 to 4. The derived image components represent image spectral, structure and textural information, and account for 80 percent of the total variance found in the original set of image variables.

The first component explains the variance in spectral information and accounts for 39.2% of the variance found in the original set of image variables. Specifically, it explained an increase in average red brightness (Red) accompanied by a decrease in NDVI (negative sign). As NDVI is related to vegetation abundance, this component is inversely related to the amount of vegetation present in an image subscene.

Both the second and third components represent image textural information from different bands as well as texture variation. Specifically, the second component is related to the texture and texture variation extracted from the red band (Tex2, Texv2) and the third component is related to the texture of the Green band (Tex3). The second component also explains the variation of the transitional (S23) and deep shadow fractions (S1), as an increase of the transitional shadow fraction is accompanied by a decrease of the deep shadow fraction (negative sign). Visual examination of image subscenes revealed that deep shadow is located at forest canopy openings, while the transitional shadow is brighter than deep shadow and is located in canopy gaps where new tree

growth has taken place or understory vegetation is visible. Therefore, as new trees grow in forest gaps the transitional shadow fraction increases while deep shadow decreases.

Finally, the last component represents 10.9% of the total variance and is related to crown information such as the sunlit crown fraction (S4), as well as the mean spectral brightness from the near infrared band (Nir). Hence, this component is directly related to tree crown coverage and condition.

5.5.2. Canonical analysis of the 1997 data and interpretation of the canonical variates.

A canonical correlation analysis was conducted for the image and forest structure variable sets of the 1997 data (Appendix 3). Three canonical variate pairs were extracted, of which only the first one was significant ($r=0.727$, $P=0.005$). It described variation in three forest structure components and four image components (Table 5.4).

Canonical variate (CV1): Forest structure	Canonical Variate (CV2): Image components	Canonical Correlation (r)	Sig. (P)
(0.199) STR1, (-0.973) STR2 (-0.118) STR3	(0.181) IM1, (-0.597) IM2, (-0.747) IM3, (0.231) IM4	0.727	0.005

Table 5.4. First canonical variate pair of forest structure and image variates, 1997 data.

The squared canonical correlation represents the amount of variance in one canonical variate explained by the opposite variate (Hair *et al.*, 1998). In this case the image variate (independent) explained 53% ($r^2=0.53$) of the variance present in the forest structure canonical variate (dependent). In contrast to multiple regression, canonical

correlation has multiple dependent variables instead of just one. hence the variate represents only a portion of the total variance (100%) of each dependent variable.

The contribution of each component to its canonical variate is represented by its canonical loading (weight) and the squared loading is the percent of variance in each variable shared by its own canonical variate. From the forest structure components the second component (STR2) had the highest loading (0.973), which shows that 94% of its variance is shared by its variate (CV1). Both the second and third component (STR2 and STR3), blowdown and dead stem densities and volume, are inversely related to the first component. Interpretation of these loadings indicates that an increase in blowdown trees and live stem density is accompanied by an increase in dead tree density and basal area, and a decrease in live basal area, canopy closure, and leaf area index (LAI_c).

From the image variate, the second and third components (IM2 and IM3) represent image textural and structural information. These components have significantly higher loadings and are inversely related to component one and four (IM1 and IM4), which represent spectral information and the sunlit crown fraction.

The canonical correlation analysis revealed a relationship between forest structure parameters and image structure, texture and spectral information. Specifically, a decrease in live tree volume and forest canopy closure, and an increase in blowdown, dead, and live stem counts (new tree growth) is associated with an increase in texture and transitional shadow fraction and a decrease in average scene brightness and sunlit crown fraction. Therefore, forest structure deterioration indicated by an increase in tree die-back and canopy openness and transparency manifests as an increase in image texture, and a decrease in average image brightness and sunlit crown fraction.

5.5.3. Forest health index.

The forest structure canonical variate (CV1, Table 5.4.) derived from the canonical analysis was used as an integrated index of forest health. The variate consisted of forest structure components which are directly related to indicators of forest health such as tree blowdown and die-back, live tree density, canopy closure and canopy vertical structure. As forest deterioration increases due to an increase of dead stems and blowdown trees, the forest canopy becomes more open and leaf coverage decreases. It should be noted, however, that this index formulation is dominated strongly by blowdown and thus may not be a representative measure of total forest health. Nevertheless, this index was generated by statistical correlation with the image data and represents a measure that can be detected by remote sensing.

The forest health index was formulated as a linear combination of the forest structure components (Table 5.4.). This index was then applied to the 1997 and 1999 field plot data to produce forest health estimates for all field plots.

5.5.4. Development of an image-based model of the forest health index.

The canonical analysis revealed a significant relation between the forest structure and image variates, each being represented by linear combinations of forest and image components respectively (Table 5.4). A stepwise regression was conducted using the original image variables to predict the forest health index. The goal of this analysis was to produce an image-based model of the forest health index. It was considered appropriate to use all the image variables instead of their components, to simplify the

regression and ease the interpretability of the results. Furthermore, the image components only represented 80.5% of the variance found in the original data set. therefore, by using the original variables, more variance could be utilized to increase the predictability of the image-based model. The results of the regression are summarized in Table 5.5. A detailed report of the regression analysis is presented in Appendix 4 including the model summaries, correlation coefficients, and descriptive statistics.

Step	Variable*	R	R ²	Adjusted R ²	Std. Error of Estimate (SE)	Sign.
1	Texv2	.632	.399	.381	.786	.000
2	Blue	.694	.482	.450	.741	.000
3	Tex2	.748	.560	.519	.694	.000
4	S4	.780	.609	.558	.665	.000
5	Tex3	.815	.664	.608	.626	.000

*a variable is added in each step of the regression

Table 5.5. Stepwise regression results of the forest health index (forest structure canonical variate) against image variables, 1997 data.

All variables entered in the regression had an F-probability between 0.059 and 0.1. In each step of the analysis a variable was added to the regression model, starting with the variable that had the highest correlation with the dependent variable. The combination of these five image variables produced the best-fit model with the highest adjusted R² (0.608) and the lowest standard error (0.626). The standard error decreased from step 5, from 0.78 to 0.626. The selected best-fit model (Table 5.5.) included: texture and texture variation from the Red band (Tex2, Texv2), texture from the Green band (Tex3), sunlit crown fraction (S4), and mean brightness from the blue band (Blue). The variable inflation ratio (VIF) for step 5 (best-fit model) of the regression ranged from 1.218 to 4.735 (Table 5.6.). Therefore, multicollinearity of all variables included in the

model was within acceptable levels, as the variance inflation ratio (VIF) was less than 5.3.

Model from step 5:	Coefficients	Standard Error	Sig.	VIF
Constant	-0.176	0.829	0.833	NA
Texv2	-1.214	0.259	0.000	4.735
Blue	0.018	0.005	0.002	1.310
Tex2	0.446	0.172	0.015	3.744
S4	0.057	0.023	0.022	1.218
Tex3	-0.350	0.158	0.034	1.586

* dependent variable: field based forest health model

Table 5.6. Unstandardized coefficients and their standard errors for the best-fit regression model.

Figure 5.10. represents the normal probability plot of the residuals for the best-fit regression model of the forest health index. The straight line on the plot represents the occurrence of perfect normality. Overall, it can be seen that the residuals were normally distributed. Departures from the plot appeared minimal and isolated to no more than a few sample points. These results indicate that the selected best-fit model is appropriate to predict the forest health index.

A residual plot was also constructed for the best-fit model, as a graphical representation of the relationship between the dependent variable, the forest health index, and the standardized residuals of the regression (Figure 5.11.). The sample points used in

Figure 5.10. Normal probability plot of residuals for best-fit model of the forest health index from image variables.

Figure 5.11 Residual plot from the best-fit multiple regression model.

the plot correspond to the 36 image subscenes. The residual plot showed no systematic variation or trends from the regression line. Most residuals fell within the ± 2.5 standard deviations of the regression line, and only one observation (plot F10) slightly exceeded this threshold (-2.69). Therefore, no serious outliers were detected from the residual plot. This suggested that the selected model was effective in accounting for most of the observed variance found in the forest health index.

5.6. Temporal analysis of forest health.

The image model of the index was applied to both the 1997 and 1999 plot data. The 1999-1997 difference was then calculated as a measure of image-predicted change in the forest health index. The image-predicted forest change score (IM99-IM97) and the actual forest change score (STR99-STR97) (see section 4.7.) and are presented in Table 5.7. A positive sign in the change of the forest health index indicates decreased blowdown and increased vegetation cover, the negative sign indicates greater blowdown and decreased vegetation cover. The image-predicted score was 83% correct in detecting forest improvement and only 15% correct in detecting forest degradation. However, the magnitude of change is different for both scores. In most cases, the image-predicted health index was positively biased in relation to the actual change in the forest health index. The difference of the two forest change scores (error) was derived in order to determine discrepancies between them. Plots B10, C60, D10, D510, F10, F60, and F210 have the highest errors in the image-predicted forest health index. These errors might have occurred due to significant increase of tree blowdown. In fairly open overstories, the imagery detects both overstory changes and understory vegetation.

PLOTS	STR97	STR99	STR99-STR97	IM97	IM99	IM99-IM97	ERROR
A10	-2.52	-1.58	0.94	-1.64	-0.07	1.57	-0.63
A210	-1.53	-0.70	0.83	0.17	0.48	0.31	0.52
A310	0.47	0.67	0.20	0.22	1.30	1.08	-0.88
A410	0.70	1.60	0.90	0.58	0.18	-0.40	1.30
A510	1.38	1.75	0.37	1.06	1.38	0.32	0.06
A710	1.27	1.32	0.06	1.82	2.22	0.39	-0.34
B10	0.85	-0.82	-1.67	0.44	1.47	1.03	-2.70
B60	0.62	0.00	-0.62	0.57	1.46	0.89	-1.51
B110	-0.61	-0.06	0.56	-0.14	0.17	0.31	0.24
B210	-1.07	-0.37	0.70	-0.02	-0.19	-0.17	0.87
B310	0.90	0.23	-0.67	1.06	1.94	0.89	-1.55
B410	0.30	0.95	0.65	0.15	1.76	1.61	-0.96
B510	1.04	0.79	-0.25	1.09	0.92	-0.17	-0.08
B710	0.77	0.90	0.13	-0.16	0.89	1.05	-0.92
C10	-0.87	-0.46	0.41	-0.15	0.95	1.11	-0.70
C60	0.01	0.36	0.35	-0.81	1.16	1.97	-1.63
C110	-0.71	-1.10	-0.40	-0.60	0.27	0.87	-1.27
C210	1.16	1.29	0.13	0.84	1.43	0.59	-0.46
C310	0.23	-0.35	-0.58	-0.41	-0.36	0.05	-0.63
C410	0.09	0.17	0.09	-0.82	-0.40	0.43	-0.34
C710	-0.59	-0.40	0.18	-0.10	0.17	0.27	-0.09
D10	-0.74	-1.72	-0.97	-0.76	1.16	1.92	-2.89
D60	0.11	-0.66	-0.77	0.03	0.48	0.45	-1.21
D110	0.05	0.20	0.15	-0.20	1.13	1.33	-1.18
D210	-1.00	-0.63	0.37	-0.96	-0.69	0.27	0.10
D310	-0.32	-0.89	-0.57	-0.16	-0.98	-0.82	0.25
D410	-0.91	-0.41	0.50	-0.58	0.52	1.09	-0.59
D510	-0.01	-1.04	-1.04	0.11	0.82	0.71	-1.74
D710	1.03	1.42	0.39	0.35	-0.42	-0.77	1.16
E210	0.64	0.77	0.13	0.41	0.78	0.37	-0.24
E310	0.62	1.14	0.52	0.20	0.39	0.19	0.33
F10	-2.70	-2.10	0.60	-2.10	2.69	4.78	-4.19
F60	-0.59	-1.37	-0.78	-1.44	1.32	2.76	-3.54
F110	-0.02	-0.09	-0.07	0.39	1.21	0.82	-0.89
F210	1.02	0.01	-1.01	0.50	3.03	2.52	-3.53
F310	0.95	1.19	0.24	1.04	1.01	-0.03	0.27

Table 5.7. Image-predicted and (actual) forest change scores.

Other plots such as A510, B510, and C710 have low errors, as blowdown is low in these cases and the actual forest change score indicates that very little has changed between 1997 and 1999. Also, in some cases (A410, A510) the low stem density per plot might have introduced some error due to high canopy openness. The image-predicted and the actual forest change scores for each plot were used to interpolate forest change maps for the entire study site.

Classification of forest change and interpretation

Cluster analysis was conducted to determine the representative number of forest change classes. A moderate Euclidean distance of 8 was used to select the cutoff point for the cluster solution by a visual examination of the dendrograms (Figure 5.12. and Figure 5.13.). The cluster arrangement up to a distance of 8 is orderly, while beyond this point (8 to 25) the cluster fusion points occur at erratic intervals, which means that the clusters combined in this final step are highly dissimilar. This approach ensured that the selection of classes was not arbitrary.

The interpolated forest change maps (Figure 5.14. and Figure 5.15.) were classified according to the three dendrogram clusters. Examination of the plot change scores in relation to the actual forest change score determined that the three clusters represented: forest degradation (cluster 1); little or no forest change (cluster 2); and forest improvement (cluster 3).

According to the image-predicted map (Figure 5.14.), the areas closer to the tailings seem to be remediating and have been classified as cluster 2 or cluster3. Also, areas in the northern part of the study area near B510, D410, and D510, have been

classified as unchanged. Although there are some isolated cases of forest remediation, most of the forest near the northwest and north central seep and in the central bog area seems to be deteriorating. Visual examination of the forest change map (actual forest change) shows that forest degradation is concentrated near the tailings and in the central bog area. This is a depression area with sparse forest cover that consists of black spruce (Bs), balsam poplar (Bp), and balsam-fir (Bf)(Figure 3.5.). Furthermore, the area representing forest degradation has expanded from the tailings towards the northeast, indicating that forest degradation is related to the contamination caused by the tailings and the wind direction (northeast). The elevation contour map (Figure 3.3.) also indicates a decrease in elevation towards the northeast. Therefore, forest degradation at the study site might also be a function of topography and/or drainage. In contrast to the image-predicted forest change map, the actual forest change map indicates that the forest near the north west and central seep has improved or remained unchanged

Visual comparison of the two forest change maps (image-predicted and actual) revealed that high classification errors occur at the plots that are closest to the tailings' edge. These plots are characterized by severe forest structural damage mostly due to tree blowdown and to a lesser extent by tree die-back. As the canopy becomes more open, understory vegetation increases due to increased light penetration through the forest canopy. The image model estimates forest change as a combination of forest canopy overstory and understory vegetation while the forest health index only represents the overstory canopy. It is evident that the image model may predict overstory change in relatively closed canopies, whereas in more open canopies it is also influenced by understory vegetation.

Figure 5.12. Dendrogram of the image-predicted change in forest health index.

Figure 5.13. Dendrogram of the actual change in the forest health index.

Figure 5.14. Image-predicted forest change map (1999-1997).

Image-predicted forest health change:

Figure 5.15. Forest change (actual) map (1999-1997).

Field-based (actual) forest change:

6. DISCUSSION

The image-based model was evaluated as a tool for predicting changes in forest health. The results obtained from this study are compared with similar studies in the literature and evaluated according to the objectives outlined in the introduction. Possible sources of error and limitations encountered in this study are also discussed in detail, and directions for future research are recommended.

6.1. Evaluation of the multivariate analysis results based on previous literature.

Canonical correlation analysis (CCA) was used in this study to determine the relationship between sets of multiple image and forest structure variables and to develop an integrated measure of forest structural health. However, it is difficult to compare the present study with similar literature due to methodological differences that include: 1. varying types of remote sensing imagery and resolutions; and 2. differences in sample size and types of variables included in the analysis. Nevertheless, certain aspects of previous studies are comparable to the methods and results of this thesis.

This research examined the relations between nine forest structure variables and twelve image variables. Similar to Olthof and King (2000), this study used principal component analysis (PCA) to reduce the number of variables included in the canonical analysis. The use of PCA prior to the canonical analysis of this study is advantageous for two reasons: 1. it improves the dimensionality of the data by reducing the sample/variable ratio to approximately 10:1; and 2. it provides uncorrelated (orthogonal) variables for modelling.

The image measures involved in the CCA of this research included principal components that combined spectral, textural, and structural image measures. Similar to Pellikka *et al.* (2000), it was hypothesized that the integration of spatial and spectral information from high-resolution images would improve the prediction of forest structure measures. It was found that spatial image measures were more critical to the model than spectral measures. However, most other studies have only included spectral (Korobov and Railyan, 1993; Jakubauskas, 1996; Nielsen *et al.*, 1998) and textural (Olthof and King, 2000) measures in the canonical analysis.

In this research, three forest structure components were used in the CCA that represented: canopy closure, blowdown, and mortality. Jakubauskas (1996) used similar forest structure variables (eg. stem density, basal area, and LAI) sampled from homogeneous pine stands and found that almost 59% of the first forest variate is explained by the six reflective Thematic Mapper bands. However, in the present study the spectral information (Blue band) explained only 10% of the variation found in the forest structure variate. The most probable reason for this discrepancy was the difference in image resolution between the two studies. The former used low-resolution satellite imagery, so this study's much higher-resolution (airborne multispectral digital camera) imagery provided much more detailed spatial and spectral image data. In addition, the forest structure variate of this research was dominated by blowdown parameters, which are not considered in Jakubauskas (1996).

Korobov and Railyan (1993) used canonical correlation analysis to relate four spectral measures from an airborne spectroradiometer to four phytometric variables (percent cover, biomass, height, and plant density) from 20 winter wheat fields. Similar

to Jakubauskas (1996) they reported that the spectral variables explained at most 75% of the variance in phytometric variables. However, the main deficiencies of these two studies were the high correlation between the variables used in the analysis, and the low sample/variable ratio that may have contributed to inaccurate canonical correlation results and misinterpreted canonical variates (Hair *et al.*, 1998). Therefore, although the canonical correlation obtained in the present study ($r=0.727$) is lower than those obtained in these previous studies, it represents a more realistic relationship between the image and forest variables.

The canonical analysis used in this thesis has been successful in providing an integrated measure of forest health, which is significantly related to the image variables. Hence, multiple regression analysis is incorporated in order to relate the integrated measure of forest health (variate) to the image variables. Multiple regression has also been successful in that it has provided an image-predicted forest health estimate. Korobov and Railyan (1993) also proposed the use of multiple regression to derive equations relating each canonical variate to the opposite set of variables in order to quantify the relations between the two variable sets (spectral and plant measures).

Apart from the analysis of single data sets, canonical analysis has also been used for temporal analysis. Nielsen *et al.* (1998) used a CCA to detect the spatial pattern of change in sequences of satellite data. This approach was similar to the present study as it used a maximum autocorrelation factor (MAF), an extension of PCA, to post-process the image data. Then, the differences of the linear combinations (canonical variates) of the original data (spectral bands) were used to detect changes between different dates. While their study was successful in determining the spatial pattern of change between multiple

dates using spectral data, it did not provide any quantification of the magnitude of change in relation to ground-based truth.

The present study focuses on the detection of changes in forest health between two dates (1997, 1999). Olthof and King (2000) used the 1997 field and image data from the study area to develop an initial image-based model of forest health using CCA and multiple regression. However, as the quality of the 1997 data was poor, improvements were made in this study that also improved the forest health index formulation and image model of forest health and increased the canonical correlation from 0.58 to 0.73. The earlier model included only textural and spectral image measures, while this study incorporated image structural measures to improve the predictability of the image model. In addition, the previous study had only included textural measures that were extracted from the Green band whereas the present study also included the Red band in the textural analysis, as it was deemed through initial correlation analysis to provide complementary information.

Accordingly, the new image model produced from multiple regression was able to explain 66% of the variance found in the forest health index, which represents approximately a 100% increase when compared with the previous results (34%) obtained by Olthof and King (2000). The improvement of these results can be attributed to the image subscene corrections, inclusion of image structural data, and to the various texture and texture variation variables of the Green and Red band, which contributed more than 40% of the variance accounted for by the forest health index. Likewise, in the study by Olthof and King (2000), the texture measures also accounted for more than half of the variation explained by the image model.

6.2. Evaluation of forest change detection using an image-based model.

The image-based model developed for the 1997 data was applied to the 1999 image data. For most cases, image-predicted forest change seems to have positively overestimated the measured forest change from 1997 to 1999. The image-based model was 83% accurate in detecting improvement in the forest health (positive change) but only 15% correct in detecting deterioration (negative change) of forest health.

Plots that were not correctly predicted were investigated further. In many cases, errors could be attributed to significant increases in the understory vegetation. For instance, in some plots near the tailings new vegetative growth was significant and probably influenced the image measures, such as the mean brightness, texture and structure of the image subscenes, particularly since these plots generally had fairly open overstory due to significant tree blowdown. Consequently, in open damaged stands, the image-model seems to be sensitive to both overstory and understory vegetation. It was also in these plots that understory was most abundant due to increased light penetration through the canopy. However, understory trees, shrubs, and grasses (<2m) were not measured in the field. Thus, the image model might be an accurate measure of the overall vegetation abundance in such plots. The image-predicted forest change is different than the field-based estimate because the understory vegetation was not included in the forest structure measures or in the forest health index. In addition, such abundant understory vegetation does not necessarily mean that forest health has improved, as shrubs, grasses, and alders that make up most of this growth will not produce fully grown trees. Their presence is more indicative of a dynamic, open forest that, in this case, is under a high degree of stress. More research is needed to adopt the

forest health index to such conditions, and/or develop capabilities for differentiating forest understory structure from overstory structure in the image modelling process.

6.3. Sources of error, limitations in the study, and recommendations for future research.

In any research study involving the collection, measurement, and analysis of data, there is potential for errors to arise. In isolated cases errors in field recording may result in errors in the image-based model. For example, in plot A410 the image-predicted forest change indicated that forest health had deteriorated, while the field data indicated improved health. Closer inspection of the field data revealed that in this particular plot there might have been a recording error as the number of blown down stems decreased by 50% from 1997 to 1999. Such a change must represent an error as, over a two-year period, the only means for 1997 blown down trees to be excluded from the 1999 census is if they had decomposed to a non-recognizable level.

Errors may also have occurred in the temporal analysis as it involves the processing of multiple images and field data that usually have been acquired under different conditions. Although care was taken to minimize errors, several sources of error are unavoidable and may have influenced the results.

In temporal studies errors due to radiometric and geometric distortions are common. Geometrically, errors may occur due to the registration of the images used in the change analysis, as explained in Chapter 4 (band alignment, mosaicking, and georeferencing). Although the RMS error was less than half a pixel (25cm) during the registration stage, some errors were detected in the registration of the 1997 image to the

1999 grid. These were due to the image gaps present in the 1997 data introducing errors to the pixels close to them, as there were no control points in the gaps.

Radiometrically, brightness differences between images that are not due to ground cover changes can be attributed to varying conditions (eg. sun angle) during the image acquisition. In this study, brightness differences were evident in the 1999 image set possibly due to the orientation of the camera and sun angle effects. These errors were reduced using the polynomial fitting algorithm. However, as there were no brightness differences observed in the 1997 image, this correction was only applied to the one image set and thus some error may have been introduced due to the non-consistent image processing of the two image dates.

Although the two images used in this analysis were acquired on anniversary dates, brightness differences between the two image dates were also present. Normalization techniques using absolute calibration or relative correction are commonly applied in the correction of satellite images. Absolute calibration requires conversion of the images to radiance and then to reflectance. This approach is time-consuming, labour intensive, and costly as sophisticated equipment and/or software are needed for atmospheric correction. Instead, relative normalization can be conducted using linear regression of temporarily invariant targets (spectrally constant between images). As suggested by Jensen (1996), non-vegetative, flat areas can be used for the normalization of one image scene to a reference image. Due to missing data (image gaps) present in the 1997, and lack of appropriate normalization targets, this approach was also not possible. Moreover, as the image scenes represented a forested area, only areas on the mine tailings could be used for the correction. However, these areas were typically saturated in the visible spectrum

as the sensor exposure had been set to maximize the dynamic range of the forest in these bands. Dark, unchanging areas for use in such regressions were also not present. Absolute calibration had been attempted in 1997 and 1999 using two large felt targets (one dark, the other light) and a spectroradiometer measuring their reflectance during the flights. However, the high reflectance of the surrounding tailings caused saturation in the brighter target, rendering it unusable. Instead, a correction using histogram adjustment was performed on a plot-by-plot basis in order to improve the radiometric quality of the 1997 image using the 1999 image data as reference. The application of this correction was one of the major limiting factors of this study, as the image-based model derived from the statistical analysis could not actually be applied to the entire image using the image variables as input. As an alternative, a forest change map was interpolated for the entire study area using the image-predicted forest health index from each image subscene.

Image interpolation was useful as it provided a forest change map for the entire study area. Visual inspection of the two forest change maps determined that some errors might have occurred due to the small number of sample points used for the interpolation. Therefore, areas farther away from the sample points might not have been correctly interpolated. Furthermore, some isolated points within other homogeneously classified areas might have been misclassified due to residual error.

Although the image model used in this study was capable of detecting forest change, clearly more research is needed to match forest structural changes with image data for modelling purposes. In cases of high canopy openness due to increased tree blowdown, the model was not able to detect the canopy overstory structural changes as it

was also sensitive to the understory vegetation growth in the openings. For this purpose, future forest inventories should also include understory vegetation changes in temporal analysis as it is an important factor in forests with severe overstory damage. Calibration of the image model to the specific forest conditions should also be considered, as it might be used to improve the predictability of the model. Accordingly, future temporal studies should also include monitoring of forested areas with low or insignificant changes in time that could be used as control plots for validation purposes. In addition, further research is needed to develop methods of relative radiometric calibration of imagery that can accommodate pseudo-invariant targets in the tailings area or large forest openings as well as the forested areas of interest. In the same manner, improved absolute calibration for image correction should also be considered if this method is to be repeated both spatially and temporally.

7. CONCLUSIONS

A temporal analysis was used to assess the changes in forest health for an area affected by pollution from adjacent mine tailings. To that end an integrated measure of forest structure was used in order to describe forest canopy conditions and to detect forest changes using high-resolution remote sensing imagery. Whereas forest canopy condition is difficult to resolve using individual canopy structural attributes, a combination of forest structure measures is more appropriate to describe the overall forest canopy geometry.

Canonical correlation analysis was useful in this study as it provided an integrated measure of forest structure, which was indicative of forest health and was highly related to image measurements. This forest structure variate was a linear combination of three orthogonal principal components, which included tree blowdown, mortality, and canopy closure. The contribution of these three components was unequal, being dominated by the large forest changes caused by blowdown.

The image-based model of the forest health index quantified the relationship between the forest structure variate and image spectral and spatial information. The forest health index measures forest structural damage, indicated by a decrease in canopy closure (due to blowdown and mortality) and an increase in tree die-back. In the imagery, it is manifested as a decrease in average image brightness and sunlit crown fraction and an increase in image texture. Overall, texture was the most significant image variable as it explained more than 40% of the variance found in the forest health index. Furthermore, the inclusion of sunlit crown fraction in the model as a measure of image structure improved its predictability.

In forests, the cumulative effect of acid mine contamination over time may cause structural changes of decreased stem density and basal area, increases in tree mortality, die-back, and crown thinning. Significant changes in forest canopy structure such as tree blowdown may occur over a short period due to strong winds developing over large non-remediated tailings. The quantification of such changes presents a great challenge for research in remote sensing. As the forest canopy becomes more open, the understory vegetation also contributes partially to the vertical canopy geometry. Hence, the image model proposed in this study detects forest changes that include both overstory canopy degradation and understory vegetation growth. Research should continue on efforts to partition the effects of this re-growth from overstory effects, or to integrate measurement of re-growth into the model.

The methodology used to develop the image model in this thesis may be applied to the monitoring of forest structural changes in other settings such as around smelters or in mine rehabilitation. Furthermore, it could also be used as a forest management tool in assessing structure and health status of licensed management areas for ecological studies of wildlife habitats, and for provision of forest structure parameters such as LAI for climate models.

8. REFERENCES

- Anderson, J. E., and E.I. Robbins,** (1998). Spectral reflectance detection of iron oxide precipitates associated with acid mine drainage. *Photogrammetric Engineering and Remote Sensing*, 64(12): 1201-1208.
- Anderson, J.E., and M.B. Satterwhite,** (1995). Remote sensing of acid mine drainage using high resolution, narrow-band digital multispectral video. *In Proceedings of the 15th Biennial Workshop on Color Photography and Videography in Resource Assessment*. Terre Haute, Indiana. May 2-3 (American Society of Photogrammetry and Remote Sensing, Bethesda MD). pp.192-209.
- ArcView GIS,** (1997). ArcView GIS Extension Products: Introducing ArcView Spatial Analyst. Chapter 28: Introducing Arcview Network Analyst. 2nd edition. Environmental Systems Research Institute. Redlands, CA. Inc. 25pp.
- Avery, T.E.,** (1975). Natural Resources Measurements. 2nd edition. McGraw-Hill series in forest resources. Toronto, Ontario. 339pp.
- Avery, T.E. and G.L. Berlin,** (1992). Fundamentals of Remote Sensing and Airphoto Interpretation. 5th edition. Macmillan. Toronto, Ontario. 472pp.
- Bannari, A., Morin, D., Bonn, F., and A.R. Huete,** (1995). A review of vegetation indices. *Remote Sensing Reviews*, 13(1-2): 95-120.
- Barrie, C.T. and D.W. Davis,** (1990). Timing and magmatism and deformation in the Kamiskotia-Kidd Creek area, western Abitibi Subprovince, Canada. *Precambrian Research*, 46(3): 217-240.
- Bohnam-Carter, G.,** (1994). Geographic Information Systems for Geoscientists: Modelling with GIS. 1st edition. Pergamon. Oxford, England. 398pp.
- Brady, N.C.,** (1990). The Nature and Property of Soils. 10th edition. Macmillan. New York, United States. 621pp.
- Card, K.D. and A. Ciesielski,** (1986). DNAG#1. Subdivisions of the Superior Province of the Canadian Shield. *Geoscience Canada*. 13(1): 5-13.
- Chavez , P.S. and D.J. MacKinnon,** (1994). Automatic detection of vegetation changes in the Southwestern United States using remote sensing imagery. *Photogrammetric Engineering and Remote Sensing*, 60(5): 571-583.
- Chen, J.M. and J. Cihlar,** (1995). Plant canopy gap size analysis theory for improving optical measurements of leaf area index. *Applied Optics*, 34(27): 6211- 6222.

- Chen, J.M., and J. Cihlar, (1996).** Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sensing of Environment*, 55(2): 153-162.
- Courtin, G., Pappin, S., Beckett, P.J., and D. Carlsson, (1993).** Remote Sensing project: Elliot Lake field Station. *Proceedings of the '93 Conference of Mine Environment Neutral Drainage Program (MEND) Ontario (Abstract)*. Ministry of Northern Development and Mines. September 28-30. Sudbury, Ontario. 2pp.
- Cowan, W.R., and J.G.A. Robertson, (1999).** Mine rehabilitation in Ontario, Canada: Ten years of progress. *Proceedings of the '99 Conference on Mining and the Environment II*. September 13-17. Sudbury, Ontario. (CANMET, Ottawa, Ontario) Vol.3, pp.1037-1043.
- Davis, J.C., (1986).** Statistics and Data Analysis in Geology. 2nd Edition. John Wiley and Sons. New York, United States. 646pp.
- Deblonde, G., Penner, M., and A. Royer, (1994).** Measuring leaf area index with the LI-COR LAI-2000 in pine stands. *Ecology*, 75(5): 1507-1511.
- Doran, R.J., and J.A. McIntosh, (1995).** Preparation review and approval of mine closure (rehabilitation) plans in Ontario. *Proceedings of the '95 Conference on Mining and the Environment*. May 28- June 1. (CANMET, Ottawa, Ontario) Sudbury, Ontario. Vol. 1, pp. 281-288.
- Eckhardt, D.W., Verdin, J.P., and G.R. Lyford, (1990).** Automated update of an irrigated lands GIS using SPOT HRV imagery. *Photogrammetric Engineering and Remote Sensing*, 56(11): 1515-1522.
- Eschenbach, C. and L. Kappen, (1996).** Leaf area determination in an alder forest: a comparison of three methods. *Journal of Experimental Botany*, 47(302): 1457-1462.
- Everham, E.E., (1996).** Forest damage and recovery from catastrophic wind. *The Botanical review*, 62(2): 113-185.
- Ferretti, M., (1997).** Forest health assessment and monitoring-issues for consideration. *Environmental Monitoring and Assessment*, 48(1): 45-72.
- Feasby, D.G., Tremblay, G.A., and C.J. Weatherell, (1997).** A decade of technology improvement to the challenge of acid drainage - A Canadian perspective. *Proceedings of the Fourth International Conference on Acid Rock Drainage*. May 31 - June 6. (MEND) Vancouver, BC. 8pp.

- Ferguson, R.I.**, (1993). Environmental baseline study at the Kam-Kotia mine site. *Proceedings of the '93 Conference of Mine Environment Neutral Drainage Program (MEND) Ontario* (Abstract). Ministry of Northern Development and Mines. September 28-30. Sudbury, Ontario. 1pp.
- Filion, M.P., and K. Ferguson**, (1989). Acid mine drainage research in Canada. *Proceedings of the International Symposium on Tailings and Effluent Management (28th Annual Conference of Metallurgists of CIM)*. August 20-24. Halifax, pp. 61-72.
- Fishbein, E. and R.T. Patterson**, (1992). Error-weighted maximum likelihood (EWML): A new statistically based method to cluster quantitative micropaleontological data. *Journal of Paleontology*, 67(3): 475-486.
- Fortin, D., Davis, B., and T.J. Beveridge**, (1996). Role of Thiobacillus and sulfate-reducing bacteria in iron biocycling in oxic and acidic tailings. *FEMS Microbiology Ecology*, 21(1): 11-24.
- Forest Research Advisory Council of Canada (FRACC)**, (1994). Forest research priorities in Canada, 1993. An overview for the Canadian council of forest ministers. *The Forestry Chronicle*, 70(1): 84-87.
- Fraley, C.**, (1999). Algorithms for model-based gaussian hierarchical clustering. *SIAM Journal of Scientific Computing*, 20(1): 270-282.
- Franklin, S.E., Wulder, M.A., and M.B. Lavigne**, (1996). Automated derivation of geographic window sizes for use in remote sensing digital image texture analysis. *Computers and Geosciences*, 22(6): 665-673.
- Frazer, G.W., Trofymow, J.A., and K.P. Lertzman**, (2000). Canopy openness and leaf area in chronosequences of coastal temperate rainforests. *Canadian Journal of Forest Research* 30(2): 239-256.
- Gagnon, J.Y., Bruce, B.D., and A.A. Crowder**, (1985). The use of remote sensing for describing and evaluating the regeneration potential of an abandoned mining waste site, Western Quebec, Canada. *Proceedings of Symposium on Surface Mining, Hydrology, Sedimentology, and Reclamation*. December 9-13. (University of Kentucky Colleges of Engineering and of Agriculture, and Institute for Mining and Minerals Research) Lexington, Kentucky. pp. 273-277.
- Geological Testing Consultants Ltd.** (1984). KamKotia Tailings Reclamation project-detailed hydrological investigations program (1983-1984), Ottawa.
- Gitelson, A.A., and Y.J. Kaufman**, (1998). MODIS NDVI optimization to fit the AVHRR data series – spectral considerations. *Remote Sensing of Environment*, 66(3): 343-350.

- Glasser, C., Birger, J., Herrmann, B., and J. Boine.** (1999). Airborne hyperspectral data for the assessment of open cast lignite mining impacts in central Germany. *Proceedings of the Fourth International Airborne Remote Sensing Conference and Exhibition*. Ottawa, Ontario, June 21-24. (ERIM, Annual Airborne, MI). Vol. I. pp. 361-362.
- Gorham, E., and A.G. Gordon** (1960). The influence of smelter fumes upon chemical composition of lake waters near Sudbury, Ontario, and upon the surrounding vegetation. *Canadian Journal of Botany*. 38(1): 477-487.
- Goser, B.,** (1999). Acidic mining lakes – Acid mine drainage, limnology and reclamation. Book Review. *Aquatic Ecology*, 33(2): 213-214.
- Gray, N.F.,** (1997). Environment impact and remediation of acid mine drainage: a management problem. *Environmental Geology*, 30(1): 62-72.
- Hagner, O., and O. Rigina,** (1998). Detection of forest decline in Monchegorsk Area. *Remote Sensing of Environment*, 63(1): 11-23.
- Hair, J.F., Anderson, R.E., Tatham, R.L., and W.C. Black,** (1998). Multivariate Data Analysis. 4th edition. Prentice Hall. Upper Saddle River, New Jersey. 730pp.
- Hall, F.G., Strebel, D.E., Nickelson, J.E., and S.J. Goetz,** (1991). Radiometric rectification: Toward a common radiometric response among multitemporal, multisensor images. *Remote Sensing of Environment*, 35(1): 11-27.
- Hall F.G., Shimabukuro, Y.E., and K.F. Huemmrich,** (1995). Remote sensing of forest biophysical structure using mixture decomposition and geometric reflectance models. *Ecological applications*, 5(4): 993-1013.
- Hall F.G., Peddle, D.R., and E. F. LeDrew,** (1996). Remote sensing of biophysical variables in boreal forest stands of *Picea mariana*. *International Journal of Remote Sensing*, 17(15): 3077-3081.
- Hall, J.P.,** (1995). Forest health monitoring in Canada: How healthy is the boreal forest? *Water Air and Soil Pollution*, 82(1): 77-85.
- Haralick, R.,** (1979). Statistical and structural approaches to texture. *Proceedings of the IEEE*. 67(5): 786-804.
- He, M., Wang, Z., and H. Tang,** (1997). Spatial and temporal patterns of acidity and heavy metals in predicting the potential for ecological impact on Le An River polluted by acid mine drainage. *Science of the Total Environment*. 206(10): 67-77.

- Heo, J., and T.W. Fitzhugh, (2000).** A standardized radiometric normalization method for change detection using remote sensed imagery. *Photogrammetric Engineering and Remote Sensing*, 66(2): 173-181.
- Jakubauskas, M.E., (1996).** Canonical correlation analysis of coniferous forest spectral and biotic relations. *International Journal of Remote Sensing*, 17(12): 2323-2332.
- Jensen, J.R., (1996).** Introductory Digital Image Processing. A Remote Sensing Perspective. 2nd edition. Prentice Hall. Upper Saddle River, New Jersey. 316pp.
- Kaiser, H.F., (1960).** The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, 20(1): 141-151.
- Kallin, M., Van Everdingen, R.O., and G. Mallory, (1989).** Ecological Engineering measures developed for acid generating waste – the close-out of the decant pond. *Proceedings of the International Symposium on Tailings and Effluent Management (28th Annual Conference of Metallurgists of CIM)*. August 20-24. Halifax. pp. 195-204.
- King, D.J., (1995).** Airborne multispectral digital camera and video systems: A critical review of system design and applications. *Canadian Journal of Remote Sensing*, 21(3): 245-273.
- Kilborn Limited, (1983).** Kam-Kotia Tailings Reclamation Project. Final Report to the Ontario Ministry of the Environment. Timmins, Ontario.
- Korobov, R. M. and V.Y. Railyan, (1993).** Canonical correlation relationships among spectral and phytometric variables for twenty winter wheat fields. *Remote Sensing of Environment*, 43(1): 1-10.
- Latifovic, R., Cihlar, J., and J. Beaubien, (1999).** Clustering methods for unsupervised classification. *Proceedings of the Fourth International Remote Sensing Conference and Exhibition (21st Canadian Symposium on Remote Sensing)*. June 21-24. Ottawa, Ontario. (ERIM, Annual Airborne, MI). Vol. II, pp. 509-515.
- Lawrence, R.L., and W.J. Ripple, (1998).** Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape: Mount St. Helens, Washington. *Remote Sensing of Environment*, 64(1): 91-102.
- Legasy, K.L., Beadman-LaBelle, S., and B. Chambers, (1995).** Forest plants of Northeastern Ontario. Lone Pine publication. Edmonton, AB. 352pp.
- Lévesque, J. and D.J. King, (1996).** Semivariance analysis of tree crown structure in airborne digital camera imagery. *In Proceedings of the 26th International Symposium on Remote Sensing of Environment*. March 23-26. Vancouver, BC. pp. 275-278.

- Lévesque, J. and D.J. King, (1999).** Airborne digital camera image semivariance for evaluation of forest structural damage at a mine site. *Remote Sensing of Environment*, 68(2): 112-124.
- Lévesque, J., Staenz, K., Shang, J., Neville, B., Yearwood, P., and V. Singhroy, (1999).** Temporal monitoring of mine tailings revegetation using hyperspectral data. Sudbury . Ontario. Presented at the Thirteenth International Conference on Applied Geologic Remote Sensing, Vancouver, BC, CA. March 1-3. (Canada Center for Remote Sensing, Ottawa, Ontario) (unpublished).
- Li-Cor, Inc., (1991).** LAI-2000 PCA Operating Manual. Li-Cor, Inc., Lincoln. Nebraska.
- Lillesand, T.M., and R.W. Kiefer, (1999).** Remote Sensing and Image Interpretation. 4th edition. New York. United States. John Wiley and Sons Inc. 724pp.
- Lyon, J.G., Yuan, D., Lunetta, R.S., and C.D. Elvidge, (1998).** A change detection method using vegetation indices. *Photogrammetric Engineering and Remote Sensing*, 64(2): 143-150.
- Mackasey, W.O., (1989).** Concepts of dealing with abandoned mine hazards. *International Conference Proceedings, Surface Crown Pillar Evaluation for Active and Abandoned Metal Mines*. Nov. 15-17. Timmins, Ontario, pp. 135-141.
- Mackasey, W.O., (1993).** Ontario abandoned mines initiative. *Mine Environment Neutral Drainage Program (MEND) Ontario Conference (abstract)*. Ministry of Northern Development and Mines. September 28-30. Sudbury, Ontario.
- Mikkola, K., (1996).** A remote sensing analysis of vegetation damage around metal smelters in the Kola peninsula in Russia. *International Journal of Remote Sensing*. 17(18):3675-3690.
- Milton, N.M., Ager, C.M., Eiswerth, B.A., and M.S. Power, (1989).** Arsenic and selenium induced changes in spectral reflectance morphology of soybean plants. *Remote Sensing of the Environment*, 30(3): 263-269.
- Mitchell, A., and W.O. Mackasey, (1997).** A systematic inventory of abandoned mines- A powerful tool for risk assessment. *International Journal of Surface Mining Reclamation and Environment*. 11(2): 83-91.
- More, T.A., (1996).** Forestry's fuzzy concepts: An examination of Ecosystem management. *Journal of Forestry*, 94(4): 19-23.

- Mueller, A., Strobl, P., Lehmann, F., and G. Reinhaeckel, (1997).** Case studies of airborne remote sensing for the assessment of mining impacts. *Proceedings of the Third International Airborne Remote Sensing Conference and Exhibition*. Copenhagen, Denmark. July 7-10. Vol. I. pp. 257-264.
- Murtha, P.A., (1978).** Remote sensing and vegetation damage: A theory for detection and assessment. *Photogrammetric Engineering and Remote Sensing*, 44(9): 1147-1158.
- Murtha, P.A., (1983).** Some air photo scale effects on Douglas-fir damage. Type Interpretation. *Photogrammetric Engineering and Remote Sensing*, 49(3): 327-335.
- Mussakowski, R., and K. Chan, (1993).** Spatial modelling of abandoned mine tailings for environmental assessment-The Kam-Kotia test site. *The Geographic Information Series*. Ontario Ministry of Natural Resources (M.N.R.). Peterborough, Ontario, (unpublished).
- Nielsen, A.A., Conradsen K., and J.J. Simpson, (1998).** Multivariate alteration detection (MAD) and MAF post-processing in multispectral, bi-temporal image data: New Approaches to change detection studies. *Remote Sensing of Environment*, 64(1): 1-19.
- Olthof, I. and D.J. King, (1997).** Evaluation of textural information in airborne CIR digital camera imagery for estimation of forest stand leaf area index. *Proceedings of the First North American Symposium on Small Format Aerial Photography (American Society of Photogrammetry and Remote Sensing, Bethesda, MI)*. Oct. 14-17, Cloquet, MN. pp.154-164.
- Olthof, I., (1999).** Development of a Forest Health index using High-Resolution Remotely Sensed Multispectral Digital Imagery. Master's thesis, Carleton University, Ottawa, Ontario (unpublished), 184pp.
- Olthof, I. and D.J. King, (2000).** Development of a forest health index using multi-spectral airborne digital camera imagery. *Canadian Journal of Remote Sensing*, 26(3): 166-175.
- PCI Inc., (1994).** Using PCI software, (PCI 6.2). Richmond Hill, Ontario, Canada.
- Peddle, D.R., Hall, F.G., and E.F. LeDrew, (1999)** Spectral mixture analysis and geometric optical reflectance modeling of boreal forest biophysical structure. *Remote Sensing of Environment*, 67(3): 288-297.
- Pellikka, P., Seed, E.D., and D.J. King, (2000).** Modelling deciduous ice storm damage using aerial CIR imagery and hemispheric photography. *Canadian Journal of Remote Sensing*, 26(5): 394-405.

- Pratt, A.R., Nesbitt, H.W., and J.R. Mycroft** (1996). The increased reactivity of pyrrhotite and magnetite phases in sulphide mine tailings. *Journal of Geochemical Exploration*, 56(1): 1-12.
- Purevdorj, T., Tasheishi, R., Ishiyama, T., and Y. Honda**, (1998). Relationship between percent vegetation cover and vegetation indices. *International Journal of Remote Sensing*, 19(18): 3519-3535.
- Richards, J.A. and J. Xiuping**, (1999). Remote Sensing Digital Image Analysis: An Introduction. Springer-Verlag. Berlin. 363pp.
- Rosema, A., Verhoef, W., Noorbergen, H., and J. Borgesius**, (1992). A new forest light interaction model in support of forest monitoring. *Remote Sensing of Environment*, 42(1): 23-41.
- Revised Statutes of Ontario (RSO)**, (1990). The mining act of Ontario: Mine Development and Closure Under Part VII of the Act, *Ontario Regulation*. Chapter M.14. 114/91.
- Seed, E.D. and D.J. King**, (1997). Determination of mixed boreal forest stand biophysical structure using large scale airborne digital camera imagery. In *Proceedings of GER '97/19th Symposium on Remote Sensing*. Ottawa, Ontario, 26-29 May, CD-ROM publication. Paper #75, 8pp.
- Seed, E.D.**, (1998). Retrieval of Forest Canopy Structure from High-Resolution Airborne Digital Camera Imagery. Master's thesis, Carleton University, Ottawa, Ontario (unpublished). 164pp.
- Singh, A.**, (1989). Digital change detection using remotely sensed data. *International Journal of Remote Sensing*, 10(6): 989-1003.
- Singhroy, V.**, (1995). Spectral characterization of vegetation at mine tailings. *Proceedings of the '95 Conference on Mining and the Environment*. May 28-June 1. Sudbury, Ontario. Vol. I, pp. 193-200.
- Slater, R.**, (1995). Report: the mining environment database on abandoned mines, acid mine drainage and land reclamation. *Waste Management and Research*, 13(1): 91-92.
- Stevens, J.M.**, (1996). Applied Multivariate Statistics for the Social Sciences. 3rd Edition. Lawrence Erlbaum Associates. Mahwah, New Jersey. 629pp.
- SPSS Inc.**, (1996). Statistical Package for Graduate Students (SPSS 7.5). Chicago, Illinois.

- Tabachnick, B.G. and L.S. Fidell**, (1996). Using Multivariate Statistics. 3rd edition. Harper Collins College Publishers. New York. 746pp.
- Tapper, G., Courtin, G., Beckett, P., and A. Beswick**, (1991). Abandoned mine waste sites and environmentally affected drainage basins in Northeastern Ontario. MEND proposal. (unpublished). 7pp.
- Thompson, B.**, (1984). Canonical Correlation Analysis: Uses and Interpretation. Sage Inc. Beverly Hills, California. 71pp.
- Thornton, I.**, (1983). Applied Environmental Geochemistry. Academic Press. New York. 501pp.
- Thurston, P.C., Williams, H.R., Sutcliffe, R.H., and G.M. Scott** (1991). Geology of Ontario. Ontario Geological Survey. Ministry of Northern Development and Mines. Toronto, Ontario. Special Volume 4, Part 1 and 2.
- Todd, S.W., and R.M. Hoffer**, (1998). Responses of spectral indices to variations in vegetation cover and soil background. *Photogrammetric Engineering and Remote Sensing*, 64(9): 915-921.
- Tremblay, G., and C. Weatherell**, (1998). MEND2000: Progress through partnerships. CIM bulletin, 91(1019): 57-59.
- Vance, J.B., Walmsley, J.R., and M.C. Betournay**, (1995). Inactive mines database. *Proceedings of the '95 Conference on Mining and the Environment*. Sudbury, Ontario. May 28- June 1. Vol. III, pp. 969-978.
- Vogelmann, J.E.**, (1990). Comparison between vegetation indices for measuring different types of forest damage in north-eastern United States. *International Journal of Remote Sensing*. 11(12): 2281-2297.
- Walsworth, N.A. and D.J. King**, (1999). Image modelling of forest changes associated with acid mine drainage. *Computers and Geosciences*. 25(5): 567-580.
- Walsworth, N.A.**, (1998). Geographic Image Modeling of Environmental Degradation Associated with Acid Mine Drainage-Kam-Kotia Mine Tailings. Master's thesis, Carleton University, Ottawa, Ontario (unpublished), 219pp.
- Weatherell, C.M., Feasby, D.G., and G. Tremblay**, (1997). The mine environment neutral drainage (MEND) program- a model of cooperative research for technology development. *Proceedings of the PMI '97, 28th Annual Seminars and Symposiums*. 26 Sep.- 20 Oct., pp. 657-667.
- Welles, J.M. and J.M. Norman**, (1991). Instrument for indirect measurement of canopy architecture. *Agronomy Journal*, 83(5): 818-825.

- Winterhalder, K.,** (1992). The experimental use of various covers and native transplants for the revegetation of the Kam-Kotia tailings site. Timmins. *Proceedings of the 9th National Meeting of the American Society for Surface Mining and Reclamation*. June 14-18. Duluth, Minnesota.
- Winterhalder, K.,** (1995). Approaches to engendering biodiversity in tailings regeneration. *Proceedings of the '95 Conference on Mining and the Environment*. May 28- June 1. Sudbury, Ontario. (CANMET, Ottawa, Ontario) Vol. III, pp. 1239-1248.
- Wulder, M.A., Lavigne, M.B., LeDrew, E.F. and S.E. Franklin,** (1997). Comparison of texture algorithms in the statistical estimation of LAI: first-order, second-order, and semivariance moment texture (SMT). *In proceedings of GER '97/19th Symposium on Remote Sensing (Canadian Remote Sensing Society)*. May 24-30. Ottawa, Ontario. Paper #160. 10pp.
- Wulder, M.A., LeDrew, E.F., Franklin, S.E. and M.B. Lavigne,** (1998). Aerial image texture information in the estimation of northern deciduous and mixed wood forest leaf area index (LAI). *Remote Sensing of Environment*, 64(1): 64-76.

9. APPENDICES

APPENDIX 1: Image and field plot measurements from 1997 and 1999.

(See Table 4.1. for measurements from 1997 and 1999)

plots	lstem	dstem	bdstem	lbasal	dbasal	bdbasal	lai3	lai4	canopy
a10	101	2	27	0.59	0.04	0.74	2.38	1.86	64
a210	69	7	19	1.18	0.12	0.44	2	1.72	28
a310	30	4	4	1.19	0.06	0.08	3.28	2.72	61
a410	5	1	8	0.27	0.09	0.33	1.34	1.76	21
a510	5	0	2	0.42	0	0.14	3.61	3.57	89
a710	13	6	1	1.16	0.51	0	3.52	3.53	87
b10	62	3	0	0.19	0.13	0	1.22	0.89	16
b110	44	18	17	0.58	0.27	0.2	1.7	1.68	30
b210	32	5	22	0.37	0.05	0.35	2.12	2	40
b310	49	0	0	0.64	0	0	2.87	2.95	68
b410	5	2	12	0.21	0.05	0.35	1.51	1.86	44
b510	23	6	0	0.83	0.08	0	3.39	3.12	63
b60	36	12	3	0.92	0.39	0.05	2.29	2.08	12
b710	14	0	5	0.72	0	0.14	3.73	3.51	60
c10	46	7	17	0.24	0.06	0.31	0.41	0.45	30
c110	46	10	14	0.65	0.11	0.29	2.36	2.22	65
c210	14	1	2	0.39	0	0.05	1.99	1.97	57
c310	38	13	5	1.57	0.21	0.1	5.03	4.19	82
c410	58	2	6	0.98	0.06	0.14	4.28	3.58	82
c60	26	6	10	0.7	0.07	0.18	1.64	1.56	42
c710	27	0	14	0.8	0	0.39	2.73	2.92	57
d10	59	39	17	0.63	0.29	0.19	2.11	1.9	35
d110	46	0	6	0.51	0	0.23	1.77	1.66	37
d210	28	2	18	0.28	0	0.4	2.36	2.22	56
d310	65	2	8	0.71	0.04	0.25	2.03	1.92	61
d410	34	1	14	0.48	0.01	0.46	2.31	2.48	60
d510	26	16	11	0.24	0.35	0.21	3.21	3.1	78
d60	61	15	4	0.66	0.09	0.11	2.37	2.38	42
d710	13	1	1	0.87	0.04	0.13	3.94	3.83	77
e210	24	0	5	0.86	0	0.09	3.01	3.03	76
e310	10	2	5	0.67	0.17	0.28	4.37	3.76	80
f10	118	2	36	0.39	0.02	0.72	1.83	1.73	38
f110	27	3	10	0.76	0.24	0.26	2.09	2.18	38
f210	32	0	0	0.87	0	0	2.35	2.6	63
f310	12	1	2	0.84	0.24	0.2	2.76	2.04	60
f60	117	10	7	1	0.45	0.29	2.43	2.15	38

2. 1999 forest structural data:

plots	lstem	dstem	bdstem	lbasal	dbasal	bdbasal	lai3	lai4	canopy
a10	107	2	26	0.46	0.04	0.62	0.98	1.43	28.8
a210	66	6	18	1.06	0.11	0.35	1.75	1.51	47.4
a310	26	2	8	1.08	0.04	0.14	4.49	4	86.1
a410	5	2	3	0.27	0.11	0.15	2.43	2.47	53.8
a510	5	0	2	0.41	0.00	0.13	4.15	3.56	85.2
a710	14	6	1	1.26	0.48	0.02	3.81	3.4	78.01
b10	72	3	20	0.15	0.14	0.40	1.24	1.91	47.2
b110	44	15	13	0.53	0.18	0.10	3.88	3.29	77.6
b210	26	6	22	0.23	0.05	0.27	2.01	2.16	46.2
b310	47	5	9	0.54	0.16	0.12	4.61	4.08	87.4
b410	5	2	11	0.23	0.03	0.31	2.53	2.39	63.4
b510	26	3	6	0.90	0.02	0.07	3.49	3.15	74.42
b60	64	9	10	0.74	0.30	0.11	3.87	3.62	75.1
b710	14	0	6	0.68	0.01	0.26	3.79	3.39	77.84
c10	45	2	18	0.17	0.01	0.36	1.55	1.04	32.2
c110	51	12	27	0.66	0.05	0.34	2.94	2.55	74.7
c210	16	1	3	0.33	0.00	0.05	2.72	2.41	67.8
c310	36	7	17	1.22	0.14	0.32	5.23	4.27	78.9
c410	49	2	10	0.77	0.09	0.22	3.31	2.86	66.7
c60	29	7	9	0.43	0.06	0.13	1.53	1.46	59.4
c710	27	3	17	0.70	0.05	0.49	3.16	3.2	54.3
d10	65	57	74	0.47	0.26	0.16	3.46	3.11	62.3
d110	41	0	9	0.32	0.00	0.30	1.76	1.65	53.9
d210	43	3	18	0.31	0.00	0.42	2.29	2.23	68.3
d310	86	4	14	0.53	0.00	0.46	3.61	3.03	84.1
d410	40	3	15	0.46	0.01	0.40	2.38	2.47	63.8
d510	37	11	25	0.18	0.20	0.45	2.32	2.19	70.5
d60	54	18	18	0.48	0.06	0.24	1.89	2.29	60.9
d710	14	1	1	0.77	0.03	0.10	3.91	3.73	84.7
e210	41	0	5	1.00	0.00	0.09	1.79	1.87	70.7
e310	11	2	5	0.72	0.20	0.19	3.47	3.08	69.1
f10	168	1	32	0.36	0.00	0.73	3.6	2.91	82.7
f110	69	0	10	0.66	0.00	0.32	0.86	1.35	55.9
f210	28	1	15	0.78	0.03	0.40	3.65	3.25	86
f310	16	1	2	0.70	0.23	0.20	4.35	3.8	92.3
f60	122	0	15	0.59	0.00	0.96	2.55	2.27	77.9

3. 1997 image data:

plots	nir	red	green	blue	tex2	texv2	tex3	texv3	s1	s23	s4	ndvi
a10	123.1	51.05	108.7	103.84	6.64	4.75	4.02	3.58	26.5	59.44	14.06	0.41
a210	84.02	79.61	125.9	123.73	4.36	3.21	2.16	1.97	28.63	58.63	12.75	0.03
a310	99.99	69.34	103.1	131.15	4.99	3.71	1.79	1.48	38.44	46.69	14.88	0.18
a410	94.02	56.85	84.99	130.46	3.82	2.69	2.1	1.64	44.44	44.81	10.75	0.25
a510	99.54	90.95	96.8	147.12	4.69	3.09	2.38	1.95	34.56	48.25	17.19	0.05
a710	116.54	80.4	122.2	149.49	2.95	2.31	1.98	1.97	33	42.75	24.25	0.18
b10	111.65	96.33	142.7	134.06	3.54	2.72	4.21	3.62	32.63	44.44	22.94	0.07
b110	96.73	72.12	94.55	124.35	5.91	3.92	3.06	2.67	31.88	52.25	15.88	0.15
b210	120.4	73.25	121.4	131.9	5.48	4.04	2.32	1.85	26.06	57.19	16.75	0.24
b310	113.17	55.76	113.8	132.74	3.99	2.99	1.65	1.35	38.88	40.5	20.63	0.34
b410	143.37	131.97	154.6	159.92	6.41	4.42	2.94	2.3	21.06	63.69	15.25	0.04
b510	119.81	102.18	142.5	148.1	4.18	2.93	2.19	1.95	22.63	60.63	16.75	0.08
b60	107.27	93.91	121.5	131.97	3.64	3	2.12	2.12	25.56	56.38	18.06	0.07
b710	101.92	65.13	92.91	118.41	5.19	3.87	2.17	2.19	38.88	44.63	16.5	0.22
c10	109.17	110.01	126.5	159.85	6.25	4.5	4.05	2.91	30	50.19	19.81	0
c110	104.7	80.01	120.5	115.57	5.02	3.99	2.54	2.78	34.06	50.06	15.88	0.13
c210	154.04	93.74	152.3	136.17	3.46	2.9	3.15	3.25	25.44	47.44	27.13	0.24
c310	128.53	84.65	127.3	131.91	4.58	3.97	3.13	2.8	17	62.63	20.38	0.21
c410	99.33	64.56	99.62	90.25	5.78	3.62	2.76	2.56	39.31	52.81	7.88	0.21
c60	115.69	76.4	126.9	142.45	7.24	5.38	3.2	2.73	23.5	56.81	19.69	0.2
c710	89.1	70.93	92.89	120.51	2.76	2.38	2.25	1.96	49.63	45.69	4.69	0.11
d10	130.25	136.79	153.9	162.78	5.14	4.34	4.82	3.81	37.56	44.31	18.13	-0.02
d110	116.99	90.58	148.7	150.35	3.84	3.61	3.11	3.23	25	58.94	16.06	0.13
d210	106.99	87.59	114	124.35	3.91	3.57	2.93	2.69	32.5	58.75	8.75	0.1
d310	82.77	61.55	105.4	89.2	2.92	2.22	3.21	2.93	34.13	50.63	15.25	0.15
d410	103.65	110.28	145.8	154.45	5.9	4.56	3.02	2.44	23.19	65.13	11.69	-0.03
d510	87.76	86.07	104.1	142.44	3.18	3.23	1.97	2.15	42.63	43.06	14.31	0.01
d60	112.57	100.87	126.2	159.24	5	3.87	3.21	2.59	37.13	48.69	14.19	0.05
d710	84.37	85.06	108	135.23	3.19	2.97	2.08	1.73	28.25	55.81	15.94	0
e210	84.91	79.19	118.2	153.14	2.85	2.59	3.47	3.64	32	53.81	14.19	0.03
e310	104.29	84.24	110.5	160.09	4.01	3.15	3.77	3.1	28.56	58.63	12.81	0.11
f10	99.3	67.9	159.1	172.65	4.43	5.75	4.88	6.26	24.94	47.63	27.44	0.19
f110	94.57	128.23	150.4	181.89	3.97	3.68	3.88	4.65	30.56	48.19	21.25	-0.15
f210	89.39	72.75	98.12	148.07	3.34	2.74	2.66	2.34	45.75	42.5	11.75	0.1
f310	106.72	61.16	101.2	187.98	3.6	2.96	2.46	2.55	36.06	54.44	9.5	0.27
f60	106.12	102.72	132.9	167.02	5.65	5.4	3.97	3.47	23.56	58.25	18.19	0.02

4. 1999 image data:

plots	nir	red	green	blue	tex2	texv2	tex3	texv3	s1	s23	s4	ndvi
a10	137.19	56.11	121.1	97.12	3.7	2.91	3.23	2.37	0.42	16.25	61.75	22
a210	102.22	91.3	129.5	135.1	3.57	2.98	2.33	1.91	0.06	23.63	59.45	16.93
a310	116.76	74.38	111.6	140.39	2.87	2.38	2.26	1.88	0.22	20.06	58.07	21.88
a410	98.14	59.91	95.48	132.23	3.35	2.78	2.76	2.38	0.24	32.44	54.71	12.88
a510	103.56	69.09	101	134.63	2.1	1.71	2.3	2.12	0.2	34.25	48.63	17.13
a710	111.14	98.34	135.5	163.69	2.32	2.08	2.26	2	0.06	15.13	56.63	28.25
b10	122.42	80.29	125.7	131	2.42	1.97	3.08	2.32	0.21	22.57	49.52	27.89
b110	104.74	78.29	103.4	131.41	2.5	3.09	3.15	2.57	0.14	18.75	52.6	28.58
b210	120.09	74.28	117.6	140.04	3.83	3.68	2.9	2.62	0.24	27.38	52.69	19.94
b310	116.31	81.41	125.5	141.51	2.77	2.06	2.56	2.06	0.18	33.5	37.75	28.75
b410	159.6	104.45	165.6	153.92	2.47	2.06	2.27	1.69	0.21	10.25	67.88	21.88
b510	122.63	102.07	136.3	154.29	2.97	2.67	2.04	1.56	0.09	21.13	64.19	14.69
b60	108.51	90.27	120.9	141.84	2.21	2.09	1.87	1.64	0.09	25.5	53.69	20.81
b710	107.77	68.92	104.3	132.33	2.61	2.42	1.29	0.99	0.22	29.88	62.75	7.38
c10	110.94	122.47	142.7	153.97	3.3	2.58	3.61	3.03	-0.05	14.49	65.07	20.43
c110	102.25	82.21	125.9	131.56	3.3	2.98	2.43	2.2	0.11	31.81	51.06	17.13
c210	145.14	101.9	154.1	153.31	3.8	2.84	2.97	2.4	0.18	16.44	56.81	26.75
c310	108.29	82.71	119.5	132.84	4.09	3.86	2.27	2	0.13	22.38	60.44	17.19
c410	102.42	78.38	113.4	124.74	3.92	3.43	2.75	2.29	0.13	34.38	53.44	12.19
c60	121.3	89.39	131.2	136.76	2.92	2.74	2.67	2.67	0.15	24.94	44.56	30.5
c710	90.72	87.22	114	136.14	3.22	3.18	2.31	2.11	0.02	32.44	49.44	18.13
d10	114.61	120.54	142.8	179.76	3.53	2.87	4.04	3.19	-0.03	24.94	52.38	22.69
d110	117.6	88.26	130.1	152.61	3.79	3.13	2.93	2.72	0.14	22.63	49.56	27.81
d210	116.33	86.34	123.3	131.32	5.51	4.46	3.81	3.14	0.15	29.31	47	23.69
d310	104.58	82.17	122.9	127.88	5.02	5.78	4.44	8.12	0.12	21.94	40.63	37.44
d410	103.46	111.56	143.7	157.19	5.18	3.85	3.37	2.5	-0.04	25.19	52.25	22.56
d510	84.41	83.61	110	137.11	2.86	2.5	1.97	1.63	0	33.63	51	15.38
d60	114.63	98.5	131.1	170.24	3.95	3.19	3.95	3.03	0.08	26.06	57.19	16.75
d710	94.54	74.18	112.3	128.82	3.47	3.63	2.75	3.14	0.12	26.38	53.13	20.5
e210	103.1	81.99	136.9	151.93	4.36	3.53	2.9	2.65	0.11	21.06	53.19	25.75
e310	106.77	82.92	113	157.67	3.24	3.2	3.15	3.28	0.13	25.06	54.5	20.44
f10	101.45	143.13	140.3	187.47	2.25	2.15	1.85	1.82	-0.17	29.23	42.56	28.31
f110	106.2	123.28	149.5	180.08	3.46	3.26	2.75	2.26	-0.07	16.63	58.88	24.5
f210	148.02	120.72	188.8	158.19	1.65	1.51	2.51	2.79	0.1	15.31	43.81	40.88
f310	98.61	72.01	118.8	144.6	2.57	2.36	2.13	2.08	0.16	30.94	52.63	16.44
f60	111.12	96.98	116.7	166.99	2.86	2.57	1.75	1.35	0.07	25.75	64	10.25

APPENDIX 2: Principal component analyses.

Two principal component analyses were conducted for 1997 data one for the structural parameters and a second for the image parameters.

1. Principal Component Analysis (Structure Parameters)

Correlation Matrix

	BDBA	BDSTEM	CANOPY	DBA_L	DSTEM_L	LAI3	LAI4	LBA	LSTEM_L
Correlation									
BDBA	1.000	.879	-.206	-.290	-.087	-.315	-.339	-.309	.248
BDSTEM	.879	1.000	-.309	-.185	.212	-.407	-.441	-.317	.409
CANOPY	-.206	-.309	1.000	-.173	-.284	.799	.820	.318	-.290
DBA_L	-.290	-.185	-.173	1.000	.669	.091	.003	.351	.058
DSTEM_L	-.087	.212	-.284	.669	1.000	-.077	-.163	.193	.404
LAI3	-.315	-.407	.799	.091	-.077	1.000	.958	.590	-.221
LAI4	-.339	-.441	.820	.003	-.163	.958	1.000	.509	-.345
LBA	-.309	-.317	.318	.351	.193	.590	.509	1.000	.174
LSTEM_L	.248	.409	-.290	.058	.404	-.221	-.345	.174	1.000
Sig. (1-tailed)									
BDBA		.000	.114	.043	.308	.031	.022	.033	.072
BDSTEM	.000		.033	.139	.107	.007	.004	.030	.007
CANOPY	.114	.033		.156	.047	.000	.000	.029	.043
DBA_L	.043	.139	.156		.000	.299	.493	.018	.369
DSTEM_L	.308	.107	.047	.000		.328	.172	.129	.007
LAI3	.031	.007	.000	.299	.328		.000	.000	.098
LAI4	.022	.004	.000	.493	.172	.000		.001	.020
LBA	.033	.030	.029	.018	.129	.000	.001		.156
LSTEM_L	.072	.007	.043	.369	.007	.098	.020	.156	

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% Var.	Cum. %	Total	% Var.	Cum. %	Total	% Var.	Cum. %
1	3.739	41.55	41.546	3.739	41.55	41.546	3.057	33.96	33.964
2	2.101	23.35	64.893	2.101	23.35	64.893	2.174	24.16	58.123
3	1.484	16.49	81.379	1.484	16.49	81.379	2.093	23.26	81.379
4	.756	8.401	89.780						
5	.449	4.991	94.770						
6	.221	2.453	97.224						
7	.168	1.861	99.085						
8	.054	.595	99.680						
9	.029	.320	100.00						

Extraction Method: Principal Component Analysis.

Rotated Component Matrix^a

	Component		
	1	2	3
BDBA	-.167	.884	-.232
BDSTEM	-.260	.918	-2.574E-03
CANOPY	.861	-.112	-.279
DBA_L	-1.421E-02	-.278	.823
DSTEM_L	-.110	.129	.875
LAI3	.954	-.187	3.240E-02
LAI4	.929	-.250	-9.191E-02
LBA	.651	-.102	.507
LSTEM_L	-.107	.580	.501

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

2. Principal Component Analysis (Image Parameters)

Correlation Matrix

		BLUE	GREEN	NDVI	NIR	RED	S1	S23	S4	TEX2	TEX3	TEXV2	TEXV3
Correlation	BLUE	1.0	.483	-.429	.173	.540	-.216	.033	.281	-.026	.332	.247	.346
	GREEN	.483	1.00	-.353	.557	.694	-.645	.281	.590	.160	.548	.415	.563
	NDVI	-.43	-.353	1.00	.275	-.782	.078	-.10	.016	.111	-.226	-.012	-.214
	NIR	.173	.557	.275	1.000	.374	-.496	.239	.423	.383	.226	.310	.116
	RED	.540	.694	-.782	.374	1.000	-.352	.212	.242	.164	.387	.229	.300
	S1	-.22	-.645	.078	-.496	-.352	1.00	-.76	-.467	-.375	-.327	-.476	-.308
	S23	.033	.281	-.098	.239	.212	-.763	1.0	-.215	.391	.115	.348	.050
	S4	.281	.590	.016	.423	.242	-.467	-.21	1.000	.031	.337	.244	.398
	TEX2	-.03	.160	.111	.383	.164	-.375	.391	.031	1.000	.279	.809	.079
	TEX3	.332	.548	-.226	.226	.387	-.327	.115	.337	.279	1.000	.525	.904
	TEXV2	.247	.415	-.012	.310	.229	-.476	.348	.244	.809	.525	1.000	.426
	TEXV3	.346	.563	-.214	.116	.300	-.308	.050	.398	.079	.904	.426	1.00
Sig. (1-tailed)	BLUE		.001	.005	.157	.000	.103	.423	.048	.440	.024	.073	.019
	GREEN	.001		.017	.000	.000	.000	.049	.000	.175	.000	.006	.000
	NDVI	.005	.017		.052	.000	.325	.285	.463	.260	.092	.472	.105
	NIR	.157	.000	.052		.012	.001	.080	.005	.011	.093	.033	.250
	RED	.000	.000	.000	.012		.018	.107	.077	.169	.010	.089	.038
	S1	.103	.000	.325	.001	.018		.000	.002	.012	.026	.002	.034
	S23	.423	.049	.285	.080	.107	.000		.104	.009	.253	.019	.387
	S4	.048	.000	.463	.005	.077	.002	.104		.429	.022	.076	.008
	TEX2	.440	.175	.260	.011	.169	.012	.009	.429		.050	.000	.323
	TEX3	.024	.000	.092	.093	.010	.026	.253	.022	.050		.001	.000
	TEXV2	.073	.006	.472	.033	.089	.002	.019	.076	.000	.001		.005
	TEXV3	.019	.000	.105	.250	.038	.034	.387	.008	.323	.000	.005	

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Var.	Cum. %	Total	% of Var.	Cum. %	Total	% of Var.	Cum. %
1	4.697	39.146	39.146	4.697	39.146	39.146	2.545	21.212	21.212
2	2.132	17.768	56.914	2.132	17.768	56.914	2.482	20.686	41.898
3	1.531	12.760	69.674	1.531	12.760	69.674	2.343	19.522	61.419
4	1.310	10.914	80.587	1.310	10.914	80.587	2.300	19.168	80.587
5	.891	7.427	88.015						
6	.578	4.818	92.833						
7	.546	4.554	97.387						
8	.185	1.540	98.927						
9	.069	.571	99.498						
10	.057	.474	99.972						
11	.003	.028	100.0						
12	.000	.000	100.0						

Extraction Method: Principal Component Analysis.

Rotated Component Matrix

	Component			
	1	2	3	4
BLUE	.630	-.5432E-02	.267	.231
GREEN	.542	.208	.340	.649
NDVI	-.921	2.415E-02	-.8.773E-02	.253
NIR	-.2.489E-02	.337	-.1.370E-03	.806
RED	.863	.183	.123	.253
S1	-.245	-.641	-.6.997E-02	-.571
S23	.223	.850	-.174	4.167E-02
S4	6.440E-02	-.194	.343	.805
TEX2	-.182	.801	.290	5.147E-02
TEX3	.236	.158	.881	.149
TEXV2	-.2.322E-02	.672	.593	.135
TEXV3	.240	1.512E-03	.877	.172

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 8 iterations.

APPENDIX 3: Canonical correlation script and final report.

The following include: 1. the macro script used to perform the canonical analysis:
and 2. the canonical correlation matrix. The analysis was carried out in SPSS for
Windows (version 7.5)

1. Macro script: CANCELL.

```
INCLUDE 'canonical correlation.sps'.  
CANCELL SET1=STR1 STR2 STR3/  
SET2=IM1 IM2 IM3 IM4/.
```

Run MATRIX procedure:

2. Canonical correlation matrix

Run MATRIX procedure:

Correlations for Set-1 (Forest structure components)

	STR1	STR2	STR3
STR1	1.0000	.0000	.0000
STR2	.0000	1.0000	.0000
STR3	.0000	.0000	1.0000

Correlations for Set-2 (Image components)

	IM1	IM2	IM3	IM4
IM1	1.0000	.0000	.0000	.0000
IM2	.0000	1.0000	.0000	.0000
IM3	.0000	.0000	1.0000	.0000
IM4	.0000	.0000	.0000	1.0000

Correlations Between Set-1 and Set-2

	IM1	IM2	IM3	IM4
STR1	-.1614	.0011	-.2816	-.1552
STR2	-.1821	.4416	.4832	-.2162
STR3	.1132	.0377	.1426	.0971

Canonical Correlations:

1	.727
2	.389
3	.042

Test that remaining correlations are zero:

	Wilk's	Chi-SQ	DF	Sig.
1	.399	28.462	12.000	.005
2	.847	5.146	6.000	.525
3	.998	.054	2.000	.973

Standardized Canonical Coefficients for Set-1:

	1	2	3
STR1	.199	.845	.497
STR2	-.973	.231	-.004
STR3	-.118	-.483	.868

Standardized Canonical Coefficients for Set-2:

	1	2	3
IM1	.181	-.599	.450
IM2	-.597	.218	.756
IM3	-.747	-.501	-.435
IM4	.231	-.586	.193

APPENDIX 4: Stepwise regression report.

Model Summary^f

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.632 ^a	.399	.381	.78666	.399	22.557	1	34	.000
2	.694 ^b	.482	.450	.74148	.083	5.269	1	33	.028
3	.748 ^c	.560	.519	.69374	.078	5.699	1	32	.023
4	.780 ^d	.609	.558	.66476	.049	3.851	1	31	.059
5	.815 ^e	.664	.608	.62629	.055	4.925	1	30	.034

a. Predictors: (Constant), TEXV2

b. Predictors: (Constant), TEXV2, BLUE

c. Predictors: (Constant), TEXV2, BLUE, TEX2

d. Predictors: (Constant), TEXV2, BLUE, TEX2, S4

e. Predictors: (Constant), TEXV2, BLUE, TEX2, S4, TEX3

f. Dependent Variable: CVI

Descriptive Statistics

	Mean	Std. Deviation	N
CVI	1.5420E-17	.99999	36
BLUE	140.3562	22.5230	36
GREEN	120.7749	20.7335	36
NDVI	.1208	.1138	36
NIR	106.5471	15.7679	36
RED	84.8365	20.9393	36
S1	31.7740	7.5433	36
S23	52.0731	6.8293	36
S4	16.1527	4.9910	36
TEX2	4.4949	1.1895	36
TEX3	2.9339	.8443	36
TEXV2	3.5839	.8894	36
TEXV3	2.6653	.8354	36

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.545	.552		4.613	.000		
	TEXV2	-.710	.150	-.632	-4.749	.000	1.000	1.000
2	(Constant)	.991	.854		1.160	.254		
	TEXV2	-.793	.145	-.705	-5.450	.000	.939	1.065
	BLUE	1.318E-02	.006	.297	2.295	.028	.939	1.065
3	(Constant)	6.557E-02	.888		.074	.942		
	TEXV2	-1.300	.252	-1.156	-5.152	.000	.273	3.664
	BLUE	1.875E-02	.006	.422	3.201	.003	.790	1.266
	TEX2	.437	.183	.519	2.387	.023	.291	3.442
4	(Constant)	-.347	.876		-.396	.695		
	TEXV2	-1.442	.252	-1.282	-5.713	.000	.251	3.991
	BLUE	1.725E-02	.006	.389	3.045	.005	.776	1.289
	TEX2	.515	.180	.613	2.867	.007	.276	3.622
	S4	4.808E-02	.025	.240	1.962	.059	.844	1.184
5	(Constant)	-.176	.829		-.212	.833		
	TEXV2	-1.214	.259	-1.080	-4.687	.000	.211	4.735
	BLUE	1.875E-02	.005	.422	3.485	.002	.764	1.310
	TEX2	.446	.172	.531	2.592	.015	.267	3.744
	S4	5.676E-02	.023	.283	2.424	.022	.821	1.218
	TEX3	-.350	.158	-.296	-2.219	.034	.631	1.586

^a. Dependent Variable: CVI