**MODELLING FOREST STRUCTURE AND HEALTH USING
HIGH-RESOLUTION AIRBORNE IMAGERY:
INVESTIGATION OF SPECTRAL UNMIXING AND SPATIAL
ANALYSIS OF RADIOMETRIC FRACTIONS**

By

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in partial fulfillment of the requirements for the degree of
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ABSTRACT

Research was conducted in a forest adjacent to an acid mine tailings site at the abandoned KamKotia mine near Timmins, Ontario, to assess forest structural health using high spatial and spectral resolution digital camera imagery. The main goal was to develop models of forest structure and health from image spectral and spatial information. The classical approach uses raw image spectral information or basic spectral transformations and occasionally includes spatial transformations. This research introduces fractional textures and semivariance analysis of image fractions. They were compared and integrated with classical image measures in stepwise multiple regression modelling of forest structure and health variables. This analysis was conducted using canopy-scale and individual tree crown-scale samples extracted from 10 nm bandwidth spectral bands at three resolutions (0.25 m, 0.5 m, 1.0 m).

Image brightness (DN) and image fraction variables (IF) were found to be complementary. Of the best models for each forest measure at the canopy scale, 48% incorporated DN variables and 52% incorporated IF variables. More IF variables were present in the best models at the tree-crown scale (33% DN vs. 67% IF variables). IF variables alone, or in combination with DN variables, provided better models than DN variables alone in 14 of 18 cases at the canopy scale. Thus, modelling forest structure and health with image fractions has proven to be highly beneficial. More significant, however, are the spatial transformations (texture, semivariogram range) of DN and IF variables. They were the most significant variables in models at both the canopy (96% of all variables in models) and tree-crown scales (88% of all variables in models). Semivariogram variables were the most often entered into models at the canopy scale and texture variables were the most entered at the tree-crown scale. Spatial information in image fractions and image brightness has therefore proven to be more significant than spectral information in these analyses. Of the spatial resolutions evaluated, 0.5 m consistently produced similar or better models than those using the 0.25 or 1.0 m resolutions. Of the two sampling scales, the tree-crown scale analysis improved significantly the prediction of individual tree crown closure. However, all other variables were best predicted at the canopy scale as variations in gap-size distribution, tree-crown size and stem density, which respond to long-term stress, were captured in these samples. This research provides significant insight into the information contained in the image spectral/spatial data and provides a means to understand the relationships between high-resolution image data and forest structure and health.

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LIST OF ACRONYMS

AMD	Acid Mine Drainage
ASM	Angular Second Moment (image texture measure)
ANOVA	Analysis of Variance
AVHRR	Advanced Very High Resolution Radiometer
AVIRIS	Airborne Visible Infrared Imaging Spectrometer
BRDF	Bi-directional Reflectance Distribution Function
<i>casi</i>	Compact Airborne Spectrographic Imager
CON	Contrast (image texture measure)
DN	Image Brightness (Digital Number)
DN-TEX	Texture Variables Extracted from DN
DN-SEMI	Semivariogram Variables Extracted from DN
EM	Spectral Endmember
ENT	Entropy (image texture measure)
FLIM	Forest Light Interaction Model
GEMI	Global Environment Monitoring Index
ICPES	Inductively Coupled Plasma Emission Spectrometry
IF	Image Fraction
IF-TEX	Texture Variables Extracted from IF
IF-SEMI	Semivariogram Variables Extracted from IF
IGF	Indicative Goodness of Fit (for semivariogram model)
ISDAS	Imaging Spectrometer Data Analysis System
LAI	Leaf Area Index
LANDSAT MSS	LANDSAT Multispectral Scanner
LANDSAT TM	LANDSAT Thematic Mapper
LIBERTY	Leaf Incorporating Biochemistry Exhibiting Reflectance and Transmittance Yields

MEA	Mean (image texture measure)
MEIS-II	Multi-detector Electro-optical Imaging Scanner - II
MEND	Mine Environment Neutral Drainage
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NPP	Net Primary Productivity
NUTP	National Uranium Tailings Program
P	Level of Significance
PC	Principal Component
PROSPECT	Leaf Optical Reflectance and Transmittance Model
RATS	Reactive Acid Tailings Stabilization
SAIL	Scattering by Arbitrary Inclined Leaves
SAVI	Soil Adjusted Vegetation Index
SGLD	Spatial Grey Level Dependence
SHA	Shadow (image fraction)
SOILSPECT	Soil Optical Reflectance and Transmittance Model
SPOT	Satellite pour l'Observation de la Terre
SPOT HRV	SPOT Haute Résolution Visible
TSAVI	Transformed Soil Adjusted Vegetation Index
VEG	Vegetation (image fraction)
VIF	Variance Inflation Factor
VIS	Visible portion of the electromagnetic spectrum
VMS	Volcanic Massive Sulphide
WOD	Wood (image fraction)

1. INTRODUCTION

Mining activities have significant environmental side-effects that can adversely affect ecosystems. A major by-product of mining is the waste produced from the extraction of ore and the resultant concentration of minerals. It is the primary source of acid mine drainage (AMD) which, when left untreated, can be detrimental to natural and human ecosystems. In most types of mining, solid waste takes the form of mine tailings, waste rock piles, and slag dumps. As techniques used to extract metal from the ore have become more sophisticated, they allow for the mining of lower-grade ore bodies which generate even more waste (Williamson and Johnson, 1981). By 1994, there were 2.65 billion tons of acid-generating wastes in Canada with a liability of between 2 and 5 billion dollars. More than 1.9 billion tons of this waste are mine tailings which replace 12,652 ha of forested land across Canada (Feasby and Jones, 1994). Half of the acid-generating mine tailings are in the Province of Ontario. This is principally due to metallogenic concentrations in the Sudbury Basin and in the volcanic and greenstone belts, mainly in the Superior Province of the Canadian Shield. The host rocks are high in iron-bearing minerals, an important source of acid generation.

Prior to 1991, there was no legislation requiring rehabilitation of mine sites in Canada (Cowan and Robertson, 1999). The Mining Act of the late 1800s had stipulated that mineral deposits must be discovered before claiming any area. The consequences of such stipulation were disastrous. During exploration, many open pits and trenches were excavated and abandoned (Slater, 1995). Being the most economical way to proceed, waste was disposed of directly onto adjacent land with little concern of its impact on

ecosystems. Faced with increasing environmental damage and high liabilities, research on AMD became a necessity. In 1982, the National Uranium Tailings Program (NUTP) was introduced, followed by the Reactive Acid Tailings Stabilization (RATS) task force in 1988 (Feasby *et al.*, 1997). In 1989, CANMET established the Mine Environment Neutral Drainage (MEND) program with the objective of providing guidelines for the mining industry on the opening and closing of new mines. From the knowledge acquired, the Ontario Mining Act was revised in 1991 and new mines must now exercise greater responsibility and provide rehabilitation plans. Furthermore, since 1996, mined lands could only be returned to the government after being rehabilitated (Doran and McIntosh, 1995). However, the legacy from mining practices of the past century is more than 6,000 abandoned mine sites in Ontario alone (Vance *et al.*, 1995), which threaten the environment, principally forest and hydrologic ecosystems. For example, the KamKotia zinc and copper mine near Timmins, Ontario, was abandoned in 1972, prior to the establishment of the rehabilitation requirements, leaving three large sulfide tailings areas that constantly generate acid drainage that flows into the surrounding forest. According to the Ontario Ministry of Northern Development and Mines, the KamKotia mine is the largest abandoned mine environmental hazard located on crown land in the province.

This study examines the effects of AMD pollution on the forest surrounding the abandoned KamKotia mine. Environmental stresses may include lowered soil pH, elevated availability of soil metals to vegetation through drainage or windblown deposition, increased wind speeds resulting from cleared forest surrounding the mine and higher air temperatures in the forest due to hot tailings winds. Forest response to such

stresses may be expressed through physiological and morphological changes at the tree level (reduced chlorophyll content, photosynthesis, and biomass production) and at the community level (reduced stem density, canopy closure and vertical layering). Forest stress and structural changes must be predictable and accountable before measures can be taken to alleviate the problems. Hence, there is a clear need to develop techniques to identify and quantify symptoms of forest decline. Ground-based methods to evaluate and monitor forests are costly, tedious, and often ineffective, especially in remote areas where accessibility is limited. For spatial analysis and mapping of forests, remote sensing methods are often proposed. These technologies are rapidly advancing, currently providing imaging and analysis capabilities that are significantly more advanced than just a decade ago. As spatial and spectral resolutions get finer and as image analysis techniques improve, the information provided by remote sensing imagery becomes richer and more precise.

This research introduces new spatial analysis methods that contribute to better understanding of the relationships between image variables and forest measures at sub-meter resolution. The primary goal is to develop image-based models of forest structure and health from spectral and spatial information sensitive to forest structural change. This was achieved through a number of steps in two research stages comprised of initial field studies and image modelling.

Initial field studies:

- Establish a study site in a forest adjacent to an abandoned mine site with a known acid drainage problem.
- Determine if soil metal content in the forest is elevated and if a gradient with distance from the tailings edge is present.
- Evaluate the potential for spectral modelling of individual tree stress through spectral analysis of leaf samples.

Image modelling:

- Determine suitable spectral and spatial methodologies for analysis of tree and forest structural health.
- Evaluate the impact of sampling scale (canopy and individual tree) on prediction of forest structural health.
- Evaluate forest structural health models derived from imagery acquired at various spatial resolutions.
- Identify image variables which are best related to the forest measures.
- Combine spectral and spatial image variables to develop image models for each forest measure.

This research design is summarized in Figure 1.

Figure 1. Summary of the research design. Part A is in green and Part B is in blue.

The thesis is structured as follows. Part A includes chapters 2 to 5 and corresponds to background research, study plot establishment, site characterization, and data acquisition. Chapter 2 describes the acid mine problem and its effect on forest ecosystems. Chapter 3 is a literature review of the theory and methods of remote sensing for forest health and structure. Chapter 4 describes the KamKotia mine site and the reasons for its selection. Previous research at the site is also described. Ground and airborne data acquisition are given in Chapter 5.

Part B includes chapters 6 to 8 and corresponds to the analysis and modelling of relations between image and field variables. Chapter 6 evaluates relations of raw spectral data and derived image fractions with forest measures. Chapter 7 investigates the use of spatial analysis of image brightness and image fractions in relation to forest measures. It includes evaluations of semivariogram parameters and texture measures. In Chapter 8, spectral and spatial image variables are combined to form multiple regression models for each forest measure.

The overall thesis results, including the benefits and limitations, are discussed in Chapter 9. Chapter 10 presents the conclusions of this research. Soil chemical analyses are presented in detail in Appendix 1 and 2.

--- PART A ---

Background and initial field studies

INTRODUCTION TO PART A

Initially, AMD was presumed to be a primary cause of forest degradation that was observed at the KamKotia mine in August 1992. Consequently, background research was conducted on effects of acid mining on vegetation and the potential for remote sensing of these effects. This was followed by soil chemistry, leaf spectral and forest structure analyses to determine if a gradient with distance from the tailings existed. Chapter 2 to 5 present this research.

2. THE ACID MINE DRAINAGE PROBLEM

2.1 SOURCES OF ACID MINE DRAINAGE

The uncontrolled release of acidic drainage water into the soil is one of the most detrimental environmental legacies of mining activities. Abandoned mines, especially in non-buffering bedrock and soils, pose a great challenge to the health of the surrounding living organisms because their wastes are left unattended. Abandoned mines are responsible for about half of the acid mine drainage production, while the remaining is mainly due to operating mines (Gibson, 1976). In 1994, it was estimated that more than 500 000 abandoned mine sites were located in Canada and the United States (Feasby and Jones, 1994). Such sites exhibit highly acidic surface drainage, contaminated groundwater, and environmentally harmful chemicals in the soil and water (Plumlee, 1999). Toxic concentrations of dissolved heavy metals are often found in the soil and water around mine wastes.

Mining and milling operations are the primary sources of acid mine waste. Typically, in the mining of base metals such as zinc, copper, and nickel, the ore sent to the mill for processing represents a small portion of the total amount of rock mined. The remaining waste rock and tailings have to be disposed of and are a potential source of acid introduction into the environment if not contained properly.

After being mined, the ore is sent to the mill for processing where it is combined with water and ground to a fine sand size. This mixture goes through a series of steps that separate ore-mineral particles from the rock and float them to the surface as a concentrate. The mill produces separate concentrates of the mined metals. These concentrates are shipped to the smelters for further processing. The material, which has been separated from the concentrate, has no commercial value. It is known as mine tailings and contains the unwanted wastes, including a large portion of sulfide minerals.

The sulfide minerals in the waste rocks and tailings oxidize and through chemical processes, produce sulfuric acid and other by-products if exposed to air and water (Kelley and Tuovinen, 1988). It is this acid generation that most adversely affects the immediate environment. Although it is rare to find pH values below 1.0 in acidic drainage systems, Williams and Smith (2000) recorded a pH value of 0.52 around an iron mine in Zimbabwe.

2.1.1 The oxidation of pyrite

Complex chemical reactions are triggered when sulfuric waste rock and tailings are exposed to oxygen and water. The weathering of pyrite is commonly considered as the major source of acid generation from rock and mine waste since pyrite occurs in many rock types (Nordstrom *et al.*, 1979).

The initial products of pyrite oxidation are ferrous iron, sulfate, and hydrogen ions (equation 1).

The ferrous iron is then converted into ferric iron by reaction with further oxygen and the hydrogen ions produced (equation 2) (Plumlee, 1999). Singer and Stumm (1970) describe this step (2) as the “rate determining step” for the production of acid from pyrite.

In the next step, the hydrolysis of ferric iron with water forms solid ferric hydroxide (ferrihydrite) and releases more hydrogen ion (equation 3). This reaction is pH dependent. If pH remains less than 3.5, there is no solid phase and the ferric iron remains in solution which means that the reaction of equation 3 does not happen:

If the ferric iron remains in solution, additional pyrite is oxidized by the ferric iron produced in the first two reactions (equation 4). This step does not require free oxygen and will continue until the supply of pyrite and production of ferric iron is exhausted (Nordstrom *et al.*, 1979; Singer and Stumm, 1970):

Whether the reaction stops at equation 3 ($\text{pH} > 3.5$) or if equation 4 occurs ($\text{pH} < 3.5$), exactly the same amount of H^+ is produced per unit of FeS_2 that reacts. However, the pathway of equations 1, 2 and 4 produces 16 as opposed to 12 H^+ for each unit of free oxygen involved.

Note that a similar process is involved with, but not limited to, the oxidation of other iron bearing sulfide minerals, such as pyrrhotite (iron sulfide), sphalerite (zinc iron sulfide), and chalcopyrite (copper iron sulfide).

2.1.2 Factors influencing the rate of sulfide mineral oxidation

The rate of oxidation of sulfide minerals is not solely dependent on pH. The oxidation of ferrous iron to ferric iron, a very slow process (Nordstrom *et al.*, 1979), is accelerated by a factor of as much as a million times in the presence of certain species of bacteria such as *Thiobacillus ferrooxidans* which thrive at pH lower than four (Mills, 1999). Particle size and shape also have a major influence on the surface area available for oxidation. Fine grain sized tailings particles offer a large reaction surface area and produce a high rate of acid generation (Plumlee, 1999). Furthermore, the pressures and stresses inflicted on some minerals during mining and milling, can produce more reactive mineral phases as described by Pratt *et al.* (1996) for pyrrhotite and magnetite. Void inter-connectivity, and pore pressure and saturation are other factors which influence the rate of sulfide minerals

oxidation (Walsworth, 1998). Soil and substrate mineralogy can also contribute to increase or reduce the rate of oxidation. For example, a substrate and /or soil with a high percentage of carbonate minerals may act as a buffering agent to counter acidification in the soil. Over a long period, this buffering capacity of the substrate will decrease if the acid generation is high enough to counteract its effect. Soil temperature and moisture are other factors affecting the rate of pyrite oxidation. Warm and humid soils have a higher rate of oxidation than soils in arid or cold climates (Plumlee, 1999). Sulfide oxidation also increases the temperature in the mine waste and creates a temperature gradient which causes convective air to be transported. This process significantly increases the oxygen supply and therefore the production of ferrous iron (Nordstrom and Alpers, 1999). Photoreduction of iron also has an effect on the rate of acid production in surface water streams. The more exposed the water is to the sun, the higher the rate of oxidation (Nordstrom and Alpers, 1999). Surface water entering the forest area from open tailings may have been through this accelerating process of photoreduction while contaminated ground water may not have. Secondary minerals formed after the dissolution of primary minerals can contribute to attenuate the level of acidity and slow down the mobility of toxic metals. (Nordstrom and Alpers, 1999).

2.2 POTENTIAL EFFECTS OF MINING ON ADJACENT FORESTS

The principal effect of sulfide mine waste is an increase of soil acidity. Soil pH determines the free ion activity in the interstitial water and therefore is a major determinant of element bioavailability. In general, more soluble elements (weakly bonded) increase in bioavailability with decreasing pH (Krieger *et al.*, 1999). Furthermore, the speciation of elements is strongly influenced by soil pH. The speciation of an element, unlike its total concentration, refers to its chemical, physical, or morphological state (Nieboer and Fletcher, 1996). The bioavailability and/or toxicity of an element are highly influenced by its chemical partitioning (Smith and Huyck, 1999).

High acidity in soil can cause a shortage of available elements such as calcium, and an excess of other elements such as aluminium and manganese (Russell, 1961; Shum and Lavkulich, 1999). Excess manganese tends to accumulate in plant tissues and interferes with the plant metabolism. Excess aluminium tends to accumulate at the root level and may interfere with the uptake of other nutrients such as phosphate.

An increase of soil acidity has other subsequent effects that can lead to vegetation stress. For example, the presence of one soil element can affect plant absorption of another in two ways: synergistically, i.e., the presence of one element will favour the absorption of another, or antagonistically, i.e., the presence of an element prevents or reduces the absorption of another. For example, a high concentration of iron may lead to phosphorus

deficiency (Hale and Orcutt, 1987). An increased concentration of both copper and zinc may reduce cadmium uptake by plants (Page *et al.*, 1981). In great concentrations, copper can affect the permeability of the cell membranes allowing nickel to flow into the cell (Hutchinson, 1981). If more elements are available to the plant because of an increase of acidity in the soil, it is very probable that complex synergistic and antagonistic reactions will take place and accentuate the effect of the mine pollution on the adjacent forest.

Increased soil acidity also affects the availability of essential elements to plants. Too much or too little of an essential element will induce stress. Bowen (1966) defines three criteria to establish whether an element is essential or not to a plant: (1) the plant cannot grow or complete its vital cycle without this element; (2) the element cannot be replaced by another one; (3) the element has a direct influence on the organism and its metabolism. An element is toxic if it interferes with plant growth and metabolism. An essential element can become toxic in high concentrations, but a non-essential element could be toxic in low concentrations if conditions are favourable for its absorption. As an example, zinc is an essential element that plays a role in some enzymatic processes during cellular division and development. However, if uptake in the plant is too high, it can retard growth, interfere with iron absorption, and impair the permeability of cellular membranes which cannot retain other essential elements (Collins, 1981).

A plant root system acts as a powerful mechanism of exclusion, selection, and regulation by controlling the uptake of inorganic constituents into the plant. Many equilibrium relationships are involved from the moment soil elements are in contact with plant roots.

Some elements are admitted freely while others are excluded or held back to various degrees according to plant needs (Hawkes and Webb, 1962). An increase of element availability in the soil may cause the regulation mechanism to fail and thus reduce the plant tolerance level.

Soil / plant relationships are not linear. The concentration of any available metal in the soil is not reflected in the vegetation biochemistry. As an example, Kozlov *et al.* (2000) found that in a mountain birch stand close to a nickel-copper smelter, nickel was translocated from roots to leaves in large amounts but this was not the case for copper. Immobilisation of Zn, Cd, Pb, and Cu by the roots was observed by Dahmani *et al.* (2000) who concluded that plant tolerance to heavy metals is a strategy, which allows them to reproduce and survive under high soil metal contamination. Similarly, in a study to evaluate plant accumulation of Pb, Cd, and Ba from contaminated sites, Pichtel *et al.* (2000) found that Pb and Cd concentrations were higher in the roots than in the shoots. Biological systems have many complex ways in which chemicals, water, and light interact together (Waring, 1985). This gives the plants, like any other living organisms, the ability to adapt to their environment. Plants develop tolerance to the elements present in excess in their natural soil environment (Foy, 1978). Species growing on toxic metal contaminated soils often do so because they have evolved a tolerance (Bradshaw *et al.*, 1965). This is particularly the case for vegetation that has established itself over a long period of time on a geochemical anomaly. However, this may not be the case for vegetation undergoing acid mine drainage which rapidly impacts existing vegetation. It is very unlikely that an established forest is prepared to adapt quickly to a new soil

condition where the availability of soil elements is highly unbalanced by a sudden and lasting exposure to an acidic soil environment. The complexity of the chemical reactions in such disturbed soil / plant relationships is not well understood. Whatever the source of stress, it is usually expressed through functional disturbance and structural variation in the forest vegetation.

2.3 FOREST STRUCTURE AS AN INDICATOR OF ECOLOGICAL HEALTH

Forest structure refers to its architecture or its pattern in three dimensions. In the horizontal direction, the forest closure, crown size, stem density, and species are commonly used to define the structure. In the vertical direction, tree height and layering are the main components. Forest structural changes include changes in canopy morphology such as vegetation density, leaf mutations, and changes in the seasonal timing of physiological events (Mouat, 1982). Variation in forest structure is a result of environmental disturbances that affect vegetation competition for light, water, and soil nutrients. Tree health conditions determine the structure of the forest canopy, its dynamics, and its succession; with the latter being essentially a variation in the ratio of establishment to mortality (Peet and Christensen, 1980, 1987). In general, healthy trees, not subjected to a high degree of competition from neighbours, have symmetric crowns with a predictable branch distribution along the stem and their growth volume can be predicted from the stem diameter (Waring, 1987). Depending on the source of stress, carbon allocation in plants will be affected in various manners and will determine the structure of the tree. For example, the structure of trees adapted to chronic drought or

chronic mineral deficiency often includes small and thick leaves due to the high allocation of carbon to the roots. Tree vigour is then reduced and the trees are more vulnerable to insects and diseases. In contrast, trees subjected to extreme shade favour new foliage over other parts and are more vulnerable to wind blowdown (Waring and Schlesinger, 1985; Waring, 1987).

Forest structure can be assessed through various forest biophysical parameters such as leaf area index (LAI) and biomass production. LAI is defined as the one-sided leaf area per unit ground area (Boham, 1989) and is a good indicator of vegetation processes, such as evapotranspiration (McNaughton and Jarvis, 1983), yield, vegetation density (Price and Bausch, 1995), light interception (Pierce and Running, 1988; Fassnacht *et al.*, 1994), and canopy productivity (Gholz, 1982; Gower *et al.*, 1992). High LAI indicates a higher capacity of trees to produce dry matter (wood) because it increases their capacity to synthesise carbon compounds (Running and Hunt, 1993). Green biomass represents the total foliage production (Kozlowski *et al.*, 1991). Both LAI and biomass production are strongly influenced by the annual temperature, the length of the growing season, the availability of water (Gholz, 1982), and the soil condition, which make them good indicators of the forest productive capacity and the forest's response to its environment.

3. REMOTE SENSING FOR FOREST HEALTH AND STRUCTURE: THEORY, METHODS, AND PREVIOUS RESEARCH

Stress in forests displays a variety of symptoms, some of which may be detected by remote sensing. Symptoms of tree damage can be expressed in various physiological and morphological changes such as early senescence, chlorosis, stunted or oversized growth, and loss of foliage (Murtha, 1978; Curtiss and Maecher, 1991). Forest canopy damage may be evident as reductions in structural variables such as stem density, canopy closure, or other variables related to vegetation production. These stress and damage characteristics may be manifested as spectral and spatial characteristics in remotely sensed images at both the individual tree and forest canopy scales. Each of these topics is addressed in this thesis.

The first section of this chapter reviews the available remote sensing sensors and their characteristics. The second section reviews studies which contribute to a better understanding of the relationships between leaf reflectance and plant physiological response to stress at the leaf level. The third section reviews remote sensing methods and their application to forest canopy health and structure.

3.1 REMOTE SENSING AS A MEANS TO ASSESS FOREST STRUCTURE

Remote sensing offers a wide range of sensors with various characteristics that can be used to detect forest structural variations. Optical satellite-borne sensors, which operate in multispectral mode (two to several spectral bands), produce spatial resolutions ranging from over a kilometre (e.g. AVHRR, SPOT Vegetation sensor) to 4 m (e.g. IKONOS-2). At present, spatial resolution can be as high as 1.0 m when using the panchromatic mode (1 spectral band) of Ikonos-2, and 250 m to 1000 m when using the hyperspectral Moderate Resolution Imaging Spectroradiometer (MODIS) which records 36 spectral bands. In the near future, satellite sensors will have increased numbers of narrow spectral bands (hyperspectral sensors), each with spatial resolution on the order of tens of metres. The primary processing techniques to extract information from such multispectral and hyperspectral data include statistical or non-parametric classification (e.g. maximum likelihood or neural network, respectively), statistical modelling using sampled pixels and spectral mixture analysis. The latter is a more recently developed technique that detects information at the sub-pixel level. It is investigated in this thesis.

Although some airborne hyperspectral sensors are fully operational at this time (e.g. *casi*, Itres Research Ltd; Probe-1, Earth Search Sciences Inc.), they are costly to use, especially over large areas. There is also currently a limit in spatial resolution if one wants to retain the full spectrum capability of the hyperspectral sensor used. A pixel size of less than 1.0 m is unlikely to be obtained with actual airborne hyperspectral sensors since the area sensed on the ground instantaneously is a function of the spectral bandwidth. Narrow

bands require more area and integration time (exposure on the sensor) to accumulate enough energy to achieve a given signal to noise ratio. Hyperspectral sensors, by definition, use narrow bands (2-10 nm). With current sensitivities (quantum efficiencies) of the materials they are made from (e.g. silicon – visible/near infrared; lead sulphide – short wave infrared), the integration time has to be long and the area (pixel size) has to be fairly large. Using wider bandwidths allows a faster shutter and smaller pixels. Colour and colour infrared cameras use 100 nm bandwidths and can be shuttered to up to 1/10,000 s allowing for very low altitude imaging of small pixels (cm range). Multispectral digital frame cameras are particularly useful for detailed remote sensing studies of smaller areas. Pixel sizes can be on the order of a few centimetres, which allows analysis of spatial details not seen by satellite sensors. When properly selected, the spectral bands can be optimised to suit the need of a given application. Forest structure can be assessed in detail using such sensors. Tree structure causes variations in canopy reflectance because of the great variety of three-dimensional orientations of scatterers such as leaves and stems (Asner, 1998). Tree leaves are visible to the sensor at sub-metre pixel sizes. This allows detection of information within individual tree crowns.

3.2 REMOTE DETECTION OF LEAF STRESS

Any variation in leaf reflectance spectra may indicate a functional disturbance in plant metabolism (Murtha, 1978). Foliar chemistry can directly measure plant productivity, soil nutrient availability, and the rate at which litter decomposes (Curran, 1989). However, detecting these features in the reflectance spectra of tree leaves requires knowledge of the

interaction of light with the leaf components at the cellular level (e.g. chlorophyll and other pigments, chloroplasts, cell walls).

3.2.1 Leaf spectral absorption features

Figure 2 shows a typical spectral reflectance curve of healthy green vegetation between 350 nm and 2600 nm. Photosynthesis is responsible for the strong absorption of light energy by leaf pigments (chlorophylls and carotenoids) in the 400 nm to 700 nm spectral range (Gates *et al.*, 1965) due to transitions of electron energy (Lichtenhaler, 1987; Mackinney, 1941). Chlorophyll pigments a and b absorb incident light at 430-450 nm and 650-660 nm (Jensen, 1983). They act as photoreceptors and catalysts that convert the incident light into chemical energy for the synthesis of carbohydrates (Vernon and Seely, 1966) which are the primary products of photosynthesis and the major constituents of plant dry matter (Kozlowski *et al.*, 1991). Leaf chlorophyll pigment content is therefore a good indicator of photosynthetic potential, stage of development (e.g. senescence), and nutrition status (Collins, 1978; Milton and Mouat, 1989; Curran *et al.*, 1990). Leaf reflectance in the 700 nm to 1100 nm spectral range is due to larger cell structures such as nuclei, stomata, cell walls, cytoplasm, and intercellular air spaces (Gates *et al.*, 1965; Gausman, 1977) where oxygen and carbon dioxide exchange occur for plant photosynthesis and respiration (Jensen, 1983). In the short wave infrared region (1100 nm to 2400 nm), larger leaf components such as cellulose, lignin, starch, protein (Banninger, 1988; Fourty *et al.*, 1996; Jacquemoud *et al.*, 1996; Kokaly and Clark, 1999; Peterson *et al.*, 1998), and leaf water content (Carter, 1991; Curtis, 1980; Jacquemoud *et*

al., 1996; Jensen, 1983; Knipling 1970; Wooley, 1971) are responsible for the absorption of the incident light.

Figure 2. Typical spectral reflectance curve of healthy green vegetation between 350 nm and 2600 nm (modified from Jensen, 1983).

A reflectance increase in the visible bands indicates reduced pigment absorption which, when compared to other leaf samples, provides a means to detect leaf stress. Conversely, a decrease in near infrared reflectance can be due to less energy absorption in the visible spectrum and more energy converted to heat and fluorescence (Gates *et al.*, 1965; Laval-Martin and Mazliak, 1979), or due to a lower area of air-wall spaces (Daughtry and Biehl, 1985).

The steep gradient of vegetation reflectance change from low in the visible to high in the NIR, termed the “red edge”, has been widely studied as an indicator of leaf stress. Typically, a shift of the inflexion point of the red edge towards shorter wavelengths indicates chlorophyll reduction (Chang and Collins, 1983; Boochs *et al.*, 1990; Horler *et al.*, 1983; Miller *et al.*, 1988; Rock *et al.*, 1988). The shift towards longer wavelengths has been associated with chloroplast damage (Curtiss and Ustin, 1988, 1989) and damage to other internal cell structures (Daughtry and Biehl, 1985). The former (Collins *et al.*, 1983; Curtiss and Ustin, 1989; Lévesque *et al.*, 1995; Mariotti *et al.*, 1996; Milton and Mouat, 1989) and the latter (Hare *et al.*, 1984) have both been reported as a response to metal stress. Curran *et al.*, (1991) found that the presence of high concentrations of secondary leaf pigments may affect the direction of the red edge shift. This could be a limitation in the use of the red edge as an indicator of chlorophyll content or stress type.

3.2.2 Detection of leaf stress

The following sections describe leaf spectral response to various stress conditions.

Leaf senescence

Leaf senescence is characterised by the degradation of chlorophyll pigments (chlorosis). If related to conditions other than seasonal change, leaf chlorosis can be useful in assessing leaf stress for a given stress condition. Merzlyak *et al.* (1999) have developed a

plant senescence reflectance index (680 nm – 500 nm / 750 nm) that is sensitive to the carotenoid / chlorophyll ratio and allows quantitative estimation of the onset, stage, and rate of leaf senescence.

Leaf vigour

Carter (1994) measured the leaf reflectance of plants undergoing various types and levels of stress (herbicide, ozone damage, dehydration, fungal pathogen, air pollution and nutrient availability) in order to define the best narrow band ratios related to plant stress and vigour. The 695 nm / 420 nm and 695 nm / 760 nm band ratios were found to produce the best relationships with the various types of plant stress. Various degrees of leaf vigour for balsam fir were induced in the laboratory by Luther and Carroll (1999) in order to identify the spectral indices that are most sensitive to variation in the following vigour indicators: chlorophyll content (photosynthetic capacity), nitrogen content (plant productivity), moisture content, and length of terminal shoots (carbon allocation in growth). The most sensitive band to the variation in vigour was 711 nm while the least sensitive band was 913 nm. The normalised difference index using these two bands, showed the strongest correlation and the highest significance level ($p < 0.0001$) with chlorophyll a ($r^2 = 0.75$), chlorophyll b ($r^2 = 0.66$), nitrogen ($r^2 = 0.52$), and length of shoots ($r^2 = 0.69$).

Leaf metal stress

High levels of heavy metals cause stress in vegetation, which often produces a decrease in chlorophyll content and an increase in the ratio of chlorophyll a to b (Horler *et al.*, 1980; Salisbury and Ross, 1985). It is possible to remotely estimate leaf pigment content (chlorophylls, carotenoids), which indicates the physiological state of the plant through its photosynthetic capacity (Curtiss and Ustin, 1989). Chlorophyll a and b absorption features in the blue and red bands are well documented in plant physiology literature (Salisbury and Ross, 1985; Laval-Martin and Mazliak, 1979). Singhroy and Kruse (1991) obtained a strong relationship ($r^2 = 0.985$) between the amount of light absorbed at 680 nm and the chlorophyll content of tree leaves. More recently, Zur *et al.* (2000) found a high correlation between leaf carotenoid content of yellow to yellowish green maple leaves and the 520 nm band ($r = 0.95$). The carotenoids play an important role in plant adaptation to light stress by acting as a protection mechanism from photo oxidation (photo-protectors) in the photosynthetic reaction to high irradiance (Demming-Adams and Adams, 1996; Kramer and Kozlowski, 1979). From a study of Eucalyptus leaves, Datt (1998) developed algorithms from reflectance and band ratios to estimate chlorophyll a and b, and total carotenoid content. The most sensitive bands to variation in leaf pigment content were green at 550 nm, and far-red at 708 nm while, interestingly, the main pigment absorption bands in the blue (400 – 500 nm) and in the red (660 – 690 nm) were found to be insensitive to pigment variation. This was later explained by Gitelson *et al.* (1997) and Gitelson and Merzlyak (1997), who also found that the 350 – 500 nm and

the 640 – 680 nm spectral ranges, although characterised by strong chlorophyll absorption, were unsuitable for detecting pigment content because the chlorophyll / reflectance relationship saturated at very low (350 – 500 nm) and high (640 – 680 nm) chlorophyll content. It is between 530 nm and 630 nm and around 700 nm that the best relationship between reflectance and pigment content is found because reflectance can detect a wider variation of pigment content. Using a wide range of pigment content (0.027 to 6.29 mg*m⁻²), the authors used simple band ratios to predict chlorophyll content. Their newly developed band ratios (R_{NIR} / R_{700} , R_{NIR}/R_{550}) yielded an error of chlorophyll estimation lower than 0.42 mg*m⁻². Curvilinear relationships between leaf reflectance and a wide range of leaf chlorophyll pigment content (13 to 3235 mg*m⁻²) using narrow band reflectance of stacked leaves, band ratios, and indices using visible and near infrared bands were also observed by Blackburn (1999).

There are no universal reflectance changes that can be attributed to a specific environmental condition. It depends on how and to what extent the plant is affected by the condition. The above studies helped to clarify the relationship between leaf reflectance and its constituents. The next section will show how this information is being applied at the forest canopy level.

3.3 REMOTE DETECTION OF FOREST CANOPY STRESS

Remote sensing of the forest canopy can detect physiological stress (e.g. reduced chlorophyll and nitrogen content) or structural stress (e.g. reduced leaf area or biomass).

Changes in canopy reflectance due to geochemical stress may result in an adaptation by the plants that changes canopy architecture (Curtiss and Maecher, 1991). Forest metal stress in relation to canopy reflectance has been widely studied in the past in the context of geobotanical exploration (Birnie and Francica, 1981; Bonham-Carter *et al.*, 1986; Caney and Milton, 1984; Chang and Collins, 1983; Collins *et al.*, 1983; Hare, 1986; Hornsby and Bruce, 1986; Labovitz *et al.*, 1983; Labovitz *et al.*, 1985; Lulla, 1985; Miller *et al.*, 1988; Mouat, 1982; Rencz *et al.*, 1986; Singhroy *et al.*, 1985). Geobotany studies the nature and distribution of the forest canopy through the presence of indicator species and the observation of morphological changes in vegetation growing on underlying geochemical anomalies (Brooks, 1972). For example, Banninger (1986a, 1986b) used LANDSAT MSS and TM to detect the effects of high soil concentrations of heavy metals on the overlying vegetation. An inverse relationship was observed between soil metal content and leaf area index (LAI) while canopy stress symptoms were found to be morphological rather than physiological. By using LANDSAT TM, Banninger (1987) also looked at the effect on a mixed forest canopy (deciduous and coniferous) of high soil contents of copper, lead, and zinc. The spectral variation associated with the high soil metal contents was masked by the mixture of species in the forest canopy. This is partly

due to the higher reflectance of broadleaf canopies, which exhibit more planar and horizontally oriented leaves than coniferous canopies. This shows the strong limitation of low spatial and spectral resolution sensors such as LANDSAT TM for detecting any type of stress in mixed forests. Improvements have been made with hyperspectral sensors as demonstrated by Martin *et al.* (1998) who used AVIRIS data (224 –10 nm spectral bands, 20 m spatial resolution) to identify species composition based on foliar chemistry and the unique chemical characteristics of each species. The resulting AVIRIS classification when compared to the classification obtained from field measurements was 75% accurate. Curtiss and Maeher (1991) successfully localised a known mineralised zone using a portable spectrometer onboard a helicopter by traversing four transects over a forest canopy. The first principal components of 512 spectral bands were associated with chlorophyll content within the field of view of the spectrometer and clearly showed the mineralised zone.

The following sections describe the most commonly used image analysis methods to detect forest biophysical parameters. They are presented in two groups: spectral methods and spatial methods. However, from the knowledge acquired at the leaf level in the previous section, it is first important to understand how a forest canopy is different from a stack of leaves and in what way the measured reflectance will be affected.

3.3.1 Factors affecting the remote sensing of forest canopies

Reflectance of the forest canopy depends greatly on the reflectance properties of tree leaves, which are controlled by light scattering from leaf surfaces and leaf internal structure, as well as absorption by leaf biochemicals (Datt, 1998). Asner (1998) found 4-5% (visible) and 14-18% (NIR) increases in canopy reflectance due to variability in leaf optical properties. Canopy reflectance is different from leaf reflectance because it includes variations in incident light combined with geometric effects related to canopy structure, total leaf area, and non-foliage background (Knippling, 1970). Other sources of variation in the interception of light by a forest canopy are leaf size, shape, and colour, and species composition (Peterson and Running, 1989). Moreover, the layering of a forest canopy adds to the variation since leaves more exposed to light develop higher leaf mass per area (Chabot *et al.*, 1979; Witkowski and Lamont, 1991) and higher nitrogen per area as means to increase photosynthesis (Field, 1983; Hirose and Werger, 1987). As pointed out by Hurcom *et al.* (1996), a forest canopy is not just a big leaf, but rather a “mosaic of leaves, background, and shadow”.

The anisotropic nature of the forest canopy makes it difficult to compare parameters acquired under different illumination and viewing angles. The bi-directional reflectance distribution function (BRDF – reflectance as a function of view and sun zenith and azimuth angles) varies with vegetation type and density, conditions of illumination, and background influence (Deering, 1989; Kimes, 1983; Kriebel, 1978). Walthall (1997)

used a model incorporating various solar zenith angles and various leaf angle distributions to describe the relationship between bi-directional reflectance of the canopy and LAI (ranging between 0 and 5). It was found that the degree of anisotropy and the variation of solar zenith angle are related to LAI when the canopy is dense ($\text{LAI} > 2.5$) and the BRDF becomes more stable as LAI increases until it reaches a level where an increase in LAI produces no change in the BRDF. In another study, Ross and Marshak (1989) showed that reflectance of vertical stems at nadir could be several times higher when the sensor faces the sun than when it faces opposite from the sun.

Radiative transfer models which take into account parameters such as canopy architecture and structure, leaf biochemistry and optical properties, soil contribution, and illumination conditions (view and solar zenith angles, and azimuth angles) have been developed to address the BRDF behaviour of forest canopies. For example, the SAIL (scattering by arbitrary inclined leaves) model developed by Verhoef (1984) assumes that canopy reflectance is due to three components (canopy optical and structural properties, and illumination conditions). Other models such as PROSPECT, a leaf reflectance and transmittance model (Jacquemoud and Baret, 1990; Jacquemoud *et al.*, 1995, 1996), SOILSPECT (Jacquemoud *et al.*, 1992), LIBERTY (Leaf Incorporating Biochemistry Exhibiting Reflectance and Transmittance Yields) (Dawson and Curran, 1996, 1997; Dawson *et al.*, 1998, Dawson *et al.*, 1999), and FLIM (Forest Light Interaction Model) (Gemmell and Varjo, 1999) specifically address the spectral variation of leaf and soil bi-directional transmittance and reflectance. Some of these models can be inverted to estimate specific forest biophysical characteristics. Model inversion is done through the

adjustment of the model parameters until the modeled reflectance best fits the measured reflectance. Not all models can be inverted. Some models are not formulated to be inverted and others are too difficult to invert (Woodcock et al., 1997).

Recent studies have addressed the effects of varying solar angle illumination on the forest canopy. Gemmell (2000) used multiple-view-angle data acquired at constant solar zenith angle to reduce the effect of background spectral variations and increase the accuracy of measuring forest stand characteristics. Gemmell and McDonald (2000) tested the effect of varying zenith angles on spectral vegetation indices. It was found that the selected indices provide better accuracy when view angle was off-nadir.

As seen above, forest canopy reflectance integrates the spectral variation of other components than green leaves (e.g. background and shadow), which can limit the strength of linear relationships between canopy image attributes and forest parameters. Image analysis techniques must take into account these other components. Forest canopies can be analysed through the study of the spectral variation of individual pixels and through the spatial variations of pixel values separated by known distances.

3.3.2 Spectral methods

Simple band ratio and vegetation index

From the knowledge acquired at the leaf level, a logical way to estimate forest canopy stress is to use simple band ratios and develop image-based vegetation indices that can indicate health status through canopy chlorophyll content and vertical structure (e.g. LAI). Image band ratios and vegetation indices present the advantage of reducing spatial variability in brightness due to atmospheric and illumination conditions and non-foliage background (Ministry of Natural Resources, 1997). They can also accentuate specific wavebands related to studied features (Cracknell and Saraf, 1989). However, some sensor limitations must be taken into account. For example, Teillet *et al.* (1997) demonstrated that with AVIRIS data the normalized difference vegetation index (NDVI) is sensitive to the position of the band centre and the bandwidth in the visible, while this is not the case in the NIR bands if the bandwidth remains less than 50 nm and an appropriate atmospheric correction has been performed.

McDonald *et al.* (1998) investigated information contained in six vegetation indices for a coniferous forest. Shadow within the canopy is related to the degree of homogeneity of the forest canopy and influences the non-linear behaviour of the studied indices. Moreover, most indices did not yield a unique value for a specific forest cover. Low vegetation cover was best estimated using the global environment monitoring index (GEMI) (Pinty and Verstraete, 1992) which characteristically minimises the effect of soil

and atmosphere. For high vegetation cover, the soil adjusted vegetation index (SAVI) (Huete, 1998) and the transformed soil adjusted index (TSAVI) (Baret and Guyot, 1991) were most suitable because their high dynamic range is less disturbed by atmospheric variations. Bare soil components are highly responsible for the sensitivity of vegetation indices, such as NDVI, at low LAI (2-4). At higher LAI (> 4), NDVI increases to an asymptotic limit and becomes insensitive to further variation in LAI (Carlson and Ripley, 1997).

Gamon *et al.* (1995) found that NDVI was a very good indicator of canopy structure (biomass, LAI) and chemical concentration (chlorophyll and nitrogen content) at low canopy closure (< 20%), while with higher closure (20%-100%), the index could not distinguish between the structure of the canopy and its chemical content. Turner *et al.* (1999) also found a decrease in the sensitivity of vegetation indices at high LAI. At high LAI, leaf optical properties dominate the canopy reflectance and NDVI (Huemmrich and Goward, 1997). Carter (1998) used a NDVI computed from the reflectance values at 701 nm and 820 nm to estimate the photosynthetic capacity of an optically dense canopy. The regression of the index against an estimator of photosynthetic capacity yielded an adjusted R^2 of 0.75. No mention was made, however, of the applicability of this index to a less dense canopy.

As previously stated, chlorophyll pigments are responsible for light absorption in the visible spectrum. A strong relationship between a normalised index, using the 671-674 nm band and a NIR band, was obtained by Yoder and Waring (1994) in relation to

canopy light absorption capacity ($R^2 = 0.71$). This relationship was much poorer when using a green band (565-575 nm, $R^2 = 0.27$), which shows that reflectance changes due to changes in chlorophyll concentration are wavelength dependent. Moreover, when compared to the photosynthetic capacity of canopies grown in sunlight, the relationship of these spectral bands is reversed. Indices using the green band produced a higher correlation ($R^2 = 0.84$) than indices using a red band ($R^2 = 0.37$). These variations suggest strong limitations for the use of NDVI to estimate chlorophyll content.

The non-linear and variable character of the relationships between reflectance-based indices and forest cover suggests that there is no specific index for all stress condition measurements. Instead, an index must be selected according to the specific vegetation condition of the studied area (e.g. based on the expected canopy closure, canopy gaps, understory, exposed soil, etc.). Furthermore, the choice of band and bandwidth used to produce the indices impacts strongly on how well they will relate to forest canopy spectral variation.

Red edge detection

The red edge position of the vegetation reflectance curve, as seen previously, is strongly related to chlorophyll content. Canopy chlorophyll content can be estimated using remote sensing, given a good understanding of canopy architecture and its interaction with the incident light. Demarez and Gastellu-Etchegorry (2000) used a model incorporating the variables LAI, viewing direction, understory reflectance, and canopy architecture to

estimate canopy leaf chlorophyll concentration using the red edge position of simulated canopy reflectance. It was demonstrated that canopy architecture has a strong influence which, if not considered, can yield errors as high as 2.3 mg / m² of chlorophyll in a sampling range of 1 to 10 mg / m². The results showed that the difference in the position of the red edge inflexion point between a mature stand with large crowns and a younger stand with small crowns, can be more than 10 nm, even with constant LAI and view directions. Filella and Peñuelas (1994) obtained a high correlation between the wavelength of the red edge peak in the first derivative of the spectra and chlorophyll content ($r = 0.91$), and between the amplitude of the red edge and LAI ($r = 0.97$) in seedlings of peppers (*Capsicum annum*) growing under controlled conditions. Lucas *et al.* (2000) found a high correlation between LAI and the red edge position ($r = 0.94$) derived from high-resolution *casi* data. According to Guyot *et al.* (1992), LAI is the dominant cause of reflectance variation in the red and NIR bands, which in turn determines the position of the red edge. Munden *et al.* (1994) point out that most of the canopy studies have reported a linear relationship between the red edge position and chlorophyll content. However, they found that this relationship is no longer linear at high chlorophyll concentrations. An asymptote was reached at high chlorophyll content (0.5 mg * g⁻¹) which indicates that chlorophyll content cannot be estimated beyond this concentration.

Spectral mixture analysis

Spectral mixture analysis, or spectral unmixing, is a recently developed image analysis technique that derives proportions of land cover types based on their contributions to pixel reflectance. Contrary to traditional methods of spectral analysis that are based on whole pixels, mixture analysis allows the extraction of information at the sub-pixel level. It is the primary spectral analysis method investigated in this thesis. The dimensionality of an image dataset is characterised by the number (m) of spatial dimensions and the number (n) of spectral dimensions. Most images consist of two spatial dimensions ($m = 2$). However, the spatial dimension could be 1 if there is only one line of data, 3 if the elevation is included, and 4 when using a temporal sequence of images. Each spectral band represents one dimension and can be assigned one axis in an n -dimensional space. Each pixel has specific coordinates in the n -dimension spectral space corresponding to its signal (radiance, reflectance) value at each wavelength. If two bands are used, all the spectral information contained in the dataset is confined to two dimensions and can be viewed in a 2-D scatterplot. Similarly, all the spectral information contained in a three band dataset can be viewed in a 3-D scatterplot, but data visualisation becomes difficult above this dimensionality (Boardman, 1995).

In a remote sensing image, a pixel digital number represents a weighted average of radiance from all reflecting elements within the pixel boundaries. Minor additional radiance may be contributing from adjacent areas because of atmospheric scattering and the atmospheric contribution itself while some radiance from the pixel space may be

scattered away by the atmosphere (Shimabukuro and Smith, 1991). Thus, a pixel spectrum incorporates the spectral variation of different cover types (e.g. vegetation, shadow, soil) and is a mixture of all the surface material spectra within its field of view. Any given image pixel can be modeled as a linear combination of pure reflectance components, or endmember spectra, that represent each pure cover type (Figure 3) (Boardman, 1995; Shimabukuro and Smith, 1991). The endmembers are the basic constituents of the imaged area on the ground. A pixel spectrum can be decomposed into these constituents. The coefficients in this decomposition represent the fractions of each pixel occupied by the various target components. An image, referred to as a fraction image or an abundance image, can be generated for each target constituent. Each pixel value corresponds to the fraction of the constituent, as represented by each endmember spectrum.

Figure 3. Schematic of spectral mixture analysis.

Endmember selection

The selection of endmembers is the first step in spectral mixture analysis. Depending on the number of spectral bands used and the ground scene spectral variability, data dimensionality can be reduced to fewer dimensions using a principal component (PC) transformation prior to the endmember extraction (Boardman, 1995). Figure 4a illustrates the “endmember” concept showing the possible mixture space of three endmember spectra (shaded area). All the image pixels are confined within the mixture zone, which is defined by joining the endmember vertices (Boardman, 1995). Adding a fourth

endmember would require viewing the mixture area in three dimensions, and so forth. In two dimensions, as seen in Figure 4a and 4b, endmember pixels are found at the vertices. Pixels containing a combination of two endmembers are found along lines that form the edges of the mixture zone (Figure 4b). If one more dimension were added, pixels containing three endmembers would be found on the planes, which form the faces of the mixture zone (Szeredi *et al.*, 1999).

Figure 4. Concept of linear mixtures of endmember spectra (from Boardman, 1995)

Endmembers are usually extracted from the image data, but can also be taken from field or laboratory spectral measurements. There are several methods for selecting endmembers from image data. Manual methods (Bateson and Curtiss, 1996; Boardman, 1993) require operator interaction and focus on the visual identification of the purest pixels since vertices are easier to identify than edges and faces. The endmember spectra are combined linearly to form all other pixel spectra. Figure 5 illustrates how endmembers are manually selected in principal component (PC) transformed data.

Figure 5. Manual endmember selection from a rehabilitated mine tailings (Lévesque *et al.*, 1997).

Automatic endmember selection methods are not limited to the purest endmembers located at the vertices. They may also find endmembers composed of a few mixtures (at the faces and edges) which are very common in natural scenes. Szeredi *et al.* (2001) reviewed four automatic endmember selection algorithms. Two of the algorithms (iterative target transform factor analysis and alternating regression) are best suited for images containing no pure pixels, i.e., where every pixel is mixed. The remaining two algorithms (iterative error analysis and purest pixel clustering) apply best to images containing relatively pure pixels. Automatic endmember selection methods require less intervention from the user and are more objective but they must be validated.

Constrained linear spectral unmixing

Constrained linear spectral unmixing confines the image fraction between 0 and 1. Unconstrained unmixing produces similar results but some endmembers may be

attributed abundance values that are negative or larger than 1 (Boardman, 1990). In the constrained method, the abundance values are all positive and sum to 1. Linear constrained unmixing decomposes the image spectra $\vec{S}$ in terms of endmember spectra $\vec{S}_i$:

$$\vec{S} = \left(\sum_{i=1}^N f_i \vec{S}_i \right) + \vec{r} \quad (5)$$

where $0 \leq f_i \leq 1$, $\sum_{i=1}^N f_i = 1$ and f_i is the fraction of endmember i contributing to the pixel spectrum $\vec{S}$, N is the total number of endmembers, and $\vec{r}$ is the error term. The result of the unmixing procedure is a set of N fraction images that show the fractional abundance of the endmembers.

The unmixing errors indicate the degree to which the observed spectra fit the model spectra. It is the absolute difference between the spectrum obtained by the sum of the endmember spectra and the raw image pixel spectrum. In the event of a large unmixing error, one can assume that the set of n endmembers used in the linear decomposition is not a complete set.

In the fraction images, endmember abundances are displayed on a grey level scale which is advantageous over simple classification methods and image indices. In a study of mine tailings reclamation, Lévesque *et al.* (1997) validated the image endmember fractions using independent measurements of percentage ground cover. They obtained R^2 values of

0.96 and 0.92 between two endmember images and ground percentage of green vegetation and lime, respectively.

The linear model of spectral radiance mixing does not take into account multiple scattering between different types of cover and can yield large errors (Roberts *et al.*, 1993). This concept is expressed in a simplified way by Boardman (1989) who explains that non-linear spectral mixing occurs when photons meet more than one target before escaping the ground and finding themselves in the field of view of the sensor. Vegetation canopies produce non-linear scattering due to multiple reflections and transmissions of light between leaves, bark and soil as demonstrated by Borel and Gerstl (1994). Moreover, the shading effect produced by the obstruction of illumination by opaque objects (e.g. tree crowns) causes variations in brightness amongst similar surface types (Adams and Smith, 1986). Therefore, linear spectral models incorporate errors attributed to non-linear mixing. Figure 6 is a schematic showing the non-linear behaviour of light energy exiting a vegetation canopy. Because of the high complexity and computational demands involved in non-linear mixture modelling, it is not commonly used (Oleson *et al.*, 1995).

Figure 6. Non-linear behaviour of light energy exiting a vegetation canopy for (a) horizontal leaves and (b) non-horizontal leaves (Ray and Murray, 1996).

Spectral mixture analysis has recently been applied to detect forest canopy biophysical and structural parameters. For example, Elmore *et al.* (2000) compared the use of spectral mixture analysis and NDVI to estimate vegetation changes in a semiarid area using LANDSAT TM data from multiple years. The mixture analysis results produced a better estimation of the vegetation change direction with a precision of 4%. Spectral mixture analysis was used by Peddle *et al.* (1999a) to determine sub pixel fractions of sunlit canopy, sunlit background and shadow under various solar zenith angles. These were used to predict forest biomass, Net Primary Productivity (NPP) and Leaf Area Index (LAI). Predictive models obtained using spectral mixture analysis yielded significantly higher R^2 values and lower standard error (s_e) than models using NDVI. Piwowar and Peddle (1999) applied spectral mixture analysis in a temporal study to characterise changes of NDVI in the boreal forest. In their study, an endmember (EM) spectrum represented 14 years of NDVI values. They identified three time series endmembers that included the extents of the variability of the boreal forest ecosystem of their study area.

Peddle *et al.* (1999b) evaluated the use of image tone, image fractions, image texture, and NDVI extracted from a 3-band (green, red, NIR) video camera system at 30 cm spatial resolution to predict LAI. The best prediction model was achieved using a combination of image tones, image fractions, image textures, and NDVI with an adjusted R^2 of 0.70.

Fractional representation of endmembers in each pixel is a quantitative way to represent image cover types and separate them from each other. Images of the proportion of each cover type occupying each pixel are produced that give more details than can be achieved using analogous whole pixel-based models or classification processes (e.g. maximum likelihood classification). An endmember image is easier to interpret than digital numbers since they are directly linked to a percentage cover, whereas a single pixel digital number represents only an average radiance (Adams *et al.*, 1995). When using the image fractions of endmembers such as vegetation, shadow, and non-photosynthetic vegetation, image data are transformed to a closer representation of the ground measurements. Spectral unmixing can separate vegetation species as shown on Figure 7 for an agricultural application from Staenz *et al.* (2001) using hyperspectral data. In this case, image fractions of beans show more within-field variability than the corresponding NDVI, which displays the total green biomass and cannot make the distinction between the crop and the vegetative non-crop portions. This indicates that the non linear behaviour of vegetation indices, which is caused by saturation at high biomass values, does not apply to fraction images of basic vegetation constituents.

Figure 7. Maps of bean fractions and NDVI from an agricultural application (Staenz *et al.*, 2001).

In summary, spectral methods have shown some limitations. The red edge position is often a good tool to estimate canopy chlorophyll content, but the presence of secondary leaf pigments can make chlorophyll hard to detect. Vegetation indices do not behave in a linear way and saturate at low or high vegetation covers depending on the index used. This limitation can be overcome when using fraction images of cover types if enough bands are used to resolve the number of cover types present. For this reason, and to investigate the potential for sub-pixel modelling of forest structure and health, image fraction analysis was incorporated into this research.

3.3.3 Spatial methods

Spatial image analysis methods use the values of pixels in a region, whereas spectral methods are typically performed on a pixel-by-pixel basis. Two common groups of measures used to represent image spatial information are texture and geostatistics. Both have potential in high resolution imaging and are investigated in depth in this thesis.

Texture analysis

Tone and texture are the two primary properties of an image. Tone is the shade of grey or brightness at a point or pixel, while texture is the spatial distribution of the grey tones in a defined area. Texture can be represented using descriptors such as the “visual impression of roughness or smoothness created by some objects” (Colwell, 1983). Van Gool *et al.* (1985) define image texture as a structure made of a certain number of more or less organised patterns. In a single pixel, tone is the only property; when adding more pixels with various grey levels, texture becomes apparent. One property can be dominant over the other. For example, when the image shows little variation of grey levels, tone is dominant; when it displays a wide variation of grey levels, texture is the dominant property (Haralick *et al.*, 1973). Texture can vary from fine to coarse. When a spatial pattern involves a few pixel values, the resulting texture is fine; as the number of pixel values in the pattern increases, the texture becomes coarser (Haralick *et al.*, 1973).

Texture information can complement spectral information since objects that are difficult to separate spectrally can often be distinguished by their texture. While it is easy for human eyes to recognise variations in image texture, it is difficult to do so quantitatively using digital image analysis. There are a wide variety of texture measurement algorithms and many input parameters that must be properly defined. First order texture measures are calculated directly from the image grey tone values (e.g. mean, standard deviation, variance, fractal dimension). Second order texture measures are calculated from the spatial grey tone co-occurrence matrix and were introduced by Haralick *et al.* (1973). The spatial grey level dependence (SGLD) method involves the computation of co-occurrence matrices that synthesise the textural information from image segments. These matrices contain the occurrence frequencies of the grey levels of sampled pairs of pixels in a given direction (angle) and at a given distance apart. An example of a co-occurrence matrix is given in Figure 8.

Figure 8. Example of image data (a) and calculation of the corresponding co-occurrence matrix (b). The frequency of occurrence of pixel pairs is calculated in four directions at a lag of 1: (c) 0° , (d) 90° , (e) 135° , (f) 45° (Haralick *et al.*, 1973).

The 4 X 4 image has four grey tones (0 to 3). In this example, using a 0° (horizontal) direction from left to right and right to left (Figure 8a), there are 4 pairs of pixels with values (0,0), 2 pairs of pixels with values (0,1), 1 pair of pixels with values (0,2) and so forth. When frequencies are high along or near the diagonal of a co-occurrence matrix, less texture is present in the image since there is a high proportion of neighbouring pixels that have identical or similar grey levels. On the other hand, high frequencies away from the diagonal indicate variations of larger magnitude. Second order statistical measures can then be applied to the co-occurrence matrix. Haralick *et al.* (1973) defined 14 second

order texture measures that can be extracted. Each evaluates a different aspect of image texture such as homogeneity, contrast, and entropy.

To illustrate how the second order textures are calculated from the co-occurrence matrix, Figure 9 shows the equations and the texture values of four second order texture measures mean (MEA), entropy (ENT), angular second moment (ASM) and contrast (CON)) as defined by Haralick *et al.* (1973) for two image examples.

image a				image b			
3	0	3	0	2	1	1	0
0	3	0	3	1	1	1	1
3	0	3	0	0	0	1	1
0	3	0	3	1	1	0	1

$$\begin{pmatrix} 0 & 0 & 0 & 12 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 12 & 0 & 0 & 0 \end{pmatrix} \quad P_{(0^\circ)} \quad \begin{pmatrix} 2 & 4 & 1 & 0 \\ 4 & 12 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$MEA = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} i \frac{p(i, j)}{R} \quad \begin{matrix} \mathbf{a} = 1.50 \\ \mathbf{b} = 0.75 \end{matrix}$$

$$ENT = - \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \frac{p(i, j)}{R} \log \frac{p(i, j)}{R} \quad \begin{matrix} \mathbf{a} = 0.32 \\ \mathbf{b} = 0.62 \end{matrix}$$

$$ASM = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \left(\frac{p(i, j)}{R} \right)^2 \quad \begin{matrix} \mathbf{a} = 0.50 \\ \mathbf{b} = 0.32 \end{matrix}$$

$$CON = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (i - j)^2 \frac{p(i, j)}{R} \quad \begin{matrix} \mathbf{a} = 9.00 \\ \mathbf{b} = 0.67 \end{matrix}$$

Figure 9. Equations of the texture measures Mean (MEA), Entropy (ENT), Angular Second Moment (ASM) and contrast (CON) and their values for image a and image b using a 0° direction and a lag of 1.

The textures were calculated for a single direction (0°). In these equations, $p(i,j)$ is the frequency of occurrence in the image sample of pixel pairs with values i and j (the co-occurrence matrix entry) and R is a normalising constant which represents the total number of pairs of cells in the co-occurrence matrix. The quantity $p(i,j)/R$ is the probability of occurrence of grey levels i and j in the image sample and n is the number of possible grey levels in the image. The MEA measure is the average probability of grey level pair occurrence within the co-occurrence matrix. A higher weight (i) is attributed to pairs containing higher grey levels. ENT is a measure of the degree of organisation, i.e., the presence or absence of distinct patterns within the co-occurrence matrix. It is high when the pattern is more complex and involves more grey levels. ASM is a measure of homogeneity that detects grey-tone transition. It is the sum of the squared probabilities of each grey level pair. Because ratios are squared, highly variable texture produces smaller ASM values than blocky texture (e.g. image a) or uniform (no) texture where $ASM = 1.0$. For this reason it is expected to decrease as texture increases in natural forest images. CON is a measure of the amount of local variation. It is high when the variation within the co-occurrence matrix is high since it is strongly weighted with $(i-j)^2$ when the grey level pair difference is large. This weighting causes values of CON to be very high at transitions between bright objects (e.g. trees) and dark objects (e.g. shadow).

Image texture can be used to improve the detection of forest biophysical parameters. For example, Wulder *et al.* (1996) combined texture information with NDVI from *casi* data to improve the estimation of LAI ranging from 2.39 to 7.05. The regression model improved from an R^2 of 0.67 when using NDVI alone to an R^2 of 0.92 when

incorporating texture in the model. Olthof and King (1997) found that CON was the best amongst several tested for estimating LAI in high-resolution (0.25m) colour infrared imagery. They obtained R^2 values of 0.31 when using mean NIR spectral data alone, 0.41 using CON alone, and 0.62 using both. Pellikka *et al.* (2000) found that the CON measure increased the significance of models to assess forest canopy structural damage in 0.25 m colour infrared images.

Sampling distance and orientation play a significant role in the calculation of a texture measure. It is possible to select a given direction or calculate texture measures in all directions (omni-directional texture). In natural forest images without expected systematic structure, omni-directional texture is commonly used. In terms of distance, most applications use adjacent pixels (distance = 1) although some studies have found that larger distances provide better models (e.g. Olthof and King, 1997). The next section introduces the concept of geostatistics which considers this aspect of texture analysis from a different perspective.

Geostatistical analysis

Geostatistics are used to analyse spatially distributed data. The concept of a regionalized variable forms the basis of geostatistics. Because of the spatial continuity of a regionalized variable it is not truly random. Neither is it totally deterministic since a deterministic function can not describe the changes at any particular location (Davis, 1986). Image geostatistics merge information on the spatial relationships between pixels

at various distances apart. They are based on the assumption that pixels close to each other have more similar digital numbers (radiance or reflectance) than pixels further apart. The distance of spatial similarity within the image depends on the nature and components of the imaged scene. The semivariogram function is used to link the spatial variance of the data and to describe the scale and pattern of spatial variability in the dataset (Curran and Atkinson, 1998). It is a useful tool to quantify the correlation between spatially related samples in imagery (Armstrong, 1998).

Semivariance, S^2 , is half of the squared difference between pixel digital numbers z , at two locations, x and $x + h$ (after Curran, 1988):

$$S^2 = \frac{1}{2} [z(x_i) - z(x_i + h)]^2 \quad (6)$$

The semivariogram $Y(h)$ is a graphical representation of the average semivariance of several pixel pairs at each lag (h). It displays the spatial variability within the data set (Cohen and Spies, 1990) by capturing the variance between spatially separated pixels (Wulder *et al.*, 1997) and provides information about the intensity and the scale of the variation (Kitanidis, 1997). The semivariogram is calculated as (Curran, 1988):

$$Y(h) = \frac{1}{2m} \sum_{i=1}^m [z(x_i) - z(x_i + h)]^2 \quad (7)$$

where m is the number of pairs of pixels separated by the same lag. Thus, $Y(h)$, the average semivariance of m sample pairs, is obtained for each lag and plotted against lag.

The support size of the semivariogram refers to the size of the spatial unit and is represented by the pixel size in remote sensing images. Regionalized variables typically exhibit different characteristics with various support sizes (Davis, 1986, Atkinson and Curran, 1995).

Mathematical models are fit to the semivariogram by least squares techniques to determine the range, the sill, and the nugget. Figure 10a shows an example of a spherical shape semivariogram with the range, sill, and nugget. In this model, the pixels at small lags are more likely to have lower semivariance than at greater lags, with semivariance increasing until a maximum is reached at the **sill**, which indicates the amplitude of the variation. The lag at which this maximum is reached is called the **range** and is interpreted as a measure of spatial dependence of the data where samples at and beyond this separation are uncorrelated (Kitanidis, 1997). The range is often associated with the size of individual objects such as tree crowns in high resolution imagery or forest stands in low resolution imagery as grey levels often change abruptly at boundaries of such objects (Woodcock, 1988a, b). When the semivariance intercept is not 0, there is a nugget effect. The **nugget** is an estimate of the variability at a lag of zero and is indicative of micro-variability, i.e., variations at a scale smaller than the sample size, and/or noise (Kitanidis, 1997).

Figure 10. Example of semivariogram models: (a) spherical model showing the sill, the range and the nugget, (b) periodical model and (c) linear model.

The semivariogram function is the inverse of the autocorrelation function when the variables are stationary, i.e., when a sill is reached. In the case of non-stationarity (linearity), the autocorrelogram is not of any use (Armstrong, 1998).

The shape of the semivariogram model provides information about the structure of an image scene. A spherical model is typical of an image where pixels become completely independent above the range (Figure 10a). In contrast, a periodic semivariogram (Figure 10b) shows a repetitive pattern where the semivariance of pixels farther apart is less than pixels closer to each other (e.g. forest plantation with rows of trees). A linear semivariogram increases constantly and does not reach the range (Figure 10c). It often occurs when the maximum sample lag used is not great enough to reach the maximum variability between pixels.

Semivariograms can be calculated in a unique direction (directional) or for all directions (omni-directional). The separation distance h , in this case, is a scalar (no direction) rather than a vector (directional) (Kitanidis, 1997).

Several authors have used semivariance analysis to characterise the spatial structure of forest canopies from remotely sensed imagery. Unlike pixel-by-pixel classification, these techniques consider the spatial relationships between the values of surrounding pixels (Atkinson and Lewis, 2000). For example, Bowers *et al.* (1994) used semivariance statistics (range, sill, nugget) derived from SPOT HRV panchromatic and multispectral data to separate and model Balsam fir (*Abies balsamifera*) damage caused by the woolly adelgid. There was a net improvement in the regression model when using semivariogram estimates compared to the use of spectral bands averaged over the forest stands (R^2 increased from 0.49 to 0.96). However, because of the restrained number of points in the semivariogram plots, it is not apparent that the range was reached and no mention is made of the number of pixel pairs used to produce the semivariograms. Cohen and Spies (1990) used 1 m, 10 m, and 30 m resolution airborne video images to extract structural and textural information for Douglas fir (*Pseudotsuga menziesii*) canopies. They found that the ranges of the 1 m resolution image were related to the mean size of tree crowns while the sills were found to relate to variation caused by vertical layering and canopy closure. Semivariograms extracted from the 10 m and 30 m resolution images did not reveal any significant trends. St-Onge and Cavayas (1995) used the directional semivariogram approach with MEIS II (Multi-detector Electro-optical Imaging Scanner) 0.36 m to 2.16 m resolution images to relate forest structure to image texture in order to quantify tree size and tree density. They obtained good correspondence between the actual and predicted values for six forest stands of various species of natural and plantation stands. Treitz and Howarth (2000) used the semivariogram to determine an optimal spatial resolution to characterise forest ecosystems. They found that different

scales of variability are present in a single spatial resolution and related this to ground-based (forest ecosystem class, contribution of understory) and sensor-based (wavelength) parameters. Wulder *et al.* (1997) introduced the Semivariance Moment Texture measure, derived from the semivariogram statistics of 1 m resolution *casi* images, as a textural indicator which relates to canopy LAI for both homogenous and heterogeneous cover types. Hudak and Wessman (1998) used scanned air photographs to map vegetation density in order to monitor the intrusion of woody plants into the South African savannas. They found that the sill values of the semivariograms were highly sensitive to the density of woody plants while the range values indicated that the canopy structure varies at a scale of about 10 m.

This chapter has presented theoretical and methodological aspects of spectral and spatial analysis that are pertinent to the thesis research. Previous applications were reviewed that indicate the potential of spectral mixture analysis and spatial analysis for modelling forest structural damage. In this research, both methods are combined to derive new spatial image variables which describe the forest in terms of both texture and structure.

4. STUDY SITE: DESCRIPTION AND PREVIOUS RESEARCH

4.1 THE KAMKOTIA MINE

4.1.1 Initial observations leading to the selection of the KamKotia mine as the study site

The KamKotia mine was selected as a candidate for this study because of its known acid drainage problems (Figures 11, 12, 13) and its fairly simple physiography (as determined from a topographic map and stereo air photos). A general drainage direction from one of its tailings areas into an adjacent forest was inferred. It was first visited in May 1992 and the following observations confirmed its suitability for studying forest damage:

- There was evidence of a high water table. Some oxidized iron water pools were observed on the soil surface in the forest indicating intrusion of acid drainage. Figure 14 shows the edge of the tailings. Note the marks on the standing dead trees showing how high the water table can reach.
- The large open tailings allows strong hot winds to develop and blow into the forest producing visibly evident mechanical stress (Figure 15).
- Tailings dust was observed on leaves and bark in the forest suggesting wind transportation of tailings particulates (Figures 16, 17, 18).

- Visible evidence of tree stress was observed within an aspen stand. Individual tree leaves were paler green, had orange edges, and were smaller than normal. Leaves were often curled indicating possible disease or insect damage (Figure 19). Individual aspen crowns appeared thin and open with dead branches and often displayed clustered leaves (Figure 20).
- There was evidence of poor regeneration and many dead standing trees (Figure 21).

Figure 11. Example of seepage from the tailings area into the surrounding forest.

Figure 12. Surface water on tailings.

Figure 13. Expanding north unimpounded tailings.

Figure 14. Forest at edge of tailings showing high water mark on standing dead trees.

Figure 15. Effect of wind at edge of tailings.

Figure 16. Leaves coated with wind-transported tailings dust. (Courtesy of E. Seed, Department of Geography and Environmental Studies, Carleton University).

Figure 17. Tailings particulates on bark. (Courtesy of E. Seed, Department of Geography and Environmental Studies, Carleton University).

Figure 18. Airborne tailings dust (Cosmopoulos, 2000).

Figure 19. Stressed leaves from top of aspen near tailings.

Figure 20. Thinned aspen crowns near tailings.

Figure 21. Forest floor in proximity to tailings.

4.1.2 Description of the study site

The abandoned KamKotia zinc and copper deposit is located about 40 km north west of Timmins, Ontario (Figure 22). It is within the Kamiskotia Volcanic Complex of the Kamiskotia Assemblage, a supracrustal assemblage within the southern Abitibi Greenstone Belt. The Abitibi Greenstone Belt (2.75 – 2.69 Ga) comprises a portion of the Abitibi Subprovince within the Superior Province of the Canadian Shield. It is the largest greenstone belt in the world and is unique amongst Canadian Shield greenstone belts due to a high ratio of supracrustal to intrusive rocks, and a relatively low grade of regional metamorphism. The northern belt has undergone greenschist or higher regional metamorphism and is characterised by abundant tonalite-trondhjemite-granodiorite intrusions, large anorthosite complexes, and relatively small numbers of ultramafic flows.

Conversely, the southern belt, containing the Kamiskotia Assemblage, experienced greenschist or lower regional metamorphism, and has fewer tonalite-trondhjemite-granodiorite intrusions and abundant ultramafic flows (Jackson and Fyon, 1991). The greenschist facies Kamiskotia Assemblage is composed of the synvolcanic, tholeiitic Kamiskotia Gabbroic Complex, overlain by the younger Kamiskotia Volcanic Complex. The assemblage is bounded by the Mattagami Fault to the east, a separate metavolcanic assemblage to the north, and by the Carscallen Assemblage to the south and west. The KamKotia property is a volcanic massive sulphide (VMS) deposit, an open pit mine, found within the Kamiskotia Volcanic Complex.

Figure 22. Study site location

The complex itself consists of rhyolites, basalts, minor evolved basalts and andesites. Mafic metavolcanic rocks, host rocks to the VMS deposit, are grouped into four divisions based on geochemistry. Tholeiites, iron tholeiites, icelandites and high alumina basalts are the predominate mafic rocks, that, in association with subordinate high-silica rhyolite flows and tuffs host lenses and/or masses of sulphide mineralization (pyrite, pyrrhotite, chalcopyrite, sphalerite, minor magnetite and trace galena). Icelandite sills are also found in association with these deposits. (Jackson and Fyon, 1991).

The deposit was first mined by Hollinger Mines Ltd. from 1942 to 1950 to meet wartime needs for copper and zinc and after by KamKotia Mines Ltd. from 1950 to 1972 when it ceased operation because the company went bankrupt. During this period, 6 million tons of ore were mined and 200,000 tons of waste rock with a high content of massive sulfide minerals (mainly pyrite) were produced (Ferguson, 1993). The rate of tailings deposition at the site was estimated at 1650 tons per day at the closure of the mine (Gibson, 1976). Three large tailings areas totaling about 350 ha surround the original mine to the north and south. Approximately 3 million metric tons of tailings were discharged in the north tailings before the Ontario Water Resources Commission recommended its impoundment in 1967 (Gibson, 1976). A 7 m high dam was then built to impound part of the north tailings (Figures 23, 24). Because the dam was built from waste rock high in acid generating sulfide minerals, and no lining was used to properly confine the tailings, it continued to seep and leak. Since then, the unimpounded north tailings have received seepage from the north impounded tailings in addition to the tailings discharged prior to the establishment of the dams. Its surface was estimated to be 168 ha by Walsworth

(1998). At the time of deposition, tailings contained an average of 40% to 50% of iron sulfides, composed mainly of pyrrhotite and pyrite (1%), zinc sulphide (0.55%), and copper sulphide (0.12%) (Gibson, 1976). Surface drainage from the north unimpounded tailings follows two creeks, which exit the tailings from its northern boundary (Figure 23) and feed the Kamiskotia River which further feeds the Mattagami River (Gibson, 1976).

Figure 25 shows the eastward expansion of the north tailings from 1961 to 1991 (Walsworth, 1998). According to Mussakowski *et al.* (1993), a 10-fold increase in the rate of environmental damage from the KamKotia tailings is expected in the next 50 years, and no natural restoration is expected for the next 175 years. On September 15, 1999, the Ontario Ministry of Northern Development and Mines announced the initiation of a 27 million dollar program through the Abandoned Mine Rehabilitation Program to rehabilitate damaged land from former mine sites. From this amount, one third of the money allocated for this program will be spent on the rehabilitation of the KamKotia mine site over a 2 to 5 year period because it is the worst abandoned mine environmental hazard located on crown land.

Figure 23. Map of the KamKotia mine showing the three tailings and the study area (modified from Cosmopoulos, 2000).

North Unimpounded
Tailings

Impoundment
Wall

North Impounded
Tailings

Figure 24. Pervious dam separating the north impounded and unimpounded tailings.

Figure 25. Expansion of the north unimpounded tailings between 1961 and 1991
(Walsworth, 1998).

The pH of the water in the creeks of the north unimpounded tailings was measured at 1.4 and 2.0 in August of 1993 and 1994, respectively. This is about a ten-fold increase in acidity since 1976 when Gibson (1976) reported pH values between 2.5 and 2.8 in the effluents. While the mine was still active, pH values of deposited tailings were usually high (7 to 8) because of the lime that was used in the flotation process. The buffering capacity of the added lime must have been exhausted fairly quickly considering the pH values obtained by Gibson (1976) in 1975 only three years after the closure of the mine in 1972. Gibson (1976) also measured an increase in elements such as arsenic (110 fold), zinc (183 fold), iron (7.2 fold), and cobalt (30 fold) from 1971 to 1975. Tailings contaminants were found to decrease with distance from the impounded tailings, confirming the occurrence of seepage from the north impounded tailings into the north unimpounded tailings.

The two creeks that drain the north unimpounded tailings are approximately 1.3 km apart (Figure 23). Although both flow in a northerly direction, the western creek bends around to the east after about 400 m and flows towards the eastern creek, which it joins to form a single northerly flowing creek. The two creeks effectively delimit an area of forest about 1.3 km long (east-west) by 500 m on the west side to 800 m on the east side. While surface drainage follows the creeks around this forested area, analysis of the 1:10,000 Ontario Ministry of Natural Resources Base map for the site revealed a gentle topographic slope from the tailings edge to the northern boundary of the forest area, with an average slope of about 1° . It was therefore hypothesised that metal-contaminated near-surface groundwater originating in the tailings could flow in a near-northerly direction through the forested area perpendicular to the contour lines. Thus, a study area was selected between the two creeks (Figure 26), and six plots were established along an 800 m transect starting from the mine tailings and following the drainage direction (Figure 27). The transect was located 40 m east of a Falconbridge Inc. exploration transect. Only six plots were established since the initial goal was to sample and analyse individual trees based on a just completed research by King *et al.* (1992) on sugar maple decline. The plots were designed to be large enough to obtain at least 30 dominant trees. The transect was located across a forest of essentially uniform composition and site characteristics. Plots 1 to 3 are 100 m apart and the others are between 150 and 200 m apart. The furthest plot from the mine tailings, plot C (control), was used as a reference as it is located on slightly higher ground across the west/north creek and was expected to not be affected by the acidic drainage. It is located on a rise across the north creek in a forest that was deemed to have similar composition as the other plots but which would not be affected by

the acid mine drainage. Each plot covers an area ranging from 50 X 50 m to 60 X 60 m. Initially four plots were established every 200 m beginning 40 m from the tailings. A 5th plot was then located between the first two to capture what appeared to be forest spatial variation near the tailings. Each of the plots was installed exactly 40 m east of the Falconbridge transect with no bias. Plot 4 was, however, later moved because it was located in a gully with much more balsam poplar than the other plots. It was moved to the closest location north of the gully that was dominated by aspen.

The soils vary along the transect from predominantly sandy to more loamy but with no known spatial trend. The forest is composed of mature trembling aspen (*Populus tremuloides*) with a mean age of 76 years ($s = 12.9$, $n = 30$), a few small pockets of co-dominant balsam poplar (*Populus balsamifera*), and an understory of young black spruce (*Picea mariana*), white spruce (*Picea glauca*) and balsam fir (*Abies balsamea*). The transect was deliberately located within this aspen stand because of: i) the known sensitivity of aspen to airborne pollutants such as SO₂ and heavy metal emissions, which is analogous to windblown deposition of pollutants from the high sulfur tailings, ii) aspen's preference for alkaline soils making it less tolerant to acidic environments than other boreal forest species (Peterson and Peterson, 1992), and iii) the high potential for mechanical effects of wind from the tailings to exacerbate the gradual deterioration of this mature stand.

Figure 26. Scanned 1991 airphoto of the north unimpounded tailings showing the location of the transect.

Figure 27. Near-infrared digital camera image of the study site showing the study plots' layout.

Image from September 7, 1995. Pixel spacing is 1.0 m.

4.2 PREVIOUS RESEARCH AT THE KAMKOTIA MINE

Since 1992, a research program has been in place at the KamKotia mine site to study forest structural damage associated with the mine site. Walsworth and King (1999) evaluated the forest dynamics at the site using temporal aerial photography spanning the period from 1961, just after extensive tailings deposition began, to 1991. Using automated tree crown delineation techniques, and spatio-temporal transition modelling, they found a significant trend towards the opening of the forest canopy and the perpetuation of pioneer species over that time in an area within 200 m of the tailings edge. Further away, the trend was towards influx of later successional conifers. Thus, the area close to the tailings edge is in a constant state of disturbance from the factors described above. This spatial trend has been confirmed using field measures of crown closure and leaf area index (LAI) by Olthof and King (2000). Seed and King (1997) used spectral shadow fractions representing deep shadow between crowns, transitional shadow on crown edges and diffuse within-crown shadow, in a multivariate analysis with LAI. For a range of forest compositions from almost pure coniferous to almost pure deciduous (in 15 plots near the west creek) and a range of LAI from 2-6, a standard error of estimate of 0.3 and r^2 of 0.9 were achieved. Olthof and King (1997), using Seed and King (1997) data, evaluated several co-occurrence texture measures and texture variations and found that they were as good or better at predicting LAI than spectral measures. Olthof and King (2000) combined many of these image and field variables together in a canonical analysis in an initial attempt to formulate a suitable image-based health index for the site. Cosmopoulos (2000) applied this health index methodology in a temporal analysis of

change from 1997 to 1999 and found significant forest structure change close to the tailings edge.

The research of this thesis was initiated before the studies listed above. It was the first study at the KamKotia mine site and thus, much initial field reconnaissance was needed. It was also the first research study to apply the multispectral airborne digital camera sensor developed by King (1996), so a large amount of development effort was necessary.

The above studies were each smaller in scope and benefited from the initial understanding of the site and method of this research.

5. FIELD AND AIRBORNE DATA ACQUISITION

5.1 SOIL CHEMISTRY

To determine if soil metal concentration varied along the transect (i.e. with distance from the tailings edge), soil samples from each of the A, B, and C horizons were collected at five random locations along the axis perpendicular to the apparent drainage direction up to a distance of 25 m from the centre of each plot. Soil sampling was conducted in May and August of 1992 and 1993, and August of 1994. In total, 450 samples were analyzed. The soils consisted of fine grain sands/silts, underlain by silty clays and till or hard pan. Auger hole profiles were characterised by a thin cover of deciduous litter underlain by about 5 cm of dark organic material. A fairly abrupt transition (~1 cm) was evident culminating in a B horizon, composed of a grey-brown sandy silt which at depths of about 20-40 cm became more argillic. At greater depth (> 50 cm), soils of the C horizon generally became medium grey and more argillic.

The collected samples were dried and sieved (2 mm) prior to being analyzed. Aqua Regia, a mixture of hydrochloric and nitric acids, was used to bring the soil samples into solution (Appendix 1). It does not produce a total digestion but has an intermediate strength that does not break down the soil matrix as with a stronger digestion method. This method of soil digestion was expected to provide an indication of current bioavailability resulting from weathering and accumulation during the 25 years since the tailings deposition. Chemical analyses using ICPES (Inductively Coupled Plasma

Emission Spectrometry) technique was conducted by the Ottawa University Geochemistry Laboratory to determine concentrations of 9 elements (Al, Cr, Cu, Fe, Mn, Ni, Pb, Ti, and Zn). ICPES is a conventional spectroscopic technique that uses inductive heating to transfer power into a plasma gas (Thompson and Walsh, 1983). The solution, containing the elements whose concentrations are to be determined, is introduced into the plasma torch. Light emitted by the atoms (or ions) is recorded by the spectrometer and converted to an electrical signal that is compared to the intensity of a known element concentration. All soil chemical analysis results are reported in Appendix 2.

Figure 28a shows example per cent concentrations of aluminum and iron in each plot from the August 1993 data. Figure 28b shows example concentrations of chromium, copper, nickel, and zinc in parts per million from the same August 1993 data. These data are means of the five values in the B-horizon (where the tree root zone is mostly located). The variation in each element's measured concentration (from the five samples at each plot) was quite high and did not consistently result in statistically significant changes in concentration between any plots on the transect. However, the data do indicate a trend of decreasing metal concentration with distance from the tailings, particularly after 200-400 m. This is reinforced by correlations of metal concentration with distance, which are significant at $p \leq 0.05$ (Lévesque and King, 1993). The control plot typically had the lowest concentrations.

Figure 28. Concentration of (a) aluminum and iron (ppm) and (b) chromium, copper, nickel and zinc (ppm) in the soil B horizon of August 1993 samples, with distance (m) from the tailings.

The same trend was present for all other elements, for all horizons, and for all sample dates. It was not the objective of this study to determine if such metal concentrations, in combination with measured soil pH between 4.2 and 6.8 at the plots, were causal factors of the observed forest damage. The relatively high levels of aluminum and iron near the tailings may contribute to forest damage but the concentrations of the other elements may not be toxic. Instead, this observed trend in soil chemistry was used to verify that the transect was well positioned and to partially justify continued development of the field

and airborne experimental design. In later analysis of soil elements in plots located throughout the area between the creeks, Olthof (1999) verified these significant trends for iron, magnesium and calcium.

5.2 TREE LEAF REFLECTANCE

Initially, before designing the research of this thesis, a critical question was whether spectral stress or damage symptoms would be significant enough to warrant inclusion of spectral image analysis techniques. Literature analysis demonstrated that spectral stress symptoms may be evident in remote sensing imagery and may be linked to canopy and leaf function (see literature review Section 3.2.2). Knowing the soil metal gradient with distance from tailings was present and from visual observations of tree damage along the transect, it was decided that an understanding of the variation in spectral reflectance of foliage between plots with respect to within-plot variation had to be developed. This would aid in subsequent research design in terms of determining the relative importance to be placed on analysis of spectral or spatial image characteristics. During the first field survey at the KamKotia mine in August 1992, field reflectance measurements of individual leaves were made using a portable spectrometer to determine whether tree leaf reflectance could be a reliable measurement of tree stress. The following sections describe the method and results of this initial study.

5.2.1 Tree leaf sampling

Leaves from five cut aspen trees near each plot ($n = 30$ trees) were collected. Thirty to fifty leaves were collected from each of five locations in each tree crown (top, north side, west side, south side, bottom) for a total sample size of 150. Field observations showed that, when these trees were damaged, their top part was more affected (e.g. smaller leaves; brown speckles; nibbled, curled and holed leaves; partial and total chlorosis). To preserve the tree leaf samples during their transportation from the study site to the laboratory (3 to 6 hours), they were put in sealed plastic bags and in a dark cooler containing ice. A study by Daughtry and Biehl (1985) showed that changes in leaf optical properties are less than 5% when they are stored in the dark for a week at a temperature of 5°C. Without these precautions, significant metabolic changes could occur, thus producing changes in their reflectance.

5.2.2 Tree leaf reflectance measurements

Leaf spectral reflectance was measured in the laboratory using a VIS/NIR portable spectroradiometer (Spectron SE-590 from Spectron Engineering Inc.), which records spectral bands between 400 nm and 1100 nm at a nominal resolution of 2.8 nm (252 wavelengths). A halogene lamp was used as the source of light. Reflectance was calculated using the ratio of leaf radiance to radiance of a reference barium sulphate plate (lambertian surface):

$$\text{Reflectance} = \frac{\text{radiance leaf}}{\text{radiance BaSO}_4 \text{ surface}} * 100$$

Leaf samples (30 to 50 leaves) were placed so that they totally covered the field of view (~2 cm²) of the spectrometer. A reference measurement was taken prior to each leaf measurement. The stack of leaves was mixed and re-measured 3 times. This procedure was repeated for each of the 150 leaf samples.

5.2.3 Comparison of tree leaf reflectance between plots

Table 1 shows the results of an analysis of variance (ANOVA) on the leaf reflectance samples. The six plots represent the grouping factor. Between plot variance is significant ($p \leq 0.05$) for samples from all parts of the trees (Table 1a) and reflectance samples from the top part of the trees (viewed by sensor) (Table 1b). Because of these results, it was felt important to analyse raw spectral data and their spectral mixtures and integrate them with spatial analysis, the focus of this thesis. ANOVA was also performed on each plot to determine the within plot variation (Table 1c). The results show that the between tree variance for the 5 sampled trees of each plot is generally significant. This shows that individual tree sampling for spectral analysis is important, not just to eliminate shadows that are in canopy samples, but also to consider each tree as an individual entity. This justifies further the individual tree sampling scale analysis (see 5.4).

(a)			(b)		
	<i>F</i>	<i>P</i>		<i>F</i>	<i>P</i>
<i>Blue (450-500 nm)</i>	18.29	0.00	<i>Blue (450-500 nm)</i>	6.37	0.00
<i>Green (500-600 nm)</i>	23.56	0.00	<i>Green (500-600 nm)</i>	10.95	0.00
<i>Red (600-700 nm)</i>	19.61	0.00	<i>Red (600-700 nm)</i>	6.82	0.00
<i>Red edge (700-800 nm)</i>	22.06	0.00	<i>Red edge (700-800 nm)</i>	11.83	0.00
<i>NIR (800-950 nm)</i>	85.51	0.00	<i>NIR (800-950 nm)</i>	28.11	0.00

	Plot 1		Plot 2		Plot 3		Plot 4		Plot 5		Plot C	
	<i>F</i>	<i>P</i>	<i>F</i>	<i>P</i>	<i>F</i>	<i>P</i>	<i>F</i>	<i>P</i>	<i>F</i>	<i>P</i>	<i>F</i>	<i>P</i>
<i>Blue (450-500 nm)</i>	5.05	0.02	4.12	0.03	10.62	0.00	11.43	0.00	0.79	0.56	1.08	0.42
<i>Green (500-600 nm)</i>	4.58	0.02	8.38	0.00	5.22	0.02	7.66	0.00	18.37	0.00	2.47	0.11
<i>Red (600-700 nm)</i>	4.13	0.03	4.92	0.02	6.22	0.01	4.93	0.02	8.10	0.00	2.90	0.08
<i>Red edge (700-800 nm)</i>	3.48	0.05	2.61	0.10	0.94	0.48	3.99	0.03	4.24	0.03	1.88	0.19
<i>NIR (800-950 nm)</i>	4.53	0.02	1.82	0.20	0.76	0.58	0.66	0.63	1.85	0.20	5.46	0.01

Table 1. Results of the analysis of variance on tree leaf reflectance: F statistic and significance level (P) for (a) the between plot variation using all tree leaf samples, (b) the between plot variation using the top leaf samples and (c) the within plot variation.

5.3 FOREST AND INDIVIDUAL TREE STRUCTURE AND STRESS MEASUREMENTS

A total of 180 dominant and co-dominant trees, 30 in each plot, were measured to derive six forest canopy and tree crown variables. Only trees that had greater than half of their crown visible to the sensor were selected. This ensured that enough pixels could be sampled from the image for each tree crown. The six forest measures describe the structural health characteristics of each of the plots and were used to quantitatively relate images to field data. They were as follows. 1. **Forest canopy closure** was measured visually from the ground in 5% increments with the aid of a calibrated chart showing the proportion of a black surface on white background. Evaluation of three repetitions on different days for a sample of 15 trees in the first and last plots of the transect produced an average standard deviation of 4.3% which is less than the measurement increment. For comparison, in later analysis, measurements made using this visual technique were found to be highly correlated with LICOR LAI-2000 canopy closure measurements for the same plots ($r = 0.87$, $p = 0.03$) (Li-CoR Inc., 1990). 2. **Forest stem density** was measured as the number of dominant trees ($\geq$ half visible crown from sensor) per 10 X 10 m area. 3. **Tree crown size** was determined from the average of two measurements using a measuring tape along the major and minor axes projected to the ground. 4. **Tree height** was measured using an hypsometer. 5. **Individual tree crown closure** was measured using the same calibrated chart that was used for canopy closure. Similar repetitions of three measurements resulted in an average standard deviation of 3.51%, which is less than the measurement increment. 6. A **tree stress index** was devised and measured in

increments of 0.5 between 1 (healthy) and 5 (dead) and was assessed by viewing each tree crown from the ground from several angles. Emphasis was placed on the visual symptoms that would be manifested as image spectral or textural variations. The characteristics were adapted from a deciduous tree decline index developed by the Ontario Ministry of Environment (McIlveen *et al.*, 1989) and utilized in research on remote sensing of sugar maple (*Acer saccharum*) decline by Yuan *et al.* (1991) and King *et al.* (1992). Each sampled tree was systematically evaluated for: crown morphology (asymmetric, circular, thin), foliage density (dense, medium dense, sparse, clustered), foliage size (undersized, full size), foliage color (deep green, light green, discolored), proportion and location of dead branches, amount and type of trunk defects (cankers, cracks, moss, fungus, etc.), and tree lean, including the proportion of each leaning tree which was dying and the proportion dead. To test the precision of these health measurements, 30 trees were randomly selected three times over a period of six weeks. The average of the standard deviations derived from these measurements was 0.238, which indicates good precision for this visually-based index.

Table 2 lists the average (avg) and standard deviation (std) of the forest canopy and tree crown measurements at each plot and Figure 29 shows the spatial trend of each forest measure as distance increases from the mine tailings. Means are shown by solid circles and the bars represent the standard deviation. Only the dominant trees with at least half of their crowns visible to the sensor are represented. For any given variable there are several pairs of plots with significantly different mean values at the 0.05 level. In many of the significantly different plot pairs, one is from the first three plots (40-240 m from the

tailings) while the other is from the last three plots (440-840 m from the tailings). Only the stem density and the stress index measures correlate significantly with distance, $r = 0.88$ and -0.85 , respectively ($p \leq 0.05$).

		<i>Plot</i>					
		<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>C</i> (Control)
<i>Forest canopy closure (%)</i>	<i>avg</i>	40.83	40.00	56.67	50.00	66.67	55.00
	<i>std</i>	25.23	16.90	11.06	17.89	9.43	18.71
<i>Forest stem density (per 100m²)</i>	<i>avg</i>	7.33	5.50	5.60	9.20	18.25	16.43
	<i>std</i>	1.89	2.14	2.80	1.83	3.90	6.84
<i>Tree crown size (m)</i>	<i>avg</i>	6.42	7.79	8.14	5.54	5.43	6.38
	<i>std</i>	1.37	1.86	1.93	1.49	1.24	2.25
<i>Tree height (m)</i>	<i>avg</i>	26.88	26.60	30.32	24.58	24.93	25.67
	<i>std</i>	1.90	2.68	3.37	3.04	3.27	6.12
<i>Tree crown closure (%)</i>	<i>avg</i>	62.30	67.00	62.40	72.30	63.70	59.00
	<i>std</i>	10.90	10.70	11.80	9.37	16.70	13.40
<i>Tree stress index</i> (1=healthy to 5=dead)	<i>avg</i>	2.77	2.66	2.58	2.53	2.37	2.53
	<i>std</i>	0.62	0.75	0.70	0.59	0.82	0.67

Table 2. Average (avg) and standard deviation (std) of forest canopy and tree measures for each plot.

Thus, the most evident spatial trend in the data is the clustering of plots near the tailings (e.g., plots 1, 2, and perhaps 3), and plots farther from the tailings (e.g., 4, 5, 6) for all measurements except individual tree crown closure. The first three plots have consistently larger crown sizes, taller trees, lower stem densities, lower canopy closure (except for plot 3), and higher stress index than the last three plots. The fact that the plots closer to the mine tailings have larger crown sizes and taller trees does not mean that these plots are healthier than plots farther from the tailings. In fact, a larger number of standing dead and fallen dead trees are present in these three plots compared to the last three as expressed by their lower canopy closure and stem densities. It suggests that the remaining large trees have thus far been able to withstand the chemical and mechanical stresses and that they may experience greater growth rates because of the thinning of the

forest. Consequently, of the variables evaluated, the stress index, forest canopy closure, and stem density most directly reflect the higher structural damage in the first three plots.

Figure 29. Spatial trend of forest measures with distance from mine tailings.

These results are supported by a temporal analysis of the site conducted by Walsworth and King (1997). They evaluated individual tree mortality and re-growth for the period 1946-1991 using neighbourhood-based transition analysis of digitized aerial

photography. A statistically significant decrease in stem density over the area bounded by the first three plots of this study was found to have occurred during the period from initial deposition of the unimpounded tailings until 1991 with the forest tending towards greater heterogeneity. Forest succession closer to the tailings was found to be dominated by aspen growth, indicating a more dynamic and open forest than that beyond 240 m where a successional trend toward infilling of conifers was evident. In addition, a 1997 field study of 55 plots in the area between the two creeks (Olthof and King, 2000) has shown that with increasing distance from the mine tailings there were statistically significant decreases in leaf area index and the number of fallen trees as well as a significant increase in stem density. These results help to confirm and quantify the spatio-temporal variation in forest structure that is visually evident when the site is visited over several years.

5.4 IMAGERY ACQUISITION

A multispectral sensor incorporating a Kodak Megaplug 1.4 black and white, 1320 x 1035 pixel format digital camera was used (Figure 30). The camera is entirely computer controlled, with a rotating filter wheel providing 8-bit data in up to eight spectral bands between 430 nm and 1000 nm (King, 1996) (Figure 31). It can be mounted in small single or twin engine aircraft which have been modified for vertical aerial imaging. The view angle of the camera is $\pm 9.1 \times 7.2$ degrees using a 28 mm focal length lens. Such a small view angle was used in this research to minimize spatial non-uniformity of response from optical, BRDF and atmospheric effects (these effects are currently being

analysed in a separate research project using larger angles of view). Imagery was acquired on August 23, 1993 with 0.5 m and 1.0 m ground pixel spacing and a shutter speed of 1/300s. The spectral bands were: blue (430-470 nm), green (545-555 nm), red (665-675 nm), and near infrared (795-805 nm) corresponding to the major vegetation spectral absorption and reflectance regions in the visible and near-IR. After initial analysis of this imagery it was determined that sampling and analysis within individual tree crowns would only be possible using imagery with a smaller pixel spacing since the semivariance range was not reached in 70% of the cases when using the 0.5 m resolution images (see Chapter 7). Consequently, a second set of imagery using the same spectral bands was acquired on Sept. 7, 1995 (just before autumn leaf colour change) with 0.25 m, 0.5 m and 0.82 m pixels. The smaller plane contracted to fly the sensor this time could not achieve an altitude high enough to produce 1.0 m pixels resulting in a maximum pixel size of 0.82 m. The second set of 0.5 m pixel imagery was acquired for comparison of individual tree crown sampling with the forest canopy-based sampling of the 1993, 0.5 m pixel imagery.

Figure 30. Components of the multispectral digital camera system. (Courtesy of D. King, Department of Geography and Environmental Studies, Carleton University).

Figure 31. Schematic of the multispectral digital camera system operation (King, 1995).

The 1993 data were acquired with the sensor in a prototype state. Separate lines had to be flown for each spectral band and image exposure was not optimized, which reduced the image quality. This limitation was overcome with inflight histogram analysis and optimization of the dynamic range for the 1995 data. Figure 27 shows an image of the 800 nm band with 0.82 m pixels.

In the following chapters two scales of analysis were conducted using the image and field data. (1) **The canopy-scale:** image samples were extracted over the whole plot area (or sub-area within the plot), including trees and shadows to determine relations of plot spectral and spatial variables with forest canopy and individual tree measurements averaged over each plot. (2) **The tree-scale:** image samples were extracted from individual tree crowns within each plot (no shadows) to determine relations of individual tree spectral and spatial variables with crown closure, height and stress index. The distinction between forest canopy closure (variable 1) and individual tree crown closure (variable 5) (Table 2) as defined in this chapter is critical to the two-scale analysis of this study.

--- PART B ---

**Spectral and spatial image modelling of
forest structure and health**

INTRODUCTION TO PART B

In Part A it was hypothesized that forest spectral, structure and health measures would exhibit similar gradients to the soil chemical gradient. As shown in Figure 29, except for stem density, a trend is somewhat evident but not clear. The plots show a variety of canopy conditions that are also responding to other factors such as high wind speed and airborne contamination (Figures 15 to 18).

These findings changed the perspective of the research from mapping forest damage associated with AMD to more general modelling of forest structure and health. Therefore, methods and results of chapters 6 to 8 do not attempt to establish a direct relationship between forest damage and AMD. Instead, they focus on analysis and modelling of the relationships between forest and image measures. The models do not provide a means to assess causal factors of forest damage at the site but will be useful in establishing a temporal monitoring program of forest change.

6. RELATIONS BETWEEN SPECTRAL IMAGE VARIABLES AND FOREST MEASURES: COMPARISON OF IMAGE BRIGHTNESS AND SPECTRAL MIXTURE ANALYSIS

6.1 OBJECTIVES

In this chapter, the contribution of the non-transformed image data (brightness) in explaining the ground forest measures is evaluated. Then, using spectral mixture modeling, distinct radiometric constituents (endmembers) of the multispectral image data are identified and labeled according to the cover types they represent. Each pixel is assigned a proportion of each cover type, corresponding to the relative proportions of the endmember spectra that combine to produce the pixel's multispectral brightness vector. The proportions of these cover types are evaluated against the set of forest structure and health measures. The goal was to determine whether the transformation of image spectra into their basic constituents (endmembers) provides greater information on the state of forest health than raw image brightness values in each pixel.

Two scales of image analysis were conducted in this study. (1) Forest canopy or plot level analysis included image measures extracted from a sample taken over the whole plot. They were modeled against all six forest variables (canopy and individual tree variables). (2) Individual tree analysis included image samples extracted only from the individual tree crowns visible in each plot. They were modeled only against the individual tree variables (tree height, tree crown closure, tree stress index). The

subsequent analysis in the following chapters is based on the same image data extracted from plots and individual tree crowns. The method of image plot and tree crown extraction is also described in this chapter.

6.2 METHODOLOGY

6.2.1 Image plot extraction for forest canopy-scale analysis

The three spectral bands of the 1995 data were aligned with a root mean squared error (RMS) of less than 0.22 pixel at each spatial resolution. The six plots were extracted at the three spatial resolutions with dimensions ranging from 200 X 200 pixels at 0.25 m resolution, to 125 X 125 pixels for the 0.5 m resolution, and 75 X 75 pixels for the 1.0 m pixel image. The plot areas range from 50 m X 50 m to 60 m X 60 m (Figure 32). To minimize BRDF effects, plots were extracted from images where they were located near the image centre. Each plot appeared near the centre of at least one image as there was a significant amount of overlap between images. BRDF effects were evaluated empirically by comparing the DN values of one plot extracted from two different images that had different view and sun angles. Using a Student's t-test, the two DN distributions were not found to be significantly different in any of the spectral bands. Consequently, BRDF correction was not applied to any of the image data. Atmospheric correction was not performed since the data were all acquired on the same clear day.

Figure 32. The six plots extracted from the 0.25 m, 0.5 m and 1.0 m resolutions images. (Red: 800 nm, Green: 670 nm, Blue: 550 nm)

6.2.2 Image individual tree crown extraction for individual tree-scale analysis

At the individual tree crown-scale, the average brightness was calculated for each spectral band from 31 tree crowns (4 to 6 on each plot) at the 0.25 m and 0.5 m spatial resolutions only, since it was not possible to visually delineate most of the tree crowns in the 1.0 m pixel image. Figure 33 shows the increasing fuzziness around a well defined tree crown as the spatial resolution decreases. For analysis of the 0.25 m and 0.5 m pixel data, tree crowns were located in the image by simultaneously looking at both 0.25 m and 0.5 m resolution images and masking each visible crown, including the directly and diffusely illuminated portions. Tree ground locations provided by a previous field survey aided this process. The 31 trees represent a wide range of variation in crown closure, stress index, and height.

Figure 33. Tree crown at 0.25 m, 0.5 m and 1.0 m resolutions.

It was verified that the individual tree crowns were delineated properly at the two spatial resolutions (0.25 m, 0.5 m), i.e. that a stable ratio in the number of pixels between the

two spatial resolutions was maintained. The average ratio is 2.29 (std = 0.33) and shows that more tree crown surface is covered at 0.25 m than at 0.5 m due to a better crown delineation at higher resolution. Generally, smaller tree crowns have lower ratios (average = 2.12) than larger tree crowns (average 2.46).

Since tree crown borders are difficult to delineate by eye, the visual extraction method used was tested for its reliability. Three of the sampled tree crowns were extracted three separate times, resulting in different numbers of extracted pixels. These same tree crowns were then extracted a fourth time by masking the crowns and including 1 to 2 pixels outside the crown to see if the addition of a small portion of non-crown pixels produced more variability between the four repeats. A Student's t-test performed on the repeats did not yield any significant differences for any pair of the distributions including the one from samples incorporating 1 or 2 pixels outside the tree crown. The latter displayed the largest t values, though they were still not significant at the 0.05 level. This indicates that as long as most of the pixels are extracted from the tree crown, the average and standard deviation of the pixels is statistically representative of the tree crown.

6.2.3 Spectral mixture analysis

In order to make the spectral mixture analysis results comparable between plots, the image plots were appended to each other to form one file for each resolution. Constrained linear spectral unmixing was performed on the three resolution images using an algorithm (Boardman, 1989) implemented in ISDAS (Imaging Spectrometer Data Analysis System)

(Staenz *et al.*, 1998). This method allows quantitative spectral information extraction at the sub-pixel level. It decomposes the image spectra into a linear combination of endmember spectra. The spectrum corresponding to a pure constituent is referred to as an “endmember” spectrum. In general, each pixel is a mixture of basic constituents (endmembers), and the spectrum for that pixel is a combination of the corresponding endmember spectra (see Section 3.3.2 for theory).

$N-1$ bands are required to spectrally unmix a scene with N endmembers. Therefore, a maximum of 4 endmembers cannot be exceeded in this case study. Endmember spectra were selected using two methods that were compared:

(1) They were manually extracted from the extremities of a scatter plot of the first two image principal components (PC). The pixels at these extremities have the purest spectra of all the image data.

and

(2) They were automatically extracted based on an iterative error analysis implemented in ISDAS (Szeredi *et al.*, 1999). This method performs a series of linear constrained unmixing procedures with, as endmembers, the pixel spectra which minimize the unmixing error. The iterative process starts unmixing using the average spectrum of the image. The unmixing error, calculated for each pixel, is then used to determine the first endmember. The pixel spectra with the largest error constitute the first endmember since

they are located at an extremity of the scatterplot. To select those pixels, an angular tolerance of a few degrees (default = 2.5°) starting from the origin is used, and the pixel spectra are averaged. The user can define a maximum number of pixels to be averaged. The average spectrum of the image is then discarded and the process is repeated until the termination condition is reached, which is the number of endmembers requested by the user. In this case four endmembers represents the termination condition.

6.2.4 Extraction of image fractions

At the forest canopy-scale, image fractions for each endmember in each pixel were averaged over the given plots. This was repeated for the three image resolutions (0.25 m, 0.5 m, and 1.0 m). At the individual tree-scale, an average fraction for each endmember was calculated for each of the 31 tree crowns at the 0.25 m and 0.5 m spatial resolutions.

6.3 RESULTS AND DISCUSSION

6.3.1 Relations between image brightness and forest measures

Forest canopy-scale analysis

Table 3 shows the linear correlation values for the average plot digital number (DN) against the ground forest measurements. The underlined r-values are significant at the

0.05 level ($r \geq 0.811$). All relationships were graphed to look for non-linear behaviour.

No obvious non-linear relationships were found so only a linear correlation was used.

<i>Spectral band:</i> <i>Spatial resolution:</i>	<i>550 nm</i>			<i>670 nm</i>			<i>800 nm</i>		
	<i>0.25m</i>	<i>0.5m</i>	<i>1.0m</i>	<i>0.25m</i>	<i>0.5m</i>	<i>1.0m</i>	<i>0.25m</i>	<i>0.5m</i>	<i>1.0m</i>
<i>Forest canopy closure (%)</i>	-0.22	0.42	0.60	-0.32	-0.27	0.49	0.17	0.51	<u>0.87</u>
<i>Forest stem density (per 100m²)</i>	-0.08	0.32	0.16	-0.04	-0.05	0.52	-0.13	0.12	0.56
<i>Tree crown size (m)</i>	-0.01	0.08	-0.08	-0.23	-0.41	-0.62	-0.22	0.23	-0.52
<i>Tree height (m)</i>	-0.10	0.31	0.37	-0.24	-0.11	-0.16	-0.18	0.36	-0.27
<i>Tree crown closure (%)</i>	0.03	-0.72	-0.29	0.03	-0.11	-0.36	0.72	0.63	0.24
<i>Tree stress index (1 to 5)</i>	0.19	-0.14	-0.30	0.31	0.45	-0.25	-0.33	-0.13	<u>-0.90</u>

Table 3. Correlation coefficients (r) between the average plot image digital number and the ground forest measures at the canopy-scale (underlined r -values are significant at the 0.05 level).

Forest canopy closure only relates significantly to the 800 nm band of 1.0 m resolution ($r = 0.87$). A high canopy closure is manifested by an increase of radiance in the 800 nm band. There is a trend in both the 550 nm and the 800 nm bands that shows a decrease of the r values as the resolution gets finer. The 1.0 m resolution yields the highest correlation with forest canopy closure in the three spectral bands.

Forest stem density and tree crown size do not produce any significant relationships with the image variables. The number of stems per area and the size of individual tree crowns describes structural information about the forest canopy. The highest correlation values are with the 1.0 m resolution of the 670 nm and 800 nm bands where an increase of the stem density produces an increased brightness ($r = 0.52$ and 0.56) and larger crown size produces a decrease in brightness ($r = -0.62$ and -0.52). A greater number of samples might bring these relationships up to the significant level.

Little suggests that a greater number of samples could increase the correlation values between tree height and the image brightness since they do not exceed a probability of $p = 0.47$ in the best case ($r = 0.37$). Image brightness may not be suited to detect this tree characteristic.

Individual tree crown closure does not relate significantly to any of the image variables. However, it is interesting to note that the highest correlation coefficients ($r > 0.60$) always occur at the 0.25 m and 0.5 m resolutions. The highest r value at 1.0 m resolution is -0.36 using the 670 nm band which may indicate that this resolution is too coarse to detect this tree characteristic. The highest correlation coefficients suggest that an increase in average crown closure produces a decrease in the 550 nm band at the 0.5 m resolution ($r = -0.72$) and an increase in the 800 nm band at the 0.25 m resolution ($r = 0.72$).

Tree stress index is significantly related to the 1.0 m resolution 800 nm. A high index (more damaged trees) is expressed in the image data as low brightness in the 800 nm band. Like canopy closure, forest stress index is best captured at lower spatial resolution, possibly because the variability in the data is averaged out over larger pixel areas. This is not the case at finer spatial resolutions where spatial details are better resolved.

Individual tree-scale analysis

Table 4 shows the linear correlation values for the average digital number (DN) extracted from individual tree crowns against the ground forest measurements for the 31 trees. The

underlined r-values are significant at the 0.05 level ($r \geq 0.355$). All relationships were graphed to look for non-linear behaviours. For each variable the 31 data points form sparse clouds with no obvious non-linear trends so only a linear correlation was used.

<i>Spectral band:</i> <i>Spatial resolution:</i>	<i>550 nm</i>		<i>670 nm</i>		<i>800 nm</i>	
	<i>0.25m</i>	<i>0.5m</i>	<i>0.25m</i>	<i>0.5m</i>	<i>0.25m</i>	<i>0.5m</i>
<i>Tree height (m)</i>	-0.17	0.01	-0.04	0.02	0.05	0.20
<i>Tree crown closure (%)</i>	-0.28	<u>-0.41</u>	<u>-0.55</u>	<u>-0.68</u>	<u>0.37</u>	0.32
<i>Tree stress index (1 to 5)</i>	0.28	0.25	<u>0.56</u>	<u>0.55</u>	-0.27	-0.26

Table 4. Correlation coefficients (r) between the average tree digital number and the ground forest measures at the individual tree-scale (underlined r-values are significant at the 0.05 level).

Tree height does not relate significantly to any of the image variables. Image brightness does not seem suitable for detecting this tree characteristic.

Tree crown closure is best represented by individual tree crown pixel values rather than the average pixel values over plot areas as in the previous forest canopy-scale analysis. Significant relationships show that at both spatial resolutions (0.25 m and 0.5 m), increasing individual tree crown closure is expressed by decreasing image tones in the 670 nm band (more chlorophyll absorption, $r = -0.55$ and -0.68). Other significant relationships, although weaker, indicate a negative trend between crown closure and brightness of the 0.5 m resolution 550 nm band ($r = -0.41$) and a positive trend between crown closure and brightness of the 0.25 m resolution 800 nm band ($r = 0.37$). Since it was difficult to understand the negative relationship ($r = -0.41$) between crown closure and the 550 nm band, the data were plotted and it was found that a single dead tree with no foliage was an outsider and was responsible for the inverse relationship. Figure 34a

shows the location of the dead tree in Plot 2, and Figure 34b shows the scatterplot of the relationship between the 550 nm band and crown closure (%). Figure 34c shows that the same relationship becomes positive when the dead tree is removed. The bulk of the data cloud shows a positive trend that is reversed because of the strong influence of the dead tree.

Figure 34. (a) Image of Plot 2 showing the location of the dead tree that causes the relation with tree crown closure to be negative (b). When the dead tree is removed, the relation is positive (c).

The stress index shows significant relationships with both 0.25 m and 0.5 m spatial resolutions when using the 670 nm band. A high index (more damage) relates to less chlorophyll absorption ($r = 0.56$ and 0.55). The presence of the dead tree does not affect the sign of the relationships with stress index because increased branch exposure to the sensor causes red brightness to increase. This reinforces the positive relationship with stress index (high values – poor health). A tree with no foliage is less likely to affect the stress index, which is a measure of the overall health of the tree, than the crown closure measure.

6.3.2 Spectral mixture analysis

ISDAS provides features such as constrained unmixing and automatic endmember selection that were not available in commercial software at the time the analysis was done. For this reason, the unmixing method used was experimental (although the algorithm is very strong and reliable). The automatic endmember extraction was new and not yet commonly used.

Using manual extraction, three endmembers were selected and identified as vegetation, shadow, and tailings. Another endmember was also found at the 0.25 m resolution and was identified as wood (branches or trunks of live, or dead trees, some leaning or fallen). The automated iterative error analysis method selected the same endmembers and was able to select the wood endmember in the 0.5 m and 1.0 m resolutions. Figure 35 shows

the scatterplots of the first principal component (PC1) versus the second principal component (PC2) for each endmember at each spatial resolution. The first two PCs incorporate between 96% and 97% of the total variation in each dataset. No additional endmembers could be seen when rotating the PC cloud. The yellow highlighted pixels show where the endmember pixels are located in the cloud. Except at the 0.25 m resolution, the wood endmember was not visible in the PC transformed scatterplot which explains why it was missed when using the manual method. The automatic method is not limited to the purest endmembers located at the vertices. It can find endmembers composed of a few mixtures at the faces and edges of the scatterplot, which is very common in natural scenes. The wood endmember appears on the edge of the 0.5 m and 1.0 m scatterplots. The endmember spectra are shown in Figure 36.

Figure 35. Scatterplots of the two first principal components showing the location of the pixel endmembers in yellow.

Figure 36. Endmember spectra.

With the additional wood endmember, the unmixing error (the absolute difference between the spectrum obtained by the sum of the endmember spectra and the raw image pixel spectrum) is lower. Table 5 shows the average (avg) unmixing error when using all four endmembers and that for the three EMs found by the manual method. Since image fractions are constrained between 0 and 1, the values in Table 5 can be converted to percentages. The unmixing error has decreased from 10.2% to 1.9% for the 0.25 m resolution, 12.5% to 7 % for the 0.5 m resolution, and 10.8% to 4.1% for the 1.0 m resolution. This is in the same range as the error generated when using 65 *casi* bands to unmix a five-endmember image (mean = 6.5%, std = 3.4) (Lévesque, 2000, unpublished data). As a consequence of these findings, the automated method was selected for further analysis.

<i>Resolution:</i>		<i>0.25 m</i>	<i>0.5 m</i>	<i>1 m</i>
3 endmembers	<i>avg</i>	0.10	0.13	0.11
	<i>std</i>	0.08	0.09	0.08
4 endmembers	<i>avg</i>	0.02	0.07	0.04
	<i>std</i>	0.07	0.07	0.08

Table 5. Spectral unmixing error produced when using 3 and 4 endmembers.

Figures 37, 38 and 39 show the endmember fraction images for each spatial resolution. The tailings endmember is not included in the later statistical analyses since it generally yields a proportion of zero except in the south east portion of the first plot, located at the edge of the mine tailings. Blue represents no (zero) fraction and red the tailings.

Figure 37. Fraction images of the wood, shadow, tailings, and vegetation endmembers at 0.25 m resolution.

Figure 38. Fraction images of the wood, shadow, tailings, and vegetation endmembers at 0.5 m resolution.

Figure 39. Fraction images of the wood, shadow, tailings, and vegetation endmembers at 1.0 m resolution.

6.3.3 Relations between image brightness and image fractions

Tables 6a and 6b show the relationship between image brightness and image fractions using the average plot ($n = 6$) of the forest canopy-scale (Table 6a) and the average tree crowns ($n = 31$) of the individual tree crown-scale (Table 6b). The correlation coefficient values indicate that the average plot wood fraction is positively related to the average brightness in the 550 nm and 670 nm bands. Wood reflects more than vegetation in these bands, thus, more wood results in increased visible reflection. The 800 nm band at 0.5 m resolution is negatively correlated with the wood fraction ($r = -0.88$) indicating that vegetation presence (high near infrared brightness) masks branches and trunks so they are not visible to the sensor, resulting in a low wood fraction. The shadow fraction is inversely related to brightness in the three spectral bands, two of the resolutions (0.25 m and 1.0 m) being significant for the 800 nm band. High average image brightness is characterised by lower shadow fractions. The vegetation fraction is positively correlated with the 800 nm band at the three spatial resolutions although the 0.25 m correlation is not significant. High radiance in this band is expressed as a high vegetation fraction. A major point here is that only some relationships are significant and most are not. This indicates that image fractions derived from image brightness represent unique image information. In fact, the endmember fraction is a relative proportion of the total pixel area and provides spatial information about the radiometric structure. Because of their different nature, spectral and spatial, both image brightness and image fraction variables may be complementary. This is investigated further in Chapter 8.

(a) Canopy-scale

Resolution:	0.25 m			0.5 m			1.0 m		
Fraction:	Wood	Shadow	Vegetation	Wood	Shadow	Vegetation	Wood	Shadow	Vegetation
550 nm	<u>0.94</u>	-0.61	-0.38	0.31	-0.54	-0.07	<u>0.84</u>	-0.63	0.17
670 nm	<u>0.93</u>	-0.54	-0.48	0.24	-0.06	-0.37	0.30	-0.78	0.25
800 nm	0.16	<u>-0.97</u>	0.64	<u>-0.88</u>	-0.54	<u>0.93</u>	0.05	<u>-0.86</u>	<u>0.96</u>

(b) Tree-scale

Resolution:	0.25 m			0.5 m		
Fraction:	Wood	Shadow	Vegetation	Wood	Shadow	Vegetation
550 nm	<u>0.93</u>	<u>-0.59</u>	<u>-0.38</u>	<u>0.87</u>	<u>-0.69</u>	-0.28
670 nm	<u>0.94</u>	<u>-0.50</u>	<u>-0.48</u>	<u>0.80</u>	<u>-0.60</u>	<u>-0.41</u>
800 nm	0.18	<u>-0.99</u>	<u>0.60</u>	-0.09	<u>-0.87</u>	<u>0.72</u>

Table 6. Correlation coefficients (r) between the average tree image digital number and the image fractions at (a) the canopy-scale and (b) the tree-scale (underlined r-values are significant at the 0.05 level)

6.3.4 Relations between image fractions and forest measures

Forest canopy-scale analysis

Table 7 shows the correlations between image fractions and forest measurements for all plots. The underlined r-values are significant at 0.05 level ($r \leq 0.811$). Only significant and nearly significant ($r = 0.70$ to 0.81) relations are discussed.

Forest canopy closure relates significantly to image variables at the 1.0 m resolution only. The shadow fraction yields the only significant correlation coefficient ($r = -0.82$). An increase in canopy closure produces a decrease in shadow fraction. Although not significant, high closure is also related to increased vegetation fraction ($r = 0.75$).

<i>Spatial resolution:</i>	<i>Image fraction:</i> <i>Wood</i>			<i>Shadow</i>			<i>Vegetation</i>		
	<i>0.25m</i>	<i>0.5m</i>	<i>1.0m</i>	<i>0.25m</i>	<i>0.5m</i>	<i>1.0m</i>	<i>0.25m</i>	<i>0.5m</i>	<i>1.0m</i>
<i>Forest canopy closure (%)</i>	-0.30	0.08	0.27	-0.05	-0.14	<u>-0.82</u>	0.37	0.13	0.75
<i>Forest stem density (per 100m²)</i>	0.02	0.71	-0.26	0.17	0.45	-0.67	-0.11	-0.57	0.59
<i>Tree crown size (m)</i>	-0.03	-0.58	0.44	0.26	-0.52	0.73	-0.13	0.53	-0.62
<i>Tree height (m)</i>	-0.15	-0.68	0.75	0.19	<u>-0.81</u>	0.33	-0.02	0.65	-0.48
<i>Tree crown closure (%)</i>	-0.19	-0.37	-0.33	-0.66	0.18	0.00	0.70	0.36	0.35
<i>Tree stress index (1 to 5)</i>	0.30	-0.15	0.04	0.17	-0.16	0.74	-0.49	-0.06	<u>-0.88</u>

Table 7. Correlation coefficients (r) between image fractions and forest measures at the canopy-scale (underlined r-values are significant at the 0.05 level).

Forest stem density and tree crown size do not show any significant relationships with the image variables. The best relationships are between stem density and the wood fraction of the 0.5 m resolution ($r = 0.71$) and between tree crown size and the shadow fraction of the 1.0 m resolution ($r = 0.73$).

The only image variable that has a significant relationship with tree height is the shadow fraction of the 0.5 m resolution. This relationship ($r = -0.81$) shows that plots with taller trees on average produce less shadow than shorter average tree height. In fact, shorter trees are more likely to be in the shade of other trees. In the semivariance analysis, the 0.5 m resolution was found to best predict tree crown size using the range of the semivariogram ($r = 1.0$). The fact that tree crown sizes are better determined using this spatial resolution may explain why the other two spatial resolutions do not relate well to the tree height measure.

Tree crown closure does not relate significantly to any of the image variables. However, the highest correlation coefficients ($r = 0.70$ and -0.66) occur at the 0.25 m resolution. The highest r value is obtained when using the vegetation fraction of the 0.25 m resolution ($r = 0.70$), greater vegetation indicating greater tree crown closure.

Tree stress index is significantly related to the 1.0 m resolution vegetation fraction ($r = -0.88$). A high index ($> \text{damage}$) is expressed in the image data as a lower vegetation fraction. As for image brightness, forest stress index is best captured at lower spatial resolution possibly because the variability in the data is averaged out over larger pixel areas. This is not the case at finer spatial resolutions where spatial details are better resolved.

Individual tree-scale analysis

Table 8 shows the correlation values between image fractions extracted from individual tree crowns and ground measurements for the 31 trees. Underlined r -values are significant at 0.05 level ($r \geq 0.355$).

<i>Image fraction:</i> <i>Spatial resolution:</i>	<i>Wood</i>		<i>Shadow</i>		<i>Vegetation</i>	
	<i>0.25m</i>	<i>0.5m</i>	<i>0.25m</i>	<i>0.5m</i>	<i>0.25m</i>	<i>0.5m</i>
<i>Tree height (m)</i>	-0.18	-0.18	-0.06	-0.24	0.18	0.28
<i>Tree crown closure (%)</i>	<u>-0.54</u>	<u>-0.45</u>	-0.25	0.10	<u>0.71</u>	<u>0.58</u>
<i>Tree stress index (1 to 5)</i>	<u>0.53</u>	0.31	0.18	-0.09	<u>-0.64</u>	<u>-0.44</u>

Table 8. Correlation coefficients (r) between image fractions and forest measures at the tree-scale (underlined r -values are significant at the 0.05 level).

Tree height does not relate significantly to any of the image variables. This may be due to a sampling bias in the 31 trees. All were easy to delineate visually because their crown limits appeared more clear in the image. Smaller trees that could not be sampled may lie in shadows of surrounding taller trees and could contribute to a positive relation with shadow fraction as with canopy-scale sampling.

Tree crown samples represent individual tree crown closure better than the average plot pixel values as in the forest canopy-scale analysis. Significant relationships show that, at both spatial resolutions (0.25 m and 0.5 m), increased crown closure is expressed as decreasing wood fraction ($r = -0.54$ and -0.45) and increasing vegetation fraction ($r = 0.71$ and 0.58). There is also a decrease in shadow fraction at the 0.25 m resolution, although it is not significant.

The stress index shows significant relationships with both 0.25 m and 0.5 m spatial resolutions when using the vegetation fraction, where a high index (> damage) is expressed as decreasing vegetation fraction ($r = -0.64$ and -0.44). A high stress index also produces a higher wood fraction ($r = 0.53$ and 0.31).

6.4 CONCLUSIONS

Using image brightness, the canopy-scale analysis has shown a few relationships that are significant: 800 nm band at 1.0 m resolution with canopy closure and stress index. The limited number of samples could be responsible for the non-significance of some relationships but in general no trend can be seen in the data that might result in an improvement if more samples were used. The tree-scale analysis produced no significant relationships between image brightness and tree height. Crown closure produced a significant correlation but it is strongly affected by the presence of a dead tree with no foliage which suggests that with a better sampling range of closure, this relationship may not be linear. Stress index is significantly related to the image brightness of the 670 nm band, the chlorophyll absorption band.

When performing spectral mixture analysis, it was found that automatic selection of endmembers is preferable to manual selection. In fact, the endmember “wood” would not have been found manually in the 0.5 m and 1.0 m resolutions.

Using image fractions in the canopy-scale of analysis, a major improvement in the relationship between averaged tree height and image variables was achieved using image fractions (shadow and wood). Some other improvements are seen when using image fractions, although the correlations are not significant, are with stem density (wood and shadow fractions) and average tree crown size (shadow fraction). Both image brightness and image fraction variables are similarly related to forest canopy closure and tree stress

index. Individual tree crown closure is best represented at the individual tree-scale analysis. Significant relationships showed that decreased crown closure and increased stress index (>damage) produce a decrease of vegetation fraction and an increase of wood fraction. Both relationships are improved when using endmember fractions compared to the use of image brightness variables. The absence of a significant correlation between tree height and the image variables suggests a bias in the sampling procedure where only easily delineated tree crowns (typically tall, large trees) were sampled, thus avoiding the variability produced by shadow on smaller trees.

The knowledge acquired in this chapter shows that image fractions provide over twice the number of significant or nearly significant relationships than image brightness with the forest variables sampled at the canopy-scale. At the crown-scale, about equal numbers of relations are significant. Image brightness and image fraction variables are complementary because of the nature of their information (spectral and spatial). The next chapter investigates the spatial variability of image brightness and image fractions in relation to the forest measures.

7. RELATIONS BETWEEN SPATIAL IMAGE VARIABLES AND FOREST MEASURES: COMPARISON OF SEMIVARIANCE AND TEXTURE APPLIED TO RAW IMAGES AND IMAGE FRACTIONS

7.1 OBJECTIVES

In this chapter, spatial analysis of image brightness and derived image fractions obtained in the previous chapter is introduced as a means of integrating spectral and spatial image characteristics. These characteristics are indicative of forest structural damage. Semivariance and texture analysis are applied to image brightness and image fractions to derive new image variables representing the spatial arrangement of the two sets of image variables.

A semivariance analysis was initially conducted on the 800 nm band to determine whether semivariogram statistics from high-resolution imagery can be used to model subtle structural variations within the forest canopy and within individual tree crowns that are related to various types and degrees of damage. More specifically, images with pixel spacing of 0.25 m, 0.5 m, and 1.0 m were analysed to determine the spatial resolution required to extract such information at both the forest canopy and individual tree crown levels. Semivariogram range, sill, and nugget were derived from airborne digital camera images using the matrix and transect techniques of Cohen and Spies (1990). The goal was to test and compare the two techniques. The semivariogram statistics were used in correlation analysis (as in Chapter 6) to determine the strength of relationships with forest

canopy and individual tree crown measures. Because of the promising results obtained from this initial analysis, it was decided to apply the semivariance analysis on all image bands and image fraction variables. From the knowledge acquired using the 800 nm band, a method was developed for the subsequent semivariance analysis.

Section 7.2 of this chapter describes the method and results of the initial semivariance analysis performed on the 800 nm band. It represents a detailed account of research published in Lévesque and King (1999). The method was then applied to each spectral band and each image fraction, and the results are presented in section 7.3. The fourth section (7.4) investigates the use of 1st and 2nd order texture measures calculated from both image brightness and image fractions. In Chapter 6, DN and IF variables were introduced separately. They are combined in this chapter to avoid repeating results for each forest measure.

7.2 SEMIVARIANCE ANALYSIS FOR EVALUATING FOREST STRUCTURAL DAMAGE

7.2.1 Methodology

In this research, sample pixel matrices and transects were extracted from the imagery and used to calculate omni-directional and directional semivariograms, respectively. Omni-directional variograms measure the spatial correlation independent of orientation. The separation distance (lag), in this case, is a scalar (no direction) rather than a vector

(directional) (Kitanidis, 1997). Pixel matrices were extracted over areas of 30 X 30 pixels. A 30 X 30 matrix was deemed appropriate for the expected spatial variability of the data. Sampling over the canopy indicates that tree crowns and shadows (gaps) form the major image elements that determine canopy structure. Maximum crown size was 12.25 m so the semivariogram range was expected to be reached using samples of 30 X 30 pixels. Omni-directional semivariograms, calculated from these matrices, were derived using multiple lags from all possible directions within a 90-degree angle. This represented the calculation and modeling of 54 semivariograms at the 0.5 m resolution and 24 semivariograms at the 1.0 m resolution. The matrix range and sill of the resulting omni-directional semivariograms were averaged for each plot. For the transect method, three lines of 50 to 100 pixels were sampled in perpendicular directions (the image horizontal and vertical). This represented the calculation and modeling of 36 semivariograms at each spatial resolution. An average range and sill was calculated for each plot from the six individual semivariograms. Calculations for initial analyses were made using the program GEOEAS (Englund and Sparks, 1991) while later analyses were conducted using VARIOWIN which was easier to implement (Pannatier, 1994). Analysis was conducted at the forest canopy scale using the 0.5 m and 1.0 m pixel data, and at the individual tree crown scale using the 0.25 m and 0.5 m pixel data. Because of the level of detail picked up at the 0.25 m resolution it was not found appropriate for a semivariance analysis at the canopy-scale. In fact, pixels become independent within shorter distances so that the ranges were reached within scene objects (tree crowns, gaps). This resolution is better suited for the individual tree crown-scale analysis. On the other hand, the 1.0 m resolution was not used at the individual tree crown-scale analysis since,

beside the fact that tree crowns are difficult to delineate (see section 6.2.2), it would not have provided enough pixels in the tree crowns to produce a usable matrix. Only the 0.5 m resolution is capable of producing appropriate information from the semivariograms at the two scales of analysis.

The nugget, range, sill, and shape of the semivariogram were determined from the fitted spherical models as outputs from the software. Several model types were compared and the spherical model was adopted because it produced the best fits. The Indicative Goodness of Fit (IGF) (Pannatier, 1994) ranged from 0.004 to 0.014 for all semivariograms. The IGF is a standardized measure of fit and is calculated as follows:

$$IGF = \frac{1}{N} \sum_{k=1}^n \sum_{i=0}^{n(k)} \frac{h \max(k)}{n(k)} * \frac{P(i)}{h(i)} * \left[\frac{Y(i) - Y^{*(i)}}{\sigma^2} \right]^2 \quad (8)$$

where N is the number of directional variograms measured for the model (N = 1 for omnidirectional variograms), h max(k) is the maximum distance, n(k) is the number of lags, P(i) is the number of pairs at lag i, h(i) is the distance of lag i, Y(i) is the experimental semivariogram, and Y^{*(i)} is the modeled semivariogram.

These small deviations from a perfect goodness of fit of zero indicate that very little error in the semivariogram parameters was introduced by the spherical function fit to the semivariance data. The range and sill were then linearly correlated with the forest and tree measures for analysis of the strength of the relationships between the image and field variables.

Forest canopy-scale sampling

In canopy-scale sampling for semivariance analysis, pixel matrices and transects were placed over many trees and gaps in each plot. Figure 40a,b illustrates pixel matrix extraction for the canopy-scale analysis. For the 0.5 m pixel image (Figure 40a) nine matrices of 30 x 30 pixels (15 m x 15 m) each were extracted at each plot. The whole plot area was not used as a matrix because by splitting the plots into sub-plots it was possible to observe the within-plot variation. A good example of the within-plot variation is noticeable in plot 1 where almost one quarter of its surface in the NW part is an open area (Figure 27). Such an assessment of plot variability was expected to aid in determining if the plots were well located or if they were too heterogeneous and represented more than one forest structural condition. The number of trees sampled in these quadrants ranged from 12 to 41. For the 1.0 m pixel image (Figure 40b) only 4 matrices of 30 x 30 pixels (30 m x 30 m) needed to be extracted in order to cover the whole plot area.

Figure 40. Illustration of the canopy-scale semivariance sampling technique: (a) the matrix technique with omnidirectional sampling for the 0.5 m pixel image, (b) the matrix technique with omnidirectional sampling from the 1.0 m pixel image, and (c) the transect technique with sampling in two directions for both the 0.5 m and the 1.0 m pixel images.

Figure 40c shows schematically the use of transects for sampling at the canopy scale in both the 1.0 m and 0.5 m pixel images. A total of six transects, three in the E-W direction and three in the N-S direction, were extracted from each plot, each covering a minimum of eight trees. To cover the 2500 m² area of the plots, the transects were 25 pixels (25 m) apart in the 1.0 m pixel image and 50 pixels (25 m) apart in the 0.5 m pixel image. The transects have a length of 50 pixels (50 m) in the 1.0 m pixel image and 100 pixels (50 m) in the 0.5 m pixel image.

Individual tree crown-scale sampling

In sampling individual trees, only the matrix technique was used. The transect technique was not used because any transect within a single tree crown contained too few pixels to reach the range. For the matrix technique, many more points are accumulated and

statistically valid sampling could be achieved for most trees in each plot. In the 0.25 m pixel imagery, the support size (pixel) was between 1/20 and 1/32 the object (tree) widths and twice that in the 0.5 m pixel imagery. Pixel matrices were extracted from 30 individual tree crowns for the 0.25 m pixel image in 1995, and 20 crowns for the 0.5 m pixel images. The sampled trees are the same in both images and are divided approximately equally in numbers among all plots. These trees were selected because there was a high certainty of finding them in the field. It was not possible to sample 10 of the trees at the 0.5 m resolution because their crowns were too small leaving too few pixels to extract for the semivariance analysis. The matrix sizes varied between 10 by 10 pixels and 21 by 21 pixels depending on tree crown size and image pixel spacing. The trees used in this section are not the same trees sampled for the subsequent studies. At this time, the objective was to investigate the potential of the method. A better sample size ($n = 31$) was acquired later and became the dataset for all other analysis.

7.2.2 Results and discussion

Semivariance analysis at the forest canopy-scale

Table 9 shows the correlation coefficients and associated significance levels of the relationships between the ground-based measurements and the semivariogram range and sill for the 1993, 1.0 m and 0.5 m images derived from both the transect and matrix techniques by sampling over the forest canopy. Correlation coefficients greater than, or equal to, 0.811 are significant at the 0.05 level or better and are typed in bold face and

underlined. After looking at each scatterplot, no linear trend was found to justify the use of linear correlation.

<i>Spatial resolution:</i>	Transect				Matrix			
	<i>range</i>	<i>sill</i>	<i>range</i>	<i>sill</i>	<i>range</i>	<i>sill</i>	<i>range</i>	<i>sill</i>
	<i>0.5m</i>	<i>0.5m</i>	<i>1.0m</i>	<i>1.0m</i>	<i>0.5m</i>	<i>0.5m</i>	<i>1.0m</i>	<i>1.0m</i>
<i>Forest canopy closure (%)</i>	-0.16	0.28	<u>0.92</u>	0.36	-0.32	-0.70	<u>0.83</u>	-0.15
<i>Forest stem density (per 100 m²)</i>	-0.60	-0.38	0.44	-0.26	-0.70	-0.54	<u>0.81</u>	-0.15
<i>Tree crown size (m)</i>	<u>0.97</u>	0.59	-0.02	0.66	<u>1.00</u>	0.25	-0.71	0.59
<i>Tree height (m)</i>	<u>0.92</u>	<u>0.86</u>	0.29	<u>0.82</u>	<u>0.89</u>	0.30	-0.59	0.20
<i>Tree crown closure (%)</i>	-0.32	-0.20	-0.31	-0.27	-0.24	-0.17	0.16	-0.07
<i>Tree stress index (1 to 5)</i>	0.35	-0.01	-0.74	-0.14	0.47	<u>0.86</u>	<u>-0.96</u>	0.01

Table 9. Correlation coefficients (r) between forest canopy and tree measures and the semivariogram parameters of the 800 nm band for the transect and matrix techniques (underlined r-values are significant at the 0.05 level).

Relations with forest canopy measurements

Of the forest canopy variables, both the range of the 1.0 m pixel transect and the matrix semivariograms are positively well correlated with forest canopy closure. Figure 41 shows this relationship for the 1.0 m pixel transect semivariogram. The range increases with canopy closure in this mature boreal forest since the tree crowns are closer to each other and they produce a more homogeneous grey tone surface in the imagery. Such a relationship would not apply in sparsely-treed forest conditions unless the spatial variability of the understory and ground cover was high for the given pixel spacing. Figure 42 shows the relation between the range of the 1.0 m pixel matrix semivariogram and stem density per 100 m². As for canopy closure, as stem density increases, a more homogeneous grey tone surface is produced and the range increases. Transect

semivariograms are not highly correlated with this forest measurement possibly because they represent sparser samples than do the matrices.

Figure 41. Range of the transect semivariograms in the 1.0 m pixel image versus forest canopy closure ($r = 0.92$).

Figure 42. Range of the matrix semivariograms in the 1.0 m pixel image versus forest stem density ($r = 0.81$).

Relations with individual tree measurements

Of the individual tree variables, tree crown size is well correlated with the range values of both the 0.5 m pixel transect and matrix semivariograms extracted over the canopy. Figure 43 shows the graphical representation of the relationship between range and tree crown size for the 0.5 m pixel matrix semivariogram. Range increases linearly with tree crown size in this highly significant relationship. Thus, the range of such a semivariogram may serve as an effective measure for the automated derivation of average crown size in stands over a region. This agrees with the results of Cohen and Spies (1990). The 1.0 m semivariogram range was not sensitive to crown size for the trees in this study. The average width of trees in some plots was as low as 1.9-3.0 m (95% lower bounds for plots C, 4 and 5). The range of the semivariograms extracted from the canopy was not reached at such short lags because the support size was just less than or just larger than the object width. Consequently, the 1.0 m semivariograms cannot be used to detect such crown sizes but they are sensitive to spatial variability over larger areas as described above for canopy closure.

Figure 43. Range of the matrix semivariograms in the 0.5 m pixel image versus tree crown size ($r = 1.0$).

Similarly to tree crown size, tree height is closely associated with range values. Tree height in this forest is well correlated with crown size ($r = 0.85$) so its high correlation with the range in the 0.5 m pixel image using both the transect and matrix techniques was expected. The combined effect of height and size variations (e.g., as measured by the height-to-diameter ratio) produces variations in shadows and highlights that serve to delimit tree crowns. The sills of both the 0.5 m and 1.0 m transect semivariograms are also closely related to tree height. The matrix semivariogram sill is not significantly related to this forest parameter indicating that the transect technique is more sensitive to variation in tree height.

In analysis of the tree stress index, matrix semivariograms appear to be more suitable for determining the structural and textural information related to the visual stress symptoms included in the index. This measure represents the plot average of the overall health of

individual trees and is a more integrated measure of forest damage than the other individual measures. The sill of the 0.5 m pixel matrix semivariograms is positively correlated to the stress index (Figure 44) which indicates that when the index is high (greater damage), the amount of spatial variability within crowns is higher and this results in higher variability when sampling is conducted over the canopy. Figure 45 shows the relationship between the stress index and the range of the 1.0 m pixel matrix semivariograms. The two variables are negatively correlated indicating that when the index is high, the range is small. This can again be explained by greater plot variability when variability within individual crowns is increased causing the range to be reached at a lesser distance than in a more homogeneous canopy. In a very open and nearly dead crown, with uniform background radiance, this negative relationship may not apply, as the grey tone surface will already be homogeneous. However, in the high-resolution imagery used in this research, and particularly in the high contrast near infrared band, shadows from branches and spatial variability in understory vegetation generally produce a very heterogeneous grey tone surface. Any increase in foliage in the tree tends to increase the homogeneity of the grey tone surface and the negative relationship with semivariance range still applies.

Figure 44. Sill of the matrix semivariograms in the 0.5 m pixel image versus tree stress index ($r = 0.86$).

Figure 45. Range of the matrix semivariograms in the 1.0 m pixel image versus tree stress index ($r = -0.96$).

Among all the field measurements only the individual tree crown closure is not significantly correlated with any semivariogram parameters extracted over the forest canopy. The smallest pixel spacing analyzed at this scale, 0.5 m, is still too large to detect this individual tree measure. For typical crown sizes of 5-8 m, the individual openings in the crowns which contribute to its closure measurement are smaller than 0.5 m. Thus, subsequent analysis of 0.25 m pixel imagery (described after the next subsection) was expected to provide improved relations between tree crown closure and the semivariance parameters.

Variation amongst semivariogram parameters extracted using the matrix technique in sub-plot quadrants within the 0.5 m pixel imagery was analysed. It did not reveal significant variability between quadrants except for the open area in Plot 1 which was previously mentioned. There was also no significant correlation between the plot-level variance of the range and sill determined from the four quadrant values and the forest parameters. Thus, the plots were deemed to be well placed with each representative of a homogeneous set of forest structural parameters.

Analysis of semivariogram shapes

In plotting the semivariograms of the canopy-scale analysis, several distinct shapes were commonly produced. A variety of semivariogram shapes was obtained from either the transect or matrix technique sampled over the forest canopy in the 1993, 0.5 m and 1.0 m pixel imagery. The transect semivariograms show periodicity in the healthier plots away

from the mine tailings. The matrix semivariograms do not show this characteristic but display smooth curves which result from averaging over several directions. Some of the 1.0 m pixel semivariograms extracted from transects in plot 1 (poorest overall health) are linear in shape. In linear semivariograms the range is not reached, indicating a moderate spatial continuity within the transect. This plot is not very dense, having a low canopy closure (Table 2) and a large opening about 15 m across its northwest corner. Thus, transects passing through more open plots or large openings in the canopy, where individual objects such as tree crowns do not exist, may display more linearly shaped semivariograms as the range is not reached within a reasonable sampling distance.

The nugget effect is consistently present in the 0.5 m pixel semivariograms. This means that the pixels do not show a perfect autocorrelation and indicates that there is a lot of random variation in the data at this resolution. While sampling over the canopy at this spatial resolution is sensitive to individual tree crown size, tree height, and the tree stress index, the high variability of such small pixels can be considered to be mostly noise. Especially when the measure of interest is canopy closure within areas such as the 2500 m² sample areas of this study. The 1.0 m pixel semivariograms do not display a nugget effect, and they are more sensitive to the forest canopy closure and stem density. Thus, in canopy level sampling, semivariance analysis of 1.0 m pixel imagery appears to be better suited to the scale of measurement of forest canopy parameters while 0.5 m pixel spacing is better suited for the modeling of individual tree measures.

Semivariance analysis at the individual tree-scale

Individual tree crown closure could not be modeled well in the 1993 canopy-scale semivariance analysis of 0.5 m and 1.0 m pixel imagery. Therefore, additional tests using matrix semivariograms extracted from within individual tree crowns in the 1995 0.25 m and 0.5 m pixel imagery were conducted. Semivariogram sill, range, and nugget, were extracted from each tree crown matrix and correlated with the ground forest measures. Table 10 shows the results. Correlation coefficients greater than, or equal to 0.361 for $n = 30$ (0.25 m) and to 0.444 for $n = 20$ (0.5 m) are significant at the 0.05 level. No non-linear trend was observed in the plotted data so a linear correlation was used. Tree crown closure is strongly related to the range derived from the 0.25 m pixel image ($r = 0.85$). This result is similar to the findings for canopy closure in the canopy-scale analysis of 1.0 m pixel data as given in Table 9 and Figure 42. The range increases with crown closure because, for these poplars, in more dense crowns, the leaves are closer to each other and produce a more homogeneous grey tone surface in the imagery. This relationship is illustrated in Figure 46. As a crown becomes stressed and opens up, the size of shadowed areas within the crown becomes larger and the leaves become more clustered. The range is therefore reached at a shorter lag, as shown in Figure 43 where it varies from 0.7 m for open stressed crowns to 1.7 m for closed healthy crowns. These ranges are much smaller than all crown diameters, demonstrating the sensitivity of the semivariogram to within-crown variance. For very open and dying crowns, the same argument presented above for the stress index applies. That is, if the background signal in such a case was entirely uniform, addition of foliage would produce more heterogeneity and relations with the

range would be the inverse of that found here. However, the variability of the background and shadows in imagery with 0.25 m pixel spacing is very high and an open tree crown produces a very heterogeneous grey tone surface. Thus, dead or nearly dead trees would not be expected to produce model deviations from the positive relation with the range that was found.

<i>Spatial resolution:</i>	<i>range</i>	<i>sill</i>	<i>range</i>	<i>sill</i>
	<i>0.25m</i>	<i>0.25m</i>	<i>0.5m</i>	<i>0.5m</i>
<i>Forest canopy closure (%)</i>	<u>0.85</u>	0.29	-0.16	0.06

Table 10. Correlation coefficients (r) for the relationships between tree crown closure and the semivariogram parameters for the 0.25 m and 0.5 m pixel images derived from the matrix technique.

None of the other semivariance parameters, at either image resolution, provided a significant relationship with tree crown closure. The 1995 sampling within individual crowns at the 0.5 m pixel resolution did not produce a better relationship with tree crown closure than the 1993 canopy sampling (Table 9). The range of the 1995, 0.5 m pixel image does not show any correlation with tree crown closure. This is illustrated in Figure 47 where 14 points out of 20 are located at the 3.5m range. This distance represents the range limit above which not enough pairs of pixels are available to calculate a significant estimate of the semivariance. These semivariograms never reach the range of influence and display a linear function. The support size is too large to detect the variability caused by shadows and highlights within single tree crowns, confirming that a pixel spacing smaller than 0.5 m is needed to analyze the structure of the individual tree crowns.

Figure 46. Range of the matrix semivariograms in the 0.25 m image versus tree crown closure ($r = 0.85$).

Figure 47. Range of the matrix semivariograms in the 0.5 m image versus tree crown closure ($r = -0.16$). Note that fewer points than were generated are displayed in the scatterplot since some fall at the same position. The red points represent more than one point (2 to 3).

7.2.3 Conclusion

This study has demonstrated the usefulness of semivariogram shape and statistical analysis in discriminating forest structural damage variations at the KamKotia mine site. Matrix (omni-directional) semivariogram parameters are well correlated with a visual tree stress index and transect semivariograms are better correlated with tree height but both are sensitive to tree crown size and canopy closure. The two techniques are complementary if all the forest measurements are considered. Otherwise, the appropriate technique can be selected for the forest parameter to be evaluated.

In sampling over the forest canopy, the 0.5 m pixel semivariograms uniquely captured information about the tree crown size while the 1.0 m pixel semivariograms were better correlated with forest canopy closure and stem density. This shows that determination of the appropriate object size for a given support size is critical. Pixels of 1.0 m are not sensitive to the tree sizes in this study but are quite sensitive to the spatial variation of trees and gaps over a larger spatial extent as measured by canopy closure. Both spatial resolutions were sensitive to tree health and average tree height. The 0.5 m pixel semivariograms included some random variation (nugget effect) that was not present in the 1.0 m pixel semivariograms. This suggests that the 1.0 m pixel semivariograms are more appropriate to canopy level analysis and are better for interpretation of the shape of the semivariograms. The 1.0 m pixel semivariograms were smoother and the curves and peaks were attenuated while the 0.5 m pixel semivariograms had a nugget which flattened the function curve and masked some of its structural information.

Individual tree crown closure was not significantly correlated with any of the 0.5 m and 1.0 m pixel semivariogram parameters extracted by canopy sampling. For example, in 70% of the cases, the 0.5 m pixel image semivariograms displayed a linear shape that indicates that the range was not reached and that this resolution is too coarse to depict tree crown structural information. It is an aggregate measure of much smaller physical elements than the other forest parameters. Capture of this information in semivariograms requires finer spatial resolution and image samples collected from individual tree crowns only. This structural information of tree crowns was well modeled using images of 0.25 m pixel spacing. The range was found to increase with tree crown closure since a more homogeneous grey tone surface produces a larger range. The 0.25 m pixel image semivariograms displayed a spherical shape that shows that the range was reached at this spatial resolution. These results may have strong implications in analysis of forest damage where individual trees vary significantly in damage level.

7.3 SEMIVARIANCE ANALYSIS APPLIED TO IMAGE BRIGHTNESS AND IMAGE FRACTIONS IN RELATION TO FOREST MEASURES

The promising results of the semivariance analysis on the 800 nm band obtained in the previous section indicated that more information could be extracted using all the spectral bands and the image fraction. In this section, semivariogram ranges and sills were calculated, as described in section 7.2.1, from the two other spectral bands and from the three image fractions. The semivariograms were calculated using the matrix technique

only, because it produces better relations overall, or equal, to the transect technique and it can be extracted at both canopy and tree crown scales.

Chronologically, the semivariance analysis performed in section 7.2 was done prior to any other analysis. When this research was begun, only the 1993 data were available with two spectral resolutions (0.5 m and 1.0m). It was two years later (1995) that the final data set was acquired at three spatial resolutions (0.25 m, 0.5 m, 1.0m), providing the opportunity for analysis at the individual tree crown-scale. Because of the great number of semivariograms required with the present technique, the semivariograms calculated using the 1993, 800 nm band at the canopy-scale, were not recalculated. However, they were verified with a few samples from the 1995 data and yielded similar results. The remaining analyses that followed were all performed on the 1995 data.

7.3.1 Results and discussion

Semivariance analysis at the forest canopy-scale

Relations with forest measures

Table 11 shows the correlation coefficients between image sills and ranges (brightness and fraction), and ground variables (results for the 800 nm band are duplicated from Table 9 for convenience).

In general, when forest canopy closure is high, the range of the 550 nm and 670 nm bands, and the ranges of all the image fractions, are reached at shorter distances. In fact, for these image variables, a high range is associated with less contrast between tree crowns and the background (shadows) which is a characteristic of a less dense canopy. The range of the 800 nm band, on the other hand, increases with increasing canopy closure. The range is reached at a larger distance when the canopy is dense. The sills of most image variables, except the vegetation fraction, are negatively correlated with the closure of the canopy. Thus, a closed canopy produces less variability in the three spectral bands and in the wood fraction, while it produces a greater variability in the vegetation fraction due to a higher contrast between gaps and vegetation fractions.

	Spectral band: 550 nm				670 nm				800 nm			
	Sill	Range	Sill	Range	Sill	Range	Sill	Range	Sill	Range	Sill	Range
Spatial resolution:	0.5m	0.5m	1.0m	1.0m	0.5m	0.5m	1.0m	1.0m	0.5m	0.5m	1.0m	1.0m
Forest canopy closure (%)	-0.69	-0.85	-0.68	-0.73	-0.21	-0.12	-0.77	-0.87	-0.70	-0.32	-0.15	0.83
Forest stem density (per 100 m ²)	-0.77	-0.83	-0.58	-0.62	0.15	0.14	-0.54	-0.74	-0.54	-0.70	-0.15	0.81
Tree crown size (m)	0.20	0.25	0.68	0.67	0.24	0.32	0.67	0.59	0.25	1.00	0.59	-0.71
Tree height (m)	0.33	0.17	0.24	0.24	-0.02	0.12	0.29	0.44	0.30	0.89	0.20	-0.59
Tree crown closure (%)	0.29	0.48	0.09	0.13	-0.45	-0.54	-0.15	-0.12	-0.17	-0.24	-0.07	0.16
Tree stress index (1 to 5)	0.80	0.81	0.54	0.59	0.18	0.15	0.72	0.95	0.86	0.47	0.01	-0.96

	Image fraction: Wood				Shadow				Vegetation			
	Sill	Range	Sill	Range	Sill	Range	Sill	Range	Sill	Range	Sill	Range
Spatial resolution:	0.5m	0.5m	1.0m	1.0m	0.5m	0.5m	1.0m	1.0m	0.5m	0.5m	1.0m	1.0m
Forest canopy closure (%)	-0.48	-0.12	-0.65	-0.87	-0.04	-0.05	-0.28	-0.79	-0.38	-0.35	0.76	-0.09
Forest stem density (per 100 m ²)	0.11	0.31	-0.52	-0.83	0.06	-0.25	-0.29	-0.82	-0.68	-0.38	0.56	0.02
Tree crown size (m)	-0.03	0.19	0.57	0.76	0.20	0.44	0.66	0.84	0.39	0.79	-0.25	0.14
Tree height (m)	-0.02	0.05	0.27	0.48	-0.13	0.33	0.22	0.57	0.15	0.38	-0.18	0.05
Tree crown closure (%)	-0.50	-0.83	-0.08	0.04	0.12	0.02	0.02	-0.03	0.79	-0.12	0.02	-0.17
Tree stress index (1 to 5)	0.52	0.23	0.62	0.86	-0.17	0.04	0.11	0.81	0.15	0.26	-0.82	0.08

Table 11. Correlation coefficients (r) between image variables (spectral bands, fractions) and the semivariogram parameters at the canopy-scale.

In Chapter 6, it was hypothesized that stem density and tree crown size are not captured through the variation and spatial distribution of both image brightness and image fraction because they are measures of forest structure. In fact, the only significant relationships found between these forest measures and the image variables are with the range of image semivariograms. The range values of the 0.5 m resolution of the 550 nm band, the 1.0 m wood fraction and 1.0 m shadow fraction produce an inverse relationship ($r = -0.83$, $r = -0.83$, $r = -0.82$) with stem density. The range of these image variables is reached at a shorter distance when the stem density is high. With tree crown size, the 0.5 m range using the 800 nm band remains the most effective image measure ($r = 1.0$). It is also significantly related to the 1.0 m resolution range of the shadow fraction ($r = 0.84$). The range of the wood and vegetation fraction are also positively correlated with crown size,

although not significantly ($r = 0.76$ and 0.79 respectively). The range of these variables is reached at greater distance when the average tree crown size is large.

Tree height relates to the 800 nm / 0.5 m range as it does to tree crown size since both are statistically related ($r = 0.89$). These two variables have a combined effect that produces variations in highlight and shadow that enhance the limit between tree crowns.

Individual crown closure was not detected when sampling at the forest canopy-scale when using semivariance analysis applied on the 800 nm band alone (see section 7.2.2). However, when semivariance analysis is applied to image fractions over the forest canopy, the range of the wood fraction at 0.5 m resolution produces a significant relationship ($r = -0.83$). The range of the wood fraction is reached at a shorter distance when tree crowns are dense. Wood fractions mainly occur within tree crowns while this is not the case for the other two fractions, vegetation and shadow (Figures 37, 38, 39). The range is therefore larger when more wood is visible. Although not significant with the number of samples used, the sill of the 0.5 m resolution vegetation fraction produces a positive relationship with individual tree crown closure ($r = 0.79$). This pixel size, combined with the isolation of the vegetation component of the total brightness, shows potential for the detection of this forest measure at the canopy-scale. A larger number of samples would be required to verify this.

When the stress index is high (representing more damage) the ranges of the 550 nm and the 670 nm bands, and the range of the wood and shadow fractions are also high. In a

stressed canopy, these image variables become stronger, i.e., more visible light is reflected by bright tree branches and the understory, and more shadow and wood take the place of healthy green foliage. A larger distance is thus necessary for the pixel data to be spatially separated. This relationship is the opposite of the one obtained with the range of the 800 nm band ($r = -0.96$) where a high stress index produces a smaller range. In this case, with a stressed canopy, the strong brightness of foliage in this spectral band may produce a clustering effect which in turn produces a shorter range. When the stress index is high, the sill of the three spectral bands and the wood fraction is generally higher, indicating that more spatial variability is introduced in these image variables.

Analysis of semivariogram shapes

In analysis of semivariogram shape, 67 out of 324 semivariograms were linear at the 0.5 m resolution (20.7%) and only 16 out of 144 (4.2%) were linear at the 1.0 m resolution. In the 1.0 m resolution image, 5 of the 16 linear semivariograms (31%) come from the shadow fraction of the most damaged plot (plot 1), due to the large opening in the northwest corner (see Figure 32). This suggests that the 1.0 m resolution is more suited for forest canopy semivariance analysis than the 0.5 m resolution, as found in section 7.2.2.

Semivariance analysis at the individual tree-scale

Relations with forest measures

Table 12 shows the correlation coefficients between the sill and range of the semivariograms extracted from image measures and tree measures of height, crown closure and stress index. Underlined r-values are significant at 0.05 level. Because of the large number of linear semivariograms at the tree-scale (57.5% at 0.25 m and 63.4% at 0.5 m), the sill was extracted at a fixed lag (distance) of 1.2 m and does not relate to the semivariance of the data sets but rather to the semivariance at 1.2 m. This distance was chosen by taking a distance lower than the minimum range obtained amongst all the trees at both resolutions. The minimum range at the 0.25 m resolution was 4.2 pixels (1.22 m) and 2.68 (1.26 m) pixels at the 0.5 m resolution. The linear semivariograms were given a range value of the largest sampling distance (in pixel), which corresponds to the diagonal distance.

Tree height does not relate significantly to the image semivariance and range. However, it is interesting to note that all the correlation values of the semivariance at 1.2 m are negative, that is, smaller trees tend to have higher variability in their crowns. The consistency of this trend and the fact that many correlation coefficients are close to being

significant ($r = 0.29$ to 0.31) suggests that a larger sample size may increase the level of significance of these relationships.

Spectral band:	550 nm				670 nm				800 nm			
	SV1.2m	Range	SV1.2m	Range	SV1.2m	Range	SV1.2m	Range	SV1.2m	Range	SV1.2m	Range
Spatial resolution:	0.25m	0.25m	0.5m	0.5m	0.25m	0.25m	0.5m	0.5m	0.25m	0.25m	0.5m	0.5m
Tree height (m)	-0.18	-0.02	-0.30	-0.30	-0.20	-0.04	-0.29	0.09	-0.24	0.07	-0.27	0.03
Tree crown closure (%)	0.15	-0.21	0.31	-0.03	-0.46	0.08	-0.04	0.19	0.03	-0.13	0.43	-0.20
Tree stress index (1 to 5)	-0.08	0.17	-0.36	0.18	0.59	-0.07	0.17	-0.28	-0.11	0.09	-0.31	0.21

Image fraction:	Wood				Shadow				Vegetation			
	SV1.2m	Range	SV1.2m	Range	SV1.2m	Range	SV1.2m	Range	SV1.2m	Range	SV1.2m	Range
Spatial resolution:	0.25m	0.25m	0.5m	0.5m	0.25m	0.25m	0.5m	0.5m	0.25m	0.25m	0.5m	0.5m
Tree height (m)	-0.31	-0.01	-0.06	-0.07	-0.22	-0.16	-0.27	-0.16	-0.18	-0.14	-0.31	0.00
Tree crown closure (%)	0.00	-0.26	-0.46	-0.14	0.10	-0.03	0.13	0.12	0.55	-0.18	0.30	0.14
Tree stress index (1 to 5)	0.18	0.22	0.52	0.09	0.11	0.05	0.01	-0.04	-0.35	0.22	-0.09	-0.17

Table 12. Correlation coefficients (r) between image variables (spectral bands, fractions) and the semivariogram parameters at the individual tree-scale.

Decreasing crown closure and increasing stress index ($>$ damage) are expressed by:

- increasing semivariance at 1.2 m in the 0.25 m resolution 670 nm band ($r = -0.46$ and 0.59) and in the wood fraction ($r = -0.46$ and 0.52) of the 0.5 m resolution. More open tree crowns that show signs of stress (such as paler or discoloured leaves, undersized leaves, more clustered leaves, increased dead branches), are more likely to expose more wood and have high variation in the chlorophyll absorption band (670 nm). The remaining healthy foliage is mixed with various degrees of damaged foliage which absorbs less at this wavelength.
- decreasing semivariance at 1.2 m in the 0.5 m resolution the 550 nm band ($r = 0.31$ and -0.36), in the 0.5 m resolution 800 nm band ($r = 0.43$ and -0.31), and in the 0.25 m resolution vegetation fraction ($r = 0.55$ and -0.35). The case would probably be different if the semivariance was calculated for a larger distance. But at this distance,

there is less variability in these variables for more open and more stressed tree crowns. As tree crowns open up, more light reaches the understory which forms a vegetation carpet underneath and reduces the texture.

These correlations are similar in magnitude to those obtained using the image brightness and image fraction as variables (Table 4) but fewer significant correlations were found. This suggests that the use of more complex image variables representing spatial dependence of image brightness and fraction is unnecessary when studying individual tree crowns; the raw spectral data or derived fractions provide equivalent information. The high number of linear semivariograms also suggests that an even finer resolution would be more appropriate for this technique to reach its full potential at the tree-scale. It would also help to resolve within-crown shadow as crowns become more open.

Analysis of semivariogram shapes

Semivariogram shape in individual tree samples was either linear or spherical. In order to relate the shape of the semivariograms to the ground measurements, a semi-quantitative analysis was performed. Spherical-shaped semivariograms were assigned to group #1 and linear-shaped semivariograms were assigned to group #2. The forest measurements associated with each group were compared using a Student T-test. Results are reported in Table 13. It was found that high crown closure and low stress index ($<$ damage) are associated with linear-shaped semivariograms of the shadow fraction at both spatial resolutions. Another trend, although not always significant, shows that high crown

closure and low stress index can be associated with linear-shaped semivariograms of the vegetation fraction. In this case, only the 0.5 m resolution shows a significant difference between the two crown closure groups ($p = 0.04$).

	resolution	image variable	ground variable	spherical shape			linear shape			t-value	p-value
				n	avg	std	n	avg	std		
(a)	0.25m	800 nm	tree height	16	27.34	2.61	15	27.73	2.96	-0.39	0.35
			crown closure	16	59.69	21.09	15	66.67	9.76	-1.17	0.13
			health index	16	2.91	0.93	15	2.53	0.61	1.31	0.10
		670 nm	tree height	14	27.79	2.66	17	27.32	2.88	0.46	0.32
			crown closure	14	60.71	21.83	17	65.00	11.32	-0.70	0.24
			health index	14	2.79	1.01	17	2.68	0.61	0.37	0.36
		550 nm	tree height	8	27.50	2.92	23	27.54	2.75	-0.04	0.49
			crown closure	8	61.88	16.02	23	63.48	17.28	-0.23	0.41
			health index	8	3.00	0.76	23	2.63	0.81	1.12	0.14
	0.5m	800 nm	tree height	8	27.25	1.87	23	27.63	3.02	-0.33	0.37
			crown closure	8	70.63	5.63	23	60.43	18.52	1.52	0.07
			health index	8	2.56	0.32	23	2.78	0.91	-0.66	0.26
		670 nm	tree height	13	27.88	2.20	18	27.28	3.12	0.60	0.28
			crown closure	13	61.92	23.14	18	63.89	10.65	-0.32	0.38
			health index	13	2.77	1.05	18	2.69	0.60	0.25	0.40
		550 nm	tree height	11	27.55	2.48	20	27.53	2.94	0.02	0.49
			crown closure	11	63.64	14.85	20	62.75	18.03	0.14	0.45
			health index	11	2.68	0.81	20	2.75	0.82	-0.22	0.41
(b)	0.25m	Wood fraction	tree height	9	27.72	2.92	22	27.45	2.74	0.24	0.41
			crown closure	9	57.78	26.23	22	65.23	10.96	-1.13	0.13
			health index	9	2.83	1.17	22	2.68	0.63	0.47	0.32
		Shadow fraction	tree height	12	27.17	2.67	19	27.76	2.84	-0.58	0.28
			crown closure	12	54.58	22.51	19	68.42	8.83	-2.42	<u>0.01</u>
			health index	12	3.17	0.96	19	2.45	0.55	2.66	<u>0.01</u>
		Vegetation fraction	tree height	20	27.85	2.93	11	26.95	2.40	0.87	0.50
			crown closure	20	59.75	18.46	11	69.09	11.36	-1.52	0.07
			health index	20	2.80	0.85	11	2.59	0.74	0.07	0.25
	0.5m	wood	tree height	14	27.50	2.95	17	27.56	2.66	0.49	0.56
			crown closure	14	60.71	13.71	17	65.00	19.04	-0.70	0.24
			health index	14	2.82	0.82	17	2.65	0.81	0.59	0.28
		shadow	tree height	6	28.33	2.40	25	27.34	2.83	0.79	0.22
			crown closure	6	48.33	28.58	25	66.60	10.58	-2.63	<u>0.01</u>
			health index	6	3.25	1.21	25	2.60	0.65	1.85	<u>0.04</u>
		vegetation	tree height	16	27.66	2.52	15	27.40	3.05	0.26	0.40
			crown closure	16	58.13	19.31	15	68.33	11.90	-1.76	<u>0.04</u>
			health index	16	2.94	0.87	15	2.50	0.68	1.55	0.07

Table 13. Student t-test results between the spherical and linear shape semivariograms for each forest measure and the (a) spectral bands and (b) image fraction variables.

7.4 TEXTURE ANALYSIS APPLIED TO IMAGE BRIGHTNESS AND IMAGE FRACTIONS IN RELATION TO FOREST MEASURES

7.4.1 Methodology

Co-occurrence and grey-level difference vector texture measures (Haralick *et al.*, 1973; Haralick, 1979) were extracted from the three original bands and from the three endmember fraction images. A set of 24 texture measures (PCI Inc., 1994) were evaluated on the three brightness images (550 nm, 670 nm, 800 nm) and the three fraction images (wood, shadow, vegetation) at the three spatial resolutions (0.25 m, 0.5 m, 1.0 m). A subset of four measures (mean, entropy, angular second moment, contrast) were selected that were least correlated ($r < 0.79$) with each other. As shown in section 3.3.3, the mean (MEA) measure is the average probability of grey level pair occurrence within the co-occurrence matrix. Entropy (ENT) measures the degree of organized patterns within the co-occurrence matrix. Angular Second Moment (ASM) indicates the degree of homogeneity of the values contained in the co-occurrence matrix. Finally, contrast (CON) measures the amount of local variation within the co-occurrence matrix. Because of the nature of their information, it is expected that when texture increases, MEA, ENT and CON increase, and ASM will decrease.

To determine the most suitable window size for canopy-scale texture analysis, windows were varied from 3 x 3 pixels to 25 x 25 pixels with one extra window of large size also

selected for each spatial resolution (total of 13 window sizes tested). This large window covered one quarter of the whole plot (99 x 99 pixels for 0.25 m, 61 x 61 pixels for 0.5 m, and 37 x 37 pixels for 1.0 m). The sampling direction was spatially invariant, that is the co-occurrence matrix was calculated from sample pairs in all directions, and the lag spacing was 1 pixel. This was selected to maximize local texture information within individual tree crowns. From these tests the following pattern emerged: local texture derived from the smallest window sizes related best to forest variables such as individual tree crown closure and forest canopy closure, while regional texture derived from the largest window size related better to the visual forest stress index. Therefore, two window sizes were retained at each resolution for correlation analysis with the ground forest variables: the smallest window (3 x 3 pixels) and the largest window (as above for the three pixel sizes). For the individual tree crown analysis, a window size of 3 x 3 was also used, to minimize boundary effects, since a larger window size would calculate texture measures using too many pixels outside the sampled tree crown area.

7.4.2 Results and discussion

Texture analysis at forest canopy-scale

Table 14 shows the correlation coefficients between image texture and ground forest measures using the 3 x 3 (Table 14a) and the largest (Table 14b) window sizes of each spatial resolution. Underlined values are significant at $p \leq 0.05$ ($r \geq 0.811$). After checking each relationship scatterplot, no non-linear trends were found.

An increase in canopy closure generally produces increased texture in the 800 nm band and the vegetation, wood and shadow fractions. Since healthy vegetation is highly reflective at the 800 nm wavelength and with a closed canopy, higher grey level transitions are expected, since shadows in gaps are better defined and darker than for a less reflective, more open, and stressed canopy. Similarly, being isolated from other image constituents (wood, shadow), strong vegetation fraction transitions indicate the presence of contrast between dense vegetation within tree crowns and sparse or no vegetation in the gaps. Low canopy closure is manifested in smaller vegetation fraction transitions since the difference between the gaps (no vegetation) and the stressed canopy (low vegetation fraction) is smaller. This applies to the shadow fraction as well, except for the MEA shadow, which decreases as the canopy closure increases. In a closed canopy, wood fractions are clumped in the image, thus producing more texture. It is an indication of increased canopy health since wood fractions appear sporadically on individual trees rather than spread over the canopy. When the closure is low, on the other hand, the underlying wood is unmasked because there is less foliage. Although most of the significant relationships occur at the 1.0 m resolution, the best relationships with forest canopy closure are found at the 0.25 m resolution using the ASM texture of the wood fraction ($r = -0.95$) and the 800 nm band ($r = -0.90$).

Forest stem density does not correlate significantly with any of the image textures extracted from both image brightness and image fraction variables, as was the case when using the raw image brightness and image fractions in Chapter 6. However, it is worth noting that, as for canopy closure, texture increases when the stem density is high. Many

relationships are close to the significance level that could possibly be attained with a larger number of samples.

An increase in tree crown size produces a decreasing texture in the wood fraction at the 0.25 m resolution. It produces significant relationships with the ENT and CON texture of the wood fraction ($r = -0.94$ and $r = -0.92$ respectively). A canopy composed of large tree crowns is expressed by less complex patterns in the spatial distribution of wood fractions within the co-occurrence matrix. Similarly, large tree crowns produce lower contrast in the wood fractions. Isolated from the other basic constituents of the spectral signal (shadow and vegetation fractions), wood fractions indicate the proportion of the pixel that is occupied by bare wood. The spatial variability of the wood fraction is captured only at the 0.25 m resolution, which is fine enough to capture the narrow linear form of bare tree branches.

Tree height relates well to the contrast of the image fraction at 0.5 m resolution, where high contrast in wood, shadow, and vegetation fractions is associated with taller trees. With increasing average tree height, there is more contrast in the image fractions, since taller trees receive more illumination than lower trees. Therefore, the contrast between highly illuminated trees and the background or shadows is higher than for a uniformly shorter canopy.

Tree crown closure is not significantly related to any image variables. The highest correlation coefficients are found at the 0.5 m resolution with the ENT of the wood and

vegetation fractions ($r = 0.73$ and $r = 0.76$ respectively), and with the ASM of the vegetation fraction ($r = -0.73$). That is, high crown closure produces a high texture in those image variables.

Stress index incorporates visual symptoms of damage that are manifested as spectral and textural variations in the image. Thus, stress index is the forest measure that relates best to image texture variables; the texture measures ENT and ASM produce most of the significant relationships. In general, a high stress index (> damage) produces a low texture in all image variables. Thus, a high stress index is expressed as low variability in the spectral bands and the image fractions. For the spectral band variables and the vegetation fraction, this is explained by the fact that the high transitions between healthy green foliage and the background shadow are reduced. Wood and shadow fractions are distributed sporadically in a healthy canopy that is dominated by dense foliage. However, they are more uniformly distributed in a canopy with reduced leaf size and foliage density, and increased amounts of dead branches. The wood fraction produces significant correlations at the three spatial resolutions using ASM. For this reason it is a more reliable image variable in predicting the stress index measure.

Window size

Except for a few cases, the large window size (Table 14b) does not yield better correlation coefficients than the small window size. This can be explained by the fact that

large window sizes incorporate more of the total plot variation and have the effect of averaging out the local variation (Vistnes, 1987).

Texture analysis at individual tree-scale

Table 15 shows the correlation coefficients between image texture and tree height, tree crown closure and stress index. The underlined values are significant at $p \leq 0.05$ level ($r \geq 0.355$). All the relationships in the table showed no sign of non-linearity so linear correlations were performed.

Mean							Entropy					
Spectral band:	550nm		670nm		800nm		550nm		670nm		800nm	
Spatial resolution:	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m
Tree height (m)	-0.22	-0.11	-0.11	0.13	0.03	0.32	-0.14	-0.34	-0.18	0.02	-0.17	-0.14
Tree crown closure (%)	-0.13	<u>0.68</u>	<u>0.46</u>	0.04	0.35	-0.09	-0.05	<u>0.66</u>	<u>0.64</u>	0.33	<u>0.71</u>	<u>0.71</u>
Tree stress index (1 to 5)	0.16	<u>-0.50</u>	<u>-0.38</u>	-0.07	-0.27	0.00	-0.10	<u>-0.50</u>	<u>-0.53</u>	<u>-0.38</u>	<u>-0.62</u>	<u>-0.61</u>
Image fraction	Wood		Shadow		Vegetation		Wood		Shadow		Vegetation	
Spatial resolution:	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m
Tree height (m)	-0.27	-0.20	-0.04	-0.17	0.14	0.19	-0.07	-0.05	-0.22	-0.16	-0.32	-0.30
Tree crown closure (%)	<u>-0.40</u>	<u>-0.46</u>	-0.25	0.00	<u>0.73</u>	<u>0.70</u>	<u>0.59</u>	0.31	0.22	<u>0.42</u>	<u>0.59</u>	<u>0.51</u>
Tree stress index (1 to 5)	<u>0.44</u>	0.30	0.19	-0.02	<u>-0.67</u>	<u>-0.54</u>	<u>-0.46</u>	-0.14	-0.28	-0.34	<u>-0.48</u>	<u>-0.37</u>
Angular Second Moment							Contrast					
Spectral band:	550nm		670nm		800nm		550nm		670nm		800nm	
Spatial resolution:	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m
Tree height (m)	0.09	0.21	0.14	-0.10	0.14	0.21	-0.20	<u>-0.38</u>	-0.19	-0.21	-0.13	0.04
Tree crown closure (%)	<u>-0.71</u>	<u>-0.71</u>	<u>-0.67</u>	-0.21	0.29	<u>-0.56</u>	<u>0.47</u>	<u>0.47</u>	<u>0.54</u>	<u>0.48</u>	<u>0.65</u>	<u>0.49</u>
Tree stress index (1 to 5)	<u>0.60</u>	<u>0.58</u>	<u>0.55</u>	0.26	-0.10	<u>0.38</u>	<u>-0.50</u>	<u>-0.46</u>	<u>-0.45</u>	<u>-0.49</u>	<u>-0.63</u>	<u>-0.44</u>
Image fraction	Wood		Shadow		Vegetation		Wood		Shadow		Vegetation	
Spatial resolution:	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m	0.25m	0.5m
Tree height (m)	0.09	0.10	0.22	0.14	0.26	0.28	-0.08	-0.01	-0.13	-0.17	<u>-0.36</u>	-0.22
Tree crown closure (%)	<u>-0.68</u>	<u>-0.62</u>	-0.06	-0.35	<u>-0.66</u>	<u>-0.56</u>	0.31	-0.03	<u>0.52</u>	<u>0.51</u>	<u>0.45</u>	<u>0.42</u>
Tree stress index (1 to 5)	<u>0.56</u>	<u>0.43</u>	0.16	0.30	<u>0.55</u>	<u>0.38</u>	-0.18	0.16	<u>-0.52</u>	<u>-0.44</u>	<u>-0.39</u>	<u>-0.37</u>

Table 15. Correlation coefficients (r) between image texture and tree measures using the 3 x 3 window size of each spatial resolution (underlined r-values are significant at the 0.05 level).

For tree height, as the tree height increases, texture decreases. Significant relationships are present with the contrast texture of the 550 nm band ($r = -0.38$) and the vegetation fraction ($r = -0.36$). Taller trees receive more illumination than lower trees which produces less contrast within lower tree crowns. These relationships are the opposite of the ones obtained at the forest canopy-scale where the texture represents the contrast between the tree crowns and the background.

When tree crown closure is high and the stress index is low ($< \text{damage}$), the texture increases in all image bands and image fractions. This relationship is similar to the one obtained for the canopy closure at the canopy-scale. In this case, a more reflective tree crown produces higher contrast between the foliage and the gaps (shadow) than with a stressed open crown. Similarly, strong vegetation fraction transitions indicate the presence of contrast between dense foliage and gaps within tree crowns. A high texture in the wood and shadow fractions is also associated with healthier crowns, which indicates that wood and shadow fractions are distributed sporadically rather than uniformly as would be the case in a stressed open crown. The most significant relationships found that relate to tree crown closure are with the MEA texture of the vegetation ($r = 0.73$ and 0.70 at 0.25 m and 0.5 m resolution respectively), the ENT of the 800 nm band ($r = 0.71$ at both resolutions), and the ASM of the 550 band ($r = -0.71$ at both resolutions). These same image variables are also the most significant ones that relate to the stress index ($r = -0.54$ to -0.62 , 0.58 to 0.60).

7.5 RESULTS SUMMARY

The best relationships between image and forest variables are summarised in Table 16. The last column of the table shows the absolute r increase from the best relationship obtained using raw spectral data.

	Image variable	Resolution	r	Δr
Canopy-scale*				
Canopy closure (%)	Texture-wood	0.25	-0.95	0.08
	Range-shadow	1.00	-0.93	0.06
Forest stem density (per 100 m ²)	Texture-shadow	0.50	-0.89	0.33
Tree crown size (m)	Range-800nm	0.50	1.00	0.37
	Texture-wood	0.25	-0.96	0.33
Tree height (m)	Range-800nm	0.50	0.89	0.52
Tree crown closure (%)	Sill-vegetation	0.50	0.85	0.13
	Range-wood	0.50	-0.83	0.11
Tree stress index (1 to 5)	Range-800nm	1.00	-0.96	0.06
Tree-scale**				
Tree height (m)	Texture-550nm	0.50	-0.38	0.18
	Texture-vegetation	0.25	0.36	0.16
Tree crown closure (%)	Texture-vegetation	0.25	0.73	0.05
	Vegetation	0.25	0.71	0.03
	Texture-800nm	0.25	0.71	0.03
	Texture-800nm	0.50	0.71	0.03
	Texture-550nm	0.25	-0.71	0.03
	Texture-550nm	0.50	-0.71	0.03
Tree stress index (1 to 5)	Texture-vegetation	0.50	0.70	0.02
	Vegetation	0.25	-0.64	0.08

Table 16. Best relationships between forest / tree measures and image variables. * r values ≥ 0.811 and ** r values ≥ 0.355 are significant, respectively at $p \leq 0.05$. Δr indicates the absolute increase of r from the best relationship found using raw spectral data.

In sampling at the forest canopy-scale, all the best relationships are formed with spatial measures of the 800 nm band and image fractions. Except for canopy closure and stress index, the 0.5 m resolution is generally best. There are substantial increases of the

correlation coefficient when using spatially transformed data, especially for tree crown size and tree crown closure.

In sampling of individual tree crowns, all best relationships are formed with transformed data (spectral and spatial). A slight improvement is achieved for tree crown closure and stress index when using transformed data (0.05 and 0.08 respectively). The improvement is more pronounced for tree height (0.18), which is brought up above the significance level when using texture measures (-0.38). However, it is not expected that such a poor relationship could be used for predictive purposes.

7.6 CONCLUSIONS

The results of this chapter have shown that when sampling images at the forest canopy-scale, spatial transformation of the raw spectral data and fraction data improves the relationships between images variables and forest measures. In general, the 0.5 m spatial resolution yields the best relationships with the forest measures. At the individual tree crown-scale, spatially transformed image data provides higher correlation coefficients than the raw spectral or fraction data from individual tree measures (see section 6.3.6).

Through the last two chapters, spectral and spatial transformed data have revealed detailed information about the nature of a stressed forest canopy and a stressed tree crown, as expressed in multispectral imagery. In the next chapter, all the variables are introduced into a multiple regression analysis, in order to construct models for the forest

measures. This will allow the identification of sets of variables that behave in a synergistic manner to enhance the relationship between the image and forest measures.

8. COMBINING SPECTRAL AND SPATIAL IMAGE VARIABLES IN MODELING OF FOREST STRUCTURE AND HEALTH

8.1 OBJECTIVES

The results of Chapter 6 and 7 have allowed exploration of the bi-variate relationships between image and ground variables. In this Chapter, all the image variables described in the previous two Chapters are combined. Multiple regression models are built using the spectral bands, the derived image fractions, and their spatial transforms (texture, semivariance). The objectives were: (1) to compare models using image brightness with models using image fractions and (2) to explore the synergistic effect of the two variable types when combined. This analysis determines which image variable (s), spatial resolution (0.25 m, 0.5 m, 1.0 m), and scale of sampling (canopy-scale or tree-scale) are best suited for modeling each forest measure.

8.2 METHODOLOGY

8.2.1 Stepwise multiple linear regression

Forward stepwise multiple regression was used to determine the combination of image variables that best models each forest measure. Forest measures were entered as dependents and image variables were entered as independents. The forward method first selects the independent variable that has the highest significant correlation with the

dependent variable. The partial correlation coefficients of the remaining independent variables are then calculated and the variable with the highest significant coefficient is introduced next in the regression. This process is repeated until none of the partial correlation coefficients of the remaining independent variables is significant. The F-to-enter determines the minimum significance level of a variable in order to be added to the equation. The introduction of new variables in the regression equation sometimes decreases the contribution of previously selected variables to the point where they become insignificant and are removed. For this reason a forward stepwise regression method was used. It allows the user to monitor each step of the regression. The Complete Statistical System (CSS) (Statsoft, 1987) software was used to conduct the analysis.

In the previous two chapters, all relationships were graphed to look for non-linear behaviours. No obvious non-linear relationships were found. Prior to the multiple regression analysis, it was verified that all image variables were normally distributed. This was done by using probability plots; if the data were normally distributed, a straight line could be drawn through the bulk of the plotted points (Draper and Smith, 1981). In all cases the variables were found to be normally distributed.

Also, prior to the multiple regression analysis, multicollinearity in the x variable set was eliminated. Highly intercorrelated variables are not desirable since high standard errors for the regression coefficients may result in making them less reliable (Scherrer, 1984). In CSS, multicollinearity is addressed by entering a tolerance limit that is defined as $1-R^2$ where R^2 is the multiple correlation of the variable with all other independent variables in

the regression equation. Birkes and Dodge (1993) use a threshold of the variance inflation factor (VIF) of 10. The VIF threshold is calculated as $1/(1-R^2)$. This translates into a tolerance value of 0.1 in CSS. The significance level of F-to-enter was set to 0.05 and F-to-exit was set to 0.10.

8.2.2 Image model variables

Table 17 summarises the image variables used in the regression analysis at both canopy-scale and tree-scale. The image digital number (DN) and image fraction (IF) variables are grouped into spectral, textural and semivariogram variables. For the texture measures, the letter in brackets refers to the window size (in pixels x pixels). All the image variables listed are used in the canopy-scale analysis except for the semivariogram variables at 0.25 m resolution (variables with “**”) since this spatial resolution was not found appropriate for a semivariance analysis at the canopy-scale (see section 7.2.1). At the individual tree crown-scale, the larger texture window and the 1.0 m resolution data are not used (variables with “*”) since it was not found appropriate for a semivariance analysis at the individual tree crown-scale (see section 7.2.1).

	<i>0.25 m</i>		<i>0.50 m</i>		<i>1.0 m</i>	
	DN	IF	DN	IF	DN	IF
Spectral Variables	550 670 800	VEG SHA WOD	550 670 800	VEG SHA WOD	550* 670* 800*	VEG* SHA* WOD*
Texture Variables	MEA(3) - 550 MEA(3) - 670 MEA(3) - 800 ENT(3) - 550 ENT(3) - 670 ENT(3) - 800 ASM(3) - 550 ASM(3) - 670 ASM(3) - 800 CON(3) - 550 CON(3) - 670 CON(3) - 800 MEA(99) - 550* MEA(99) - 670* MEA(99) - 800* ENT(99) - 550* ENT(99) - 670* ENT(99) - 800* ASM(99) - 550* ASM(99) - 670* ASM(99) - 800* CON(99) - 550* CON(99) - 670* CON(99) - 800*	MEA(3) - VEG MEA(3) - SHA MEA(3) - WOD ENT(3) - VEG ENT(3) - SHA ENT(3) - WOD ASM(3) - VEG ASM(3) - SHA ASM(3) - WOD CON(3) - VEG CON(3) - SHA CON(3) - WOD MEA(99) - VEG* MEA(99) - SHA* MEA(99) - WOD* ENT(99) - VEG* ENT(99) - SHA* ENT(99) - WOD* ASM(99) - VEG* ASM(99) - SHA* ASM(99) - WOD* CON(99) - VEG* CON(99) - SHA* CON(99) - WOD*	MEA(3) - 550 MEA(3) - 670 MEA(3) - 800 ENT(3) - 550 ENT(3) - 670 ENT(3) - 800 ASM(3) - 550 ASM(3) - 670 ASM(3) - 800 CON(3) - 550 CON(3) - 670 CON(3) - 800 MEA(61) - 550* MEA(61) - 670* MEA(61) - 800* ENT(61) - 550* ENT(61) - 670* ENT(61) - 800* ASM(61) - 550* ASM(61) - 670* ASM(61) - 800* CON(61) - 550* CON(61) - 670* CON(61) - 800*	MEA(3) - VEG MEA(3) - SHA MEA(3) - WOD ENT(3) - VEG ENT(3) - SHA ENT(3) - WOD ASM(3) - VEG ASM(3) - SHA ASM(3) - WOD CON(3) - VEG CON(3) - SHA CON(3) - WOD MEA(61) - VEG* MEA(61) - SHA* MEA(61) - WOD* ENT(61) - VEG* ENT(61) - SHA* ENT(61) - WOD* ASM(61) - VEG* ASM(61) - SHA* ASM(61) - WOD* CON(61) - VEG* CON(61) - SHA* CON(61) - WOD*	MEA(3) - 550* MEA(3) - 670* MEA(3) - 800* ENT(3) - 550* ENT(3) - 670* ENT(3) - 800* ASM(3) - 550* ASM(3) - 670* ASM(3) - 800* CON(3) - 550* CON(3) - 670* CON(3) - 800* MEA(37) - 550* MEA(37) - 670* MEA(37) - 800* ENT(37) - 550* ENT(37) - 670* ENT(37) - 800* ASM(37) - 550* ASM(37) - 670* ASM(37) - 800* CON(37) - 550* CON(37) - 670* CON(37) - 800*	MEA(3) - VEG* MEA(3) - SHA* MEA(3) - WOD* ENT(3) - VEG* ENT(3) - SHA* ENT(3) - WOD* ASM(3) - VEG* ASM(3) - SHA* ASM(3) - WOD* CON(3) - VEG* CON(3) - SHA* CON(3) - WOD* MEA(37) - VEG* MEA(37) - SHA* MEA(37) - WOD* ENT(37) - VEG* ENT(37) - SHA* ENT(37) - WOD* ASM(37) - VEG* ASM(37) - SHA* ASM(37) - WOD* CON(37) - VEG* CON(37) - SHA* CON(37) - WOD*
Semivariogram Variables	SILL - 550** SILL - 670** SILL - 800** RANGE - 550** RANGE - 670** RANGE - 800**	SILL - VEG** SILL - SHA** SILL - WOD** RANGE - VEG** RANGE - SHA** RANGE - WOD**	SILL - 550 - 0.5 SILL - 670 - 0.5 SILL - 800 - 0.5 RANGE - 550 - 0.5 RANGE - 670 - 0.5 RANGE - 800 - 0.5	SILL - VEG - 0.5 SILL - SHA - 0.5 SILL - WOD - 0.5 RANGE - VEG - 0.5 RANGE - SHA - 0.5 RANGE - WOD - 0.5	SILL - 550* SILL - 670* SILL - 800* RANGE - 550* RANGE - 670* RANGE - 800*	SILL - VEG* SILL - SHA* SILL - WOD* RANGE - VEG* RANGE - SHA* RANGE - WOD*

Table 17. Summary of the image variables used at the canopy and tree crown-scales in the regression analysis. *Variables used at canopy-scale only, **variables used at individual tree-scale only.

8.3 RESULTS AND DISCUSSION

The following sections interpret and discuss the forest measure models at the forest canopy-scale and at the individual tree crown-scale. Three models were built at each spatial resolution for each forest measure using (1) DN variables only, (2) IF variables only and (3) both DN and IF variables. Thus, each forest measure has 9 models at canopy-scale (3 models X 3 resolutions) and 6 models at tree crown-scale (3 models X 2 resolutions). In all cases, the residuals of the models were distributed normally and presented no trend with the dependent variable. The serial correlation of the residuals at a lag of 1 for significant models did not exhibit any local trend.

There are seven parameters that describe each model: (1) the R^2 value represents the proportion of the total variance about the mean that is explained by the image variables in the regression. (2) The adjusted R^2 , which is similar to the R^2 value but takes into account the number of degrees of freedom (i.e., one degree of freedom is lost every time a new variable is introduced in the model), is used to compare the strength of the models. (3) The standard error indicates the variation of the predicted values about the mean. (4) The standard error as percentage of the mean determines the relative precision of the model, i.e., the % error in relation to the average value of the predicted variable (y'). (5) The R^2 change shows the contribution of each variable to the explanation of the total variation. The sum of these values is equal to R^2 . (6) The predictor significance indicates the significance level of each variable entered into the model. (7) The overall significance of the model indicates to what level fluctuation of the samples is explained by the regression

equation. The sign of the relationship between each independent variables (model variables) with the dependent variable is shown before each variable.

8.3.1 Forest canopy-scale structural models

For regression analysis, the minimum number of plots should be about 15 (Draper and Smith, 1981). In this research, for canopy-scale analysis only six plots were used. When the research was designed, the methodology was adapted from King *et al.* (1992) and Yuan *et al.* (1991) where large plots were used for analysis of individual tree health with high resolution imagery (similar to the tree-scale analysis of this study). It was not initially deemed to be possible to acquire field data for a larger number of plots near the time of the airborne data acquisition. Sampling these forest measures over more plots would have been difficult to achieve within a suitable time. However, the six plots capture a wide range of forest conditions, from highly stressed to healthy. Because of this limitation, it was assured that the significant models did not include more than five independent variables, which is the number of degrees of freedom for six observations. In fact, the following models generally include only one or two independent variables, and occasionally three. All independent variables had to be significant to be included in the final models ($P \leq 0.05$) and not highly correlated with each other ($R^2 \leq 0.80$). Final models were also verified by a biostatistician (Pitt, D., 2001, personal communication) and found to be stable and valid.

With such a limited number of plots, less emphasis was placed on the absolute magnitude of R^2 values but instead a relative comparison between models was performed. The resulting regression equations are discussed separately for each forest measure in the following sections. The tables presented show the best models obtained using: (1) image variables extracted from digital numbers (DN), (2) image variables extracted from image fractions (IF), and (3) both variables together (DN & IF) for the three spatial resolutions.

Forest canopy closure

Table 18 presents the models obtained for the forest canopy closure measure. Model 7 is the most significant model using a combination of two texture measures of the DN variables at 0.25 m resolution (adjusted $R^2 = 0.99$, $p = 0.00$). The standard error as percentage of the mean is 2.07%, representing 1.07% in the closure measurement units, which is well below the measurement increment of 5%. Texture of the 800 nm band and the 670 nm band explain 81% and 18% respectively of the variation of canopy closure. As the canopy closure increases, texture of the 800 nm bands increases and texture of the 670 nm band decreases. As described in section 7.4.2, the high reflection of healthy vegetation in the near infrared (800 nm) produces more texture in this band because of higher grey level transitions between vegetation and gaps. The opposite is true for the 670 nm band where a closed canopy absorbs more light which contributes to attenuate the differences between gaps (shadow) and foliage. Although significant, the IF model of this spatial resolution (Model 8) produces a lower adjusted R^2 value (0.87) and a higher error (7.2%) using texture of the wood fraction alone. This model is the same as the univariate

relationship described in section 7.4.2. Combining both DN and IF together produced the same model as that of the DN variables alone.

Model #	Model type	Model variables	R ²	Adjusted R ²	Std error (%)	Std error (% mean)	R ² change	Predictor significance	Overall significance
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Forest canopy closure - 1.0 m

1	DN	-RANGE/670	0.75	0.69	5.67	11.00	0.75	0.03	0.03
2	IF	-RANGE/WOD +CON(3)/WOD	0.96	0.93	2.31	4.49	0.76 0.20	0.00 0.03	0.01
3	DN & IF	-RANGE/WOD +CON(3)/WOD	0.96	0.93	2.31	4.49	0.76 0.20	0.00 0.03	0.01

Forest canopy closure - 0.5 m

4	DN	-RANGE/550 -SILL/670	0.98	0.96	1.76	3.42	0.72 0.26	0.00 0.01	0.00
5	IF	+ENT(5)/SHA	0.48	0.35	8.19	15.90	0.48	0.13	0.13
6	DN & IF	-RANGE/550 -SILL/670	0.98	0.96	1.76	3.42	0.72 0.26	0.00 0.01	0.00

Forest canopy closure - 0.25 m

7	DN	-ASM(3)/800 +ENT(3)/670	0.99	0.99	1.07	2.07	0.81 0.18	0.00 0.00	0.00
8	IF	-ASM(3)/WOD	0.89	0.87	3.72	7.21	0.89	0.00	0.00
9	DN & IF	-ASM(3)/800 +ENT(3)/670	0.99	0.99	1.07	2.07	0.81 0.18	0.00 0.00	0.00

Table 18. Results of forward stepwise multiple regression of forest canopy closure (dependent variable) and image variables (independent variables) at the forest canopy-scale for the three spatial resolutions (0.25 m, 0.5 m, 1.0 m).

Model 4 produces the second most significant model with a combination of semivariogram variables of the 550 nm and the 670 nm bands at the 0.5 m resolution (adjusted $R^2 = 0.96$, $p = 0.00$). The standard error as percentage of the mean is 3.42%, representing 1.76% in the closure measurement units. The range of the 550 nm band and

the sill of the 670 nm band explain 72% and 26% respectively of the total variation of canopy closure. Increasing canopy closure is associated with decreasing range of the 550 nm band and sill of the 670 nm band. As canopy closure increases, the range of the 550 nm band is reached at shorter distances since more well defined objects (tree crowns) occupy the canopy space. The sill (texture) of the 670 nm decreases for the same reason given in the previous canopy closure model.

Model 2 produces a significant model with a combination of semivariogram and texture variables from the wood fraction at 1.0 m resolution (adjusted $R^2 = 0.93$, $p = 0.01$). The standard error as percentage of the mean is 4.49%, representing 2.31% in the closure measurement units. Decreasing canopy closure is associated with an increasing range in the wood fraction since it detects the presence of spatially distributed wood fractions which take the place of vegetation fractions. The addition to the model of a texture component (CON), which describes the spatial arrangement and variability of the wood fraction, increases by 20% the amount of variation accounted for by the model. Although significant, the DN model of this spatial resolution (Model 1) yields a much lower adjusted R^2 value (0.69) and a higher error (11%) using the range of the 670 nm band. Combining both DN and IF variables together produced the same model as that of the IF variables alone.

In all models of canopy closure the image variables are spatial, being measures of the semivariogram (range, sill) or texture measures. The primary variables are range and sill except for the 0.25 m resolution where these variables are not available. The range

represents the structure (size) component, while sill or texture represent the spatial arrangement and variability within the structure. The 0.25 m resolution produces the best model using only texture measures. Image fractions predict forest canopy closure more strongly at lower spatial resolutions (1.0 m) and are not essential when using higher spatial resolutions (0.25 m, 0.5 m). A possible explanation is that the spatial distribution of the fractional abundance of the basic constituents of the pixels has more influence at lower spatial resolution because the variation between adjacent pixels is averaged out.

These results show that the 0.25 m resolution is the best spatial resolution for modeling forest canopy closure, but the 0.5 m and the 1.0 m models are still fairly good. If other forest measures are to be studied along with forest canopy closure, an easy trade off can be made for forest canopy closure when choosing the spectral resolution for data acquisition.

Forest stem density

Table 19 presents the models obtained for forest stem density. Model 6 is the most significant using a combination of three spatial measures derived from the DN and IF variables at 0.5 m resolution (adjusted $R^2 = 0.99$, $p = 0.01$). The standard error as percentage of the mean is 3.61%, and represents 0.37 tree per 100 m² in measurement units. The range of the 550 nm and the 800 nm bands, and the texture of the wood fraction explain respectively 68.5%, 27%, and 4% of the variation of forest stem density. As the stem density increases, the range of the 550 nm band is reached at a shorter

distance since more tree crowns (well defined objects) occupy the canopy space. At this wavelength, a low stem density would produce a higher range since the transitions between gaps and vegetation would not be as strong as with the 800 nm band, in which range decreases with decreasing stem density. Texture of the wood fraction, although not explaining much of the total variation of the relationship, decreases with increasing stem density. In fact, increased stem density is related to increased canopy closure where more foliage occupies the space and masks the wood underneath (branches, trunks). This model is a combination of DN and IF variables. Using DN variables alone at this spatial resolution produces Model 4 (adjusted $R^2 = 0.92$, $p = 0.01$) with a standard error as percentage of the mean of 12.72%, which represents 1.32 tree per 100 m² in measurement units. It is the same as Model 6 without the wood fraction texture variable.

The next best significant model (Model 3) is produced using the range of the wood fraction and the sill of the 670 nm band at the 1.0 m resolution (adjusted $R^2 = 0.97$, $p = 0.00$). The standard error as percentage of the mean is 7.79% and represents 3.48 trees per 100 m². The range of the wood fraction is the primary variable and explains 69% of the overall variation. The sill of the 670 nm band explains another 29%. Both image variables are negatively correlated with forest stem density. Increased stem density produces a lower range in the wood fraction since the visible wood becomes more masked by increased foliage. Lower sill (variance) in the 670 nm band is also evident since the foliage is more uniform. Model 2 is also significant using only the range of the wood fraction (adjusted $R^2 = 0.61$, $p = 0.04$).

Model #	Model type	Model variables	R ²	Adjusted R ²	Std error (/100m ²)	Std error (% mean)	R ² change	Predictor significance	Overall significance
<i>Forest stem density - 1.0 m</i>									
1	DN	+RANGE/800	0.65	0.57	3.68	35.46	0.65	0.05	0.05
2	IF	-RANGE/WOD	0.69	0.61	3.48	33.52	0.69	0.04	0.04
3	DN & IF	-RANGE/WOD -SILL/670	0.98	0.97	0.81	7.79	0.69 0.29	0.00 0.01	0.01
<i>Forest stem density - 0.5 m</i>									
4	DN	-RANGE/550 -RANGE/800	0.96	0.93	1.32	12.72	0.69 0.27	0.01 0.02	0.01
5	IF	+ENT(3)/SHA	0.53	0.42	4.27	41.14	0.53	0.10	0.10
6	DN & IF	-RANGE/550 -RANGE/800 -ENT(3)/WOD	1.00	0.99	0.38	3.61	0.69 0.27 0.04	0.01 0.01 0.04	0.01
<i>Forest stem density - 0.25 m</i>									
7	DN	-ASM(3)/800	0.35	0.19	5.04	48.52	0.35	0.22	0.22
8	IF	-ASM(3)/WOD	0.55	0.44	4.19	40.30	0.55	0.09	0.09
9	DN & IF	-ASM(3)/WOD	0.55	0.44	4.19	40.30	0.55	0.09	0.09

Table 19. Results of forward stepwise multiple regression of forest stem density (dependent variable) and image variables (independent variables) at the forest canopy-scale for the three spatial resolutions (0.25 m, 0.5 m, 1.0 m).

The 0.25 m resolution did not produce a significant model. The best correlated variable with forest stem density yields an adjusted R² of 0.44 (p = 0.09). The combination of DN and EM does not improve the model. No semivariogram variables are available at this resolution which could explain these low relationships.

Unlike forest canopy closure, forest stem density is better assessed using a lower spatial resolution. The primary and secondary variables of the two significant models (1.0 m and 0.5 m) are semivariogram variables. Although stem density is closely related to canopy closure (r = 0.73), the stem density model yields larger errors at 1.0 m spatial resolution,

possibly because the aggregation of trees in dense parts of the canopy is harder to separate using the range. This can be tested by comparing results of both tree stem density and forest canopy closure in a variety of canopy closures ranging from sparse (well separated trees) to very dense (no space between trees). At the 0.5 m resolution, the individual tree crown is better resolved and allows a better prediction of stem density.

Tree crown size

Table 20 presents the models obtained for tree crown size. Model 4 is the most significant model using the range of the 800 nm band at 0.5 m resolution (adjusted $R^2 = 0.99$, $p = 0.00$). The standard error represents 0.12 m in measurement units. As crown size increases, so does the range of the 800 nm band. Adding the range of the vegetation fraction in the model, as in Model 6, explains the remaining 1% of the variation in crown size that is not explained by model 4. The contribution of this latter variable is not important enough to consider in this case. However, if more forest plots were used, this contribution might become more significant.

Model 8 is the next most significant model using the texture of the wood and shadow fraction at 0.25 m resolution (adjusted $R^2 = 0.97$, $p = 0.00$) which respectively explains 89% and 9% of the variation of tree crown size. The standard error represents 0.17 m in measurement units. As crown size increases, texture of the wood and shadow fractions decreases. Combining both DN and IF variables together produced the same model as that of the IF variables alone.

Model #	Model type	Model variables	R ²	Adjusted R ²	Std error (m)	Std error (% mean)	R ² change	Predictor significance	Overall significance
<i>Tree crown size - 1.0 m</i>									
1	DN	+CON(3)/550	0.58	0.47	0.82	12.42	0.58	0.08	0.08
2	IF	+RANGE/SHA	0.71	0.64	0.68	10.26	0.71	0.04	0.04
3	DN & IF	+RANGE/SHA	0.71	0.64	0.68	10.26	0.71	0.04	0.04
<i>Tree crown size - 0.5 m</i>									
4	DN	+RANGE/800	0.99	0.99	0.12	1.80	0.99	0.00	0.00
5	IF	-ENT(3)/SHA	0.64	0.55	0.76	11.48	0.64	0.06	0.06
6	DN & IF	+RANGE/800 +RANGE/VEG	1.00	1.00	0.04	0.68	0.99 0.01	0.00 0.02	0.00
<i>Tree crown size - 0.25 m</i>									
7	DN	+ENT(3)/800	0.29	0.12	1.06	16.03	0.29	0.27	0.27
8	IF	-ENT(3)/WOD +ASM(3)/SHA	0.98	0.97	0.17	2.62	0.89 0.09	0.00 0.03	0.00
9	DN & IF	-ENT(3)/WOD +ASM(3)/SHA	0.98	0.97	0.17	2.62	0.89 0.09	0.00 0.03	0.00

Table 20. Results of forward stepwise multiple regression of tree crown size (dependent variable) and image variables (independent variables) at the forest canopy-scale for the three spatial resolutions (0.25 m, 0.5 m, 1.0 m).

Model 2 is not as strong as the previous models but it is still significant. It uses the range of the shadow fraction at the 1.0 m resolution (adjusted $R^2 = 0.64$, $p = 0.035$). In this case, increased crown size produces an increasing range of the shadow fraction. With this model, 21% of the overall variation is not explained and the standard error is large (0.68 m).

All three spatial resolutions produce significant models for predicting individual tree crown size. Semivariogram and texture variables of the 800 nm band and image fractions (shadow, vegetation, wood) are used to produce the best model at each spatial resolution.

Raw spectral variables or image fractions are not present in the models which suggests that more complex image information is required to predict this forest measure.

Tree height

Table 21 presents the models obtained for tree height. The only significant models are found at the 0.5 m resolution. The best model, Model 6, is a combination of the range of the 800 nm band and the vegetation fraction, and the texture of the 800 nm band (adjusted $R^2 = 0.99$, $p = 0.00$). The standard error represents 0.11 m in measurement units. The range of the 800 nm band and the range of the vegetation fraction account for respectively 80% and 17 % of the total variation in the model. An additional 3% is gained by adding a texture measure of the 800 nm band. Structural variables (range) are necessary for a significant prediction of average tree height. Since tree height is a measure of the vertical dimension of the forest canopy, it seems difficult to model using two dimensional spatial data. In this case however, a possible explanation of the quality of the 0.5 m model is that the contribution of the range of the 800 nm band and the range of the vegetation fraction together produce a depth perspective effect. The 800 nm band accounts for the total brightness in the model and is positively correlated with tree height ($r = 0.89$). The vegetation fraction, provides a depth component where areas of pixels of low vegetation fraction (highly mixed with shadow) are associated with lower tree height and *vice versa* ($r = 0.38$).

Model #	Model type	Model variables	R ²	Adjusted R ²	Std error (m)	Std error (% mean)	R ² change	Predictor significance	Overall significance
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Tree height - 1.0 m

1	DN	+CON(3)/550	0.36	0.20	1.83	6.92	0.36	0.21	0.21
2	IF	+WOD	0.56	0.46	1.53	5.78	0.56	0.09	0.09
3	DN & IF	+WOD	0.56	0.46	1.53	5.79	0.56	0.09	0.09

Tree height - 0.5 m

4	DN	+RANGE/800	0.80	0.75	1.04	3.91	0.80	0.02	0.02
5	IF	+CON(3)/WOD	0.88	0.86	0.79	2.98	0.88	0.01	0.01
6	DN & IF	+RANGE/800 +RANGE/VEG +ASM(5)/800	1.00	0.99	0.11	0.41	0.80 0.17 0.03	0.00 0.01 0.03	0.00

Tree height - 0.25 m

7	DN	-ENT(30)/800	0.06	-0.17	2.25	8.49	0.06	0.64	0.64
8	IF	-CON(3)/WOD	0.52	0.40	1.61	6.08	0.52	0.11	0.11
9	DN & IF	-CON(3)/WOD	0.52	0.40	1.61	6.08	0.52	0.11	0.11

Table 21. Results of forward stepwise multiple regression of tree height (dependent variable) and image variables (independent variables) at the forest canopy-scale for the three spatial resolutions (0.25 m, 0.5 m, 1.0 m).

The other two resolutions did not provide significant models of tree height. The fact that a structural variable such as the range is not available in canopy sampling at the 0.25 m resolution may explain the lack of significance of the model for predicting tree height at this spatial resolution. The 1.0 m resolution could be too coarse to resolve tree height. This follows St-Onge and Cavayas (1995) who used semivariogram variables extracted from MEIS data of 0.36 m resolution to model tree height. Their best model was obtained using 0.36 m pixels ($R^2 = 0.58$, calculated from their data).

Tree crown closure

Table 22 presents the models obtained for tree crown closure. Model 5 is the only significant model using the range of the wood fraction at the 0.5 m resolution (adjusted $R^2 = 0.68$, $p = 0.04$). The standard error represents 2.9% closure. The relationship is negative and suggests that as the crown closure increases the wood fraction decreases. Wood fractions mainly occur within tree crowns contrary to the other two fractions, vegetation and shadow (Figures 37, 38, 39). The high proportion of the total variation not explained by the model may be attributed to the fact that tree crown closure is a within crown measure, and does not incorporate information about the rest of the canopy (e.g. gaps), which is represented by the other DN, EM, and spatial measures extracted over the plot. The canopy-scale is not suited to detection of such information. It is more logical to sample individual trees to do so.

Model #	Model type	Model variables	R ²	Adjusted R ²	Std error (%)	Std error (% mean)	R ² change	Predictor significance	Overall significance
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Tree crown closure - 1.0 m

1	DN	-670	0.13	-0.09	4.84	7.50	0.13	0.49	0.49
2	IF	-ASM(3)/SHA	0.44	0.30	3.89	6.03	0.44	0.15	0.15
3	DN & IF	-ASM(3)/SHA	0.44	0.30	3.89	6.03	0.44	0.15	0.15

Tree crown closure - 0.5 m

4	DN	-550	0.52	0.40	3.58	5.55	0.52	0.10	0.10
5	IF	-RANGE/WOD	0.68	0.60	2.92	4.53	0.68	0.04	0.04
6	DN & IF	-RANGE/WOD	0.68	0.60	2.92	4.53	0.68	0.04	0.04

Tree crown closure - 0.25 m

7	DN	+800	0.52	0.40	3.60	5.58	0.52	0.11	0.11
8	IF	+VEG	0.48	0.36	3.72	5.77	0.48	0.13	0.13
9	DN & IF	+800	0.52	0.40	3.60	5.58	0.52	0.11	0.11

Table 22. Results of forward stepwise multiple regression of tree crown closure (dependent variable) and image variables (independent variables) at the forest canopy-scale for the three spatial resolutions (0.25 m, 0.5 m, 1.0 m).

Tree stress index

Table 23 presents the models obtained for tree stress index. Model 3 is the most significant using the range of the 800 nm band and texture of the wood fraction at 1.0 m resolution (adjusted $R^2 = 0.99$, $p = 0.00$). The standard error is 0.01 in the stress index measurement units and is well below the measurement increment of 0.5. The range of the 800 nm band explains 92.2% of the total variation in the tree stress index. An additional 7% is gained by adding texture of the wood fraction. Both variables are negatively correlated with the stress index measure. An increased stress index (> damage) produces a shorter range in the 800 nm band (more stressed trees in canopy = more gaps) and less texture of the wood fraction (branches and stems are uniform throughout the plots). The

DN model of this spatial resolution produces a similar model (Model 1) where texture of the wood fraction is substituted for texture of the 550 nm band where there is less texture when the stress index is high.

Model #	Model type	Model variables	R ²	Adjusted R ²	Std error	Std error (% mean)	R ² change	Predictor significance	Overall significance
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Tree stress index - 1.0 m

1	DN	-RANGE/800 -CON(3)/550	0.99	0.98	0.02	0.65	0.92 0.06	0.00 0.04	0.00
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2	IF	+ASM(3)/VEG	0.79	0.74	0.07	2.41	0.79	0.02	0.02
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3	DN & IF	-SILL/800 -CON(3)/WOD	0.99	0.99	0.01	0.44	0.92 0.07	0.00 0.01	0.00
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Tree stress index - 0.5 m

4	DN	+ASM(3)/550	0.90	0.88	0.05	1.64	0.90	0.00	0.00
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5	IF	+ASM(3)/SHA	0.80	0.75	0.07	2.35	0.80	0.02	0.02
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6	DN & IF	-ENT(5)/SHA -550	0.99	0.98	0.02	0.62	0.80 0.19	0.00 0.01	0.00
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Tree stress index - 0.25 m

7	DN	+ASM(3)/550	0.74	0.68	0.08	2.86	0.74	0.03	0.03
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8	IF	+ASM(3)/WOD	0.98	0.98	0.02	0.67	0.98	0.00	0.00
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9	DN & IF	+ASM(3)/WOD	0.98	0.98	0.02	0.67	0.98	0.00	0.00
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Table 23. Results of forward stepwise multiple regression of tree stress index (dependent variable) and image variables (independent variables) at the forest canopy-scale for the three spatial resolutions (0.25 m, 0.5 m, 1.0 m).

Model 8 is the second best model using the texture of the wood fraction at the 0.25 m resolution (adjusted $R^2 = 0.98$, $p = 0.00$). The standard error is 0.2 in the stress index measurement units. As the stress index increases, the texture ASM of the wood fraction decreases. Combining both DN and IF variables together produced the same model as that of the IF variables alone.

Model 6 combines the texture measures entropy of the shadow fraction and the DN of the 550 nm band at the 0.5 m resolution to produce a significant model (adjusted $R^2 = 0.98$, $p = 0.00$). The standard error is 0.02 in measurement units. The two variables are negatively correlated with the stress index and contribute respectively to 79.8% and 18.8% of the stress index variation. An increased stress index (> damage) is associated with decreased texture of the shadow fraction (more spread than in a closed canopy), and decreased brightness of the 550 nm band. Model 4 uses only the texture of the 550 nm band to produce a significant model (adjusted $R^2 = 0.88$, $p = 0.00$) with a standard error of 0.5 in stress index units which is equal to the measurement increment. In this case, as the stress index increases, so does texture of the 550 nm band.

All three spatial resolutions produce similar models for predicting the tree stress index. The best models combine both DN and IF variables except for the 0.25 m resolution which achieves this result using only one IF image variable. Image texture must be present to produce the best model at each spatial resolution for predicting the tree stress index. The textures of wood and shadow fractions are important variables to assess this forest measure. An interesting fact is that as the spatial resolution gets finer (from 1.0 m to 0.25 m), the stress index is detected through more subtle image texture information. Thus, at 1.0 m resolution, it is best detected using the total brightness variation (range), while at 0.5 m, the texture of the shadow fraction (a component of the total brightness), is best associated with forest stress index. At 0.25 m it is the texture of the wood fraction (a smaller component of the total brightness) that best relates to the stress index. Each spatial resolution depicts a different level of variability which relates to the stress index.

8.3.2 Individual tree crown-scale structural models

Since pixels were extracted within the 31 individual tree crowns, stepwise multiple regression models were built for individual tree crown closure, stress index, and tree height using the 0.25 m and 0.5 m resolution data. The other forest measures are not appropriate for this scale of study since they integrate information beyond the tree crown. The resulting regression equations are discussed separately for each forest measure in the next sections. Note that the number of observations at this scale of study ($n = 31$) is adequate for an absolute analysis unlike the previous canopy analysis ($n = 6$).

Tree height

Table 24 presents the models obtained for the individual tree height measure. Model 1 and Model 5 are the only significant ones and they represent the same univariate relationships found in 7.4.2. Their overall significance levels are low ($p = 0.04$ and 0.05) and they produce a large error (2.6 m). Tree height is not well predicted at the individual tree-scale since a very small portion of the total variation in tree height is explained. It is best predicted at the canopy-scale, possibly because it requires the contribution of pixels outside the crown in order to produce a depth effect. Pixels extracted from individual tree crowns do not include the pixels at the limit of the crowns. These incorporate the variation from the contrast between the high shadow values between trees and the less

dense leaf area at the edge of tree crowns, which allows the understory to contribute to the pixel value. Better results are obtained at the canopy-scale using the 0.5 m resolution.

Model #	Model type	Model variables	R ²	Adjusted R ²	Std error (m)	Std error (% mean)	R ² change	Predictor significance	Overall significance
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Tree height - 0.5 m

1	DN	-CON(3)/550	0.14	0.11	2.59	9.40	0.14	0.04	0.04
2	IF	-SILL/VEG	0.10	0.07	2.65	9.64	0.10	0.09	0.09
3	DN & IF	-CON(3)/550	0.14	0.11	2.59	9.40	0.14	0.04	0.04

Tree height - 0.25 m

4	DN	-SILL/800	0.06	0.03	2.71	9.85	0.06	0.19	0.19
5	IF	-CON(3)/VEG	0.13	0.10	2.61	9.48	0.13	0.05	0.05
6	DN & IF	-CON(3)/VEG	0.13	0.10	2.61	9.48	0.13	0.05	0.05

Table 24. Results of forward stepwise multiple regression of tree height (dependent variable) and image variables (independent variables) at the tree-scale for the two spatial resolutions (0.25 m, 0.5 m).

Tree crown closure

Table 25 presents the models obtained for the individual tree crown closure measure. All the models are highly significant ($p = 0.00$) but produce standard errors varying between 7.8% and 8.8% in crown closure units, which is slightly above the 5% measurement increment. Model 3 is the most significant model. It uses texture of the 550 nm band, and texture of the vegetation, wood and shadow fractions at the 0.5 m resolution (adjusted $R^2 = 0.76$). As tree crown closure increases, so do the image textures of the 550 nm band, and the vegetation, wood, and shadow fractions. Models produced with either DN or IF

(Model 1 and 2) also combine four image variables and produce similar adjusted R^2 (0.74).

Model #	Model type	Model variables	R^2	Adjusted R^2	Std error (%)	Std error (% mean)	R^2 change	Predictor significance	Overall significance
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Tree crown closure - 0.5 m

1	DN	-ASM(3)/550 +800 -670 -550	0.77	0.74	8.08	12.81	0.51 0.44 0.07 0.05	0.03 0.02 0.00 0.02	0.00
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2	IF	-ASM(3)/WOD +ENT(3)/WOD +VEG +CON(3)/SHA	0.77	0.74	8.14	12.90	0.38 0.23 0.11 0.06	0.00 0.00 0.01 0.02	0.00
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3	DN & IF	-ASM(3)/550 +MEA(3)/VEG -CON(3)/WOD +CON(3)/SHA	0.79	0.76	7.78	12.33	0.51 0.16 0.06 0.06	0.00 0.00 0.00 0.01	0.00
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Tree crown closure - 0.25 m

4	DN	-ASM(3)/550 +800	0.73	0.71	8.84	14.02	0.50 0.23	0.00 0.00	0.00
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5	IF	+MEA(3)/VEG +ENT(3)/VEG +SILL/VEG	0.75	0.73	8.47	13.42	0.54 0.16 0.06	0.00 0.00 0.02	0.00
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6	DN & IF	+VEG -ASM(3)/VEG +SILL/VEG -MEA(3)/550	0.79	0.76	7.84	12.42	0.51 0.17 0.07 0.04	0.00 0.00 0.03 0.04	0.00
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Table 25. Results of forward stepwise multiple regression of tree crown closure (dependent variable) and image variables (independent variables) at the tree-scale for the two spatial resolutions (0.25 m, 0.5 m).

Model 6 is the second best model and uses the vegetation fraction, the texture of the vegetation fraction, and the texture of the 550 nm band at the 0.25 m resolution (adjusted $R^2 = 0.75$). As tree crown closure increases, so do the vegetation fraction and its texture, and the texture of the 550 nm band. In this model, vegetation fraction and its texture explain 75% of the total variation in crown closure. The remaining 4% is attributed to the

texture of the 550 nm band. Similarly, the IF model (Model 5) is essentially a combination of texture measures of vegetation fraction.

Both spatial resolutions produce similar models making them suitable for modeling tree crown closure at the individual tree-scale. Many variables are required to produce the models at both spatial resolutions. Using either DN or IF variables, texture measures are essential to produce significant models for predicting tree crown closure. Little improvement is made when combining the DN and IF variables in the model. There is a common trend in each model where increasing crown closure produces increasing texture in both the DN and IF variables. In comparison to the lack of significance found in the canopy-scale models it is evident that image information must be extracted within individual tree crowns for this forest measure.

Tree stress index

Table 26 presents the models obtained for tree stress index. All the models are highly significant ($p = 0.00$) and produce standard errors varying between 0.43 and 0.55 stress index units, which is near the 0.5 measurement increment. Model 3 is the most significant. It uses the texture of five DN and IF variables at the 0.5 m resolution (adjusted $R^2 = 0.67$). As stress index increases, so do image texture of the 550 nm and 800nm bands, and the vegetation, wood, and shadow fractions. This model is complex because it combines five image variables. It explains 7% more of the variation of the stress index compared to the DN model at this resolution (Model 1). However, the

standard error (0.48) remains below the measurement increment of 0.5. For this reason, using the DN model alone is appropriate. Models produced with either DN or IF variables at this spatial resolution (Model 1 and 2) combine four and three image variables and produce similar adjusted R^2 (0.74).

Model #	Model type	Model variables	R^2	Adjusted R^2	Std error	Std error (% mean)	R^2 change	Predictor significance	Overall significance
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Tree stress index - 0.5 m

1	DN	-ENT(3)/550 -800 -ENT(3)/670 +SILL/670	0.65	0.60	0.48	17.68	0.37 0.09 0.09 0.11	0.00 0.00 0.00 0.01	0.00
2	IF	-MEA(3)/VEG +SILL/WOD +CON(3)/SHA	0.54	0.49	0.55	20.28	0.29 0.18 0.08	0.01 0.00 0.04	0.00
3	DN & IF	-ENT(3)/550 -MEA(3)/VEG +CON(3)/WOD -ENT(3)/800 +ASM(3)/VEG	0.72	0.67	0.43	16.45	0.37 0.10 0.08 0.11 0.06	0.00 0.00 0.00 0.00 0.03	0.00

Tree stress index - 0.25 m

4	DN	-CON(3)/550 +SILL/670 -SILL/800	0.68	0.64	0.47	17.10	0.40 0.19 0.09	0.01 0.00 0.01	0.00
5	IF	-MEA(3)/VEG +SILL/SHA	0.55	0.52	0.55	20.05	0.44 0.11	0.00 0.01	0.00
6	DN & IF	-MEA(3)/VEG -CON(3)/550 -CON(3)/WOD	0.68	0.65	0.46	16.90	0.44 0.13 0.11	0.00 0.00 0.00	0.00

Table 26. Results of forward stepwise multiple regression of tree stress index (dependent variable) and image variables (independent variables) at the tree-scale for the two spatial resolutions (0.25 m, 0.5 m).

Model 6 is the second most significant model and uses three texture measures at the 0.25 m resolution (adjusted $R^2 = 0.65$) which decrease as the stress index increases. Models produced with either DN or IF variables at this spatial resolution combine texture

variables and the sill of the semivariogram, which increases as stress index increases except for the sill of the 800 nm band as explained in the previous paragraph.

Both spatial resolutions produce highly significant models ($p < 0.00$) of stress index. The 0.5 m resolution models explain 3% to 4% more variation than the 0.25 m models. The standard errors of the models vary from 16.45% (0.5 m model using both DN and EM) to 20.28% (using the model with IF variables only) and translate into a range of 0.43 to 0.55 in measurement units. Since the measurement increment for estimating the stress index was 0.5, the error in using any of these models is acceptable. The proportion of the variation in the stress index that is not accounted for by these models can be attributed to the fact that the pixels were extracted from within the tree crowns. Portions of the tree crown where stress is first manifested, such as dying branches starting from the outside, and low closure near the edge where contrast with shadow is higher, were excluded. Since this information is present at the canopy-scale study it can explain why tree stress index is better predicted over the canopy. As stated in section 6.2.2, as long as most of the pixels are extracted from the tree crown, the average and standard deviation of the pixel brightness values are statistically representative of the tree crown. This applies to total brightness values and may not apply to the spatial variability of the values within the sampled tree crowns.

8.3.3 Summary of the contributions of image variables to forest structure and health models

Tables 27 to 30 summarise the frequency with which each set of image variables contributes to the best prediction model of each forest measure at both canopy (Table 27, 28) and individual tree crown scale (Table 29, 30). The sum of their contribution (R^2 change) to the explanation of the variation of the best models is also presented in the table as a means to weight their contribution rather than just their presence. These weights are used to compare the variable sets (DN, IF, texture, semivariogram) in the following manner: the sum of R^2 values are divided by the number of models the set of variables contributes to, yielding an average percentage contribution in the best models (Tables 27, 29). Tables 28 and 30 show the first variable entered into the most significant model (primary variable) of each forest measure. These tables are used to determine how frequently each type of variable (DN, IF, texture, semivariogram) is used to initiate a significant model. The same method is used to compare the three spatial resolutions (Tables 31 and 32).

The variable sets are compared in the following ways to respond to the thesis objectives: (1) digital numbers versus image fractions, (2) spatially versus non-spatially transformed variables, (3) the three spatial resolutions (0.25 m, 0.5 m, 1.0 m), and (4) canopy-scale versus individual tree crown-scale analysis. These comparisons are discussed separately in Chapter 9.

Image brightness and image fractions

Forest canopy-scale

Table 27a shows that there are 25 image variables used in 13 significant best models at the forest canopy-scale. Among them, 48% are DN ($n = 1$) and spatial variables derived from DN ($n = 11$). The other 52% come from spatial variables derived from IF ($n = 13$). Their contributions to the total variance of the models are 77% and 55%, respectively (Table 27b, Figure 48). The raw DN and IF variables are not useful for predicting the six forest measures. There is only one variable (DN) that contributes 19% of the explanation of the variance of one of the best models (stress index, 0.5 m resolution). However, significant stress index models can still be produced without the use of this DN variable (see Table 26). There are three DN texture variables (DN-TEX) that contribute 51% of the variation of two significant best models while there are seven IF texture variables (IF-TEX) that contribute a total of 51% of the variance of four significant best models. More IF texture variables appear as primary variables in significant models ($n = 3$) than DN texture variables ($n = 1$) (Table 28). There are eight DN semivariogram variables (DN-SEMI) that account for 82% of the total variance of six models. Five of these variables are the primary variables in their respective models (Table 28a, Figure 49). The IF semivariogram variables (IF-SEMI) are primary variables in four models and six variables contribute 50% to the total variance of the six significant best models. Overall, the best information contained in raw image brightness is in its derived semivariogram

variables, these being mostly range, while information contained in image fractions is approximately equally divided between their texture and semivariogram derived variables.

(a)

	<i>DN</i>			<i>IF</i>			<i>DN-TEX</i>			<i>IF-TEX</i>			<i>DN-SEMI</i>			<i>IF-SEMI</i>		
	.25m	.50m	1.0m	.25m	.50m	1.0m	.25m	.50m	1.0m	.25m	.50m	1.0m	.25m	.50m	1.0m	.25m	.50m	1.0m
<i>Forest canopy closure (%)</i>							2					1		2				1
<i>Forest stem density (/ 100 m²)</i>										1				2	1			1
<i>Tree crown size (m)</i>									2					1			1	1
<i>Tree height (m)</i>						1								1			1	
<i>Tree crown closure (%)</i>																	1	
<i>Tree stress index (1 to 5)</i>		1								1	1	1			1			
<i>Total variance accounted for</i>		0.19					0.99	0.03		1.96	0.84	0.27		3.72	1.21		0.86	2.16

(b)

	sum R ²	# of models	% contribution
DN	0.19	1	19
IF	0	0	0
Total non-spatial	0.19	1	19
DN-TEX	1.02	2	51
IF-TEX	3.07	6	51
Total texture	4.09	8	51
DN-SEMI	4.93	6	82
IF-SEMI	3.02	6	50
Total semivariogram	7.95	9	88
Total DN	6.14	8	77
Total IF	6.09	11	55
Total forest canopy-scale	12.23	13	94

Table 27. (a) Frequency with which each set of image variables contributes to the best model of each forest measure at the canopy-scale and (b) sum and % contribution of the variables to the explanation of the variation of the best models (includes all spatial resolutions).

Figure 48. Average R^2 contribution per model at the canopy scale.

Values correspond to the right column of Table 27b.

(a)

	DN			IF			DN-TEX			IF-TEX			DN-SEMI			IF-SEMI		
	.25m	.50m	1.0m	.25m	.50m	1.0m	.25m	.50m	1.0m	.25m	.50m	1.0m	.25m	.50m	1.0m	.25m	.50m	1.0m
Forest canopy closure (%)							X							X				X
Forest stem density (/ 100 m ²)														X				X
Tree crown size (m)									X					X				X
Tree height (m)														X				
Tree crown closure (%)																	X	
Tree stress index (1 to 5)									X	X					X			

(b)

	# of variables	%
DN	0	0
IF	0	0
Total non-spatial	0	0
DN-TEX	1	8
IF-TEX	3	23
Total texture	4	31
DN-SEMI	5	38
IF-SEMI	4	31
Total semivariogram	9	69
Total DN	6	46
Total IF	7	54

Table 28. (a) First entered variables in the most significant models of each forest measure at the canopy-scale and (b) frequency of variable types used to initiate a significant model.

Figure 49. Proportion (%) of each variable type first entered in the most significant models at the canopy scale.

Individual tree crown-scale

Table 29a shows that there is a total of 16 image variables (DN = 5, IF = 11) used in six most significant models at the tree crown-scale. Texture variables occupy a predominant place in these models. DN-TEX accounts for 33% of the total variation of five models and IF-TEX accounts for 27% of the total variation of five models. Overall, DN variables explain 33% of the total variance of four models and IF variables contribute to 39% of the total variation of five models (Table 29b, Figure 50). Table 30a and b and Figure 51

show that there are as many DN and IF variables that first enter the most significant models.

(a)

	<i>DN</i>		<i>IF</i>		<i>DN-TEX</i>		<i>IF-TEX</i>		<i>DN-SEMI</i>		<i>IF-SEMI</i>	
	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>
<i>Tree height (m)</i>			1			1	2	3				1
<i>Tree crown closure (%)</i>					1	2	2	1				
<i>Tree stress index (1 to 5)</i>						1	1					
<i>Total variance accounted for</i>			0.51		0.17	1.13	0.85	0.52				0.07

(b)

	sum R^2	# of models	% contribution
DN	0	0	0
IF	0.51	1	51
Total non-spatial	0.51	1	51
DN-TEX	1.3	4	33
IF-TEX	1.37	5	27
Total texture	2.67	6	45
DN-SEMI	0	0	0
IF-SEMI	0.07	1	7
Total semivariogram	0.07	1	7
Total DN	1.3	4	33
Total IF	1.95	5	39
Total tree crown-scale	3.25	6	54

Table 29. (a) Frequency with which each set of image variables contributes to the best model of each forest measure at the tree-scale and (b) sum and % contribution of the variables to the explanation of the variation of the best models (includes all spatial resolutions).

Figure 50. Average R^2 contribution per model at the tree scale.

Values correspond to the right column of Table 29b.

(a)

	<i>DN</i>		<i>IF</i>		<i>DN-TEX</i>		<i>IF-TEX</i>		<i>DN-SEMI</i>		<i>IF-SEMI</i>	
	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>	<i>.25m</i>	<i>.50m</i>
<i>Tree height (m)</i>			X			X						
<i>Tree crown closure (%)</i>						X	X					
<i>Tree stress index (1 to 5)</i>						X	X					

(b)

	# of variables	%
DN	0	0
IF	1	17
Total non-spatial	1	17
DN-TEX	3	50
IF-TEX	2	33
Total texture	5	83
DN-SEMI	0	0
IF-SEMI	0	0
Total semivariogram	0	0
Total DN	3	50
Total IF	3	50

Table 30. (a) First entered variables in the most significant models of each forest measure at the tree-scale and (b) frequency of variable types used to initiate a significant model.

Figure 51. Proportion (%) of each variable type first entered in the most significant models at the tree scale.

Spatially transformed image brightness and image fractions

Forest canopy-scale

A total of 24 out of 25 (96%) image variables entered in the most significant models are spatially transformed (texture and semivariogram) (Table 27a). Eleven are derived from digital numbers and 13 from image fractions. Among all the image variables evaluated, semivariogram variables (DN-SEMI, IF-SEMI) (mostly range) were the most often entered into models ($n = 14$). They represent 54% of all the variables of the best models (74% if the 0.25 m resolution is not counted, since no semivariogram variables are available at this resolution) and contribute for 88% of the variation of nine models (Table 27b). Texture variables ($n = 10$) are involved in eight of the 13 best significant models and account for 51% of their variance. The 25th variable (DN, 0.5 m resolution), the only one not spatially transformed, accounts for 19% of the variance of only one model. Table 28a shows that in most significant models at the 0.5 m and 1.0 m resolutions, a semivariogram variable is the primary variable. In fact, for 9 of the 13 most significant models the first variable entered is a semivariogram variable (range) which represents 69% of all the primary variables introduced in these models (Table 28b). A texture variable is the primary variable for the four remaining models and represents 31% of the primary variables. Note that among the latter four models, three are at the 0.25 m resolution where no semivariogram variables were available.

Individual tree crown-scale

A total of 14 out of 16 (88%) image variables that were entered in the most significant models are spatially transformed (Table 29a). Five are derived from digital numbers and nine from image fractions. Image texture and semivariogram variables explain 45% and 7% of the total variation of six and 1.0 models, respectively (Table 29b). One non-spatially transformed variable (IF) explain 51% of one most significant model (tree height) and is a primary variable as shown in Table 30a. The remaining five models have a texture variable as their primary variable. Table 30b shows that 83% of the primary variables are textural.

Spatial resolutions

Forest canopy-scale

It can be seen from Table 27a that 5 out of 25 image variables used in the most significant models are from the 0.25 m resolution, 13 are from the 0.5 m resolution, and 7 are from the 1.0 m resolution. However, the tabulated results do not indicate the strength of each image variable contribution. Table 31a shows the model percentage variance contribution of each set of variables at each spatial resolution. The 0.25 m, 0.5 m and 1.0 m resolutions contribute to 98%, 94% and 91% of the total variance of 3, 6 and 4 models, respectively. At the 0.25 m resolution, all the image variables are textural although no

semivariogram variables are available at this spatial resolution. At the 0.5 m and 1.0 m resolutions, most variables are derived from the semivariogram (mostly range). Without the use of semivariogram variables, their contribution would decrease to 35% and 14 % of the variance of 3 and 2 models, respectively. The primary variables of the 0.5 m resolution are 17% from texture and 83% from semivariogram variables, and 100% are from semivariogram variables at the 1.0 m resolution (Table 31b).

(a)

	<i>0.25 m</i>			<i>0.5 m</i>			<i>1.0 m</i>		
	sum R ²	# of models	% contribution	sum R ²	# of models	% contribution	sum R ²	# of models	% contribution
DN	0	0	0	0.19	1	19	0	0	0
IF	0	0	0	0	0	0	0	0	0
Total non-spatial	0	0	0	0.19	1	19	0	0	0
DN-TEX	0.99	1	99	0.03	1	3	0	0	0
IF-TEX	1.96	2	98	0.84	2	42	0.27	2	14
Total texture	2.95	3	98	0.87	3	29	0.27	2	14
DN-SEMI	NA	NA	NA	3.72	4	93	1.21	2	61
IF-SEMI	NA	NA	NA	0.86	3	29	2.16	3	72
Total semivariogram	NA	NA	NA	4.58	5	92	3.37	4	84
Total DN	0.99	1	99	3.94	5	79	1.21	2	61
Total IF	1.96	2	98	1.7	5	34	2.43	4	61
Total forest canopy-scale	2.95	3	98	5.64	6	94	3.64	4	91

(b)

	<i>0.25 m</i>		<i>0.5 m</i>		<i>1.0 m</i>	
	# of variables	%	# of variables	%	# of variables	%
DN	0	0	0	0	0	0
IF	0	0	0	0	0	0
Total non-spatial	0	0	0	0	0	0
DN-TEX	1	33	0	0	0	0
IF-TEX	2	67	1	8	0	0
Total texture	3	100	1	17	0	0
DN-SEMI	NA	NA	4	67	1	25
IF-SEMI	NA	NA	1	17	3	75
Total semivariogram	NA	NA	5	83	4	100
Total DN	1	33	4	67	1	25
Total IF	2	67	2	33	3	75

Table 31. (a) Sum and % contribution of the variable types to the explanation of the variation of the best models at the canopy-scale for each spatial resolution (b) frequency of variable types used to initiate a significant model.

Individual tree crown-scale

Table 32a shows that both spatial resolutions used eight image variables in the three models. The 0.25 m resolution uses mainly image fractions and their spatially derived variables to explain 53% of the variance in the three models (Table 32a). The 0.5 m resolution uses an equal number of texture variables derived from image brightness ($n = 4$) and image fractions ($n = 4$) to explain 55% of the total variance of the three models. The primary variables of the 0.25 m models are all from image fraction variables and the primary variables of the 0.5 m resolution models are all from image brightness variables (Table 32b).

(a)

	<i>0.25 m</i>			<i>0.5 m</i>		
	sum R ²	# of models	% contribution	sum R ²	# of models	% contribution
DN	0	0	0	0	0	0
IF	0.51	1	51	0	0	0
Total non-spatial	0.51	1	51	0	0	0
DN-TEX	0.17	1	17	1.13	3	38
IF-TEX	0.85	3	28	0.52	2	26
Total texture	1.02	3	34	1.65	3	55
DN-SEMI	0	0	0	0	0	0
IF-SEMI	0.07	1	7	0	0	0
Total semivariogram	0.07	1	7	0	0	0
Total DN	0.17	1	17	1.13	3	38
Total IF	1.43	3	48	0.52	2	26
Total tree crown-scale	1.6	3	53	1.65	3	55

(b)

	<i>0.25 m</i>		<i>0.5 m</i>	
	# of variables	%	# of variables	%
DN	0	0	0	0
IF	1	33	0	0
Total non-spatial	1	33	0	0
DN-TEX	0	0	3	100
IF-TEX	2	67	0	0
Total texture	2	67	3	100
DN-SEMI	0	0	0	0
IF-SEMI	0	0	0	0
Total semivariogram	0	0	0	0
Total DN	0	0	3	100
Total IF	3	100	0	0

Table 32. (a) Sum and % contribution of the variable types to the explanation of the variation of the best models at the tree-scale for each spatial resolution (b) frequency of variable types used to initiate a significant model.

Forest canopy and individual tree crown scales

The 13 most significant forest canopy-scale models use a total of 25 variables (Table 27a), one to three variables per model. At the individual tree crown-scale, 16 variables are separated amongst 6 models (Table 29a) (1 to 5 per model). This represents an average of 1.9 and 2.7 variables per model at each scale respectively. The canopy-scale variables explain 94% of the variance of the 13 models while the tree crown-scale variables explain 54% of the variance of the 6 models.

(a) Canopy-scale	DN			DN & IF		
	P			P		
	0.25 m	0.50 m	1.0 m	0.25 m	0.50 m	1.0 m
<i>Forest canopy closure (%)</i>	<u>0.001</u>	<u>0.004</u>	<u>0.025</u>	<u>0.001</u>	<u>0.004</u>	<u>0.008</u>
<i>Forest stem density (per 100 m²)</i>	0.217	<u>0.010</u>	0.052	0.091	<u>0.005</u>	<u>0.041</u>
<i>Tree crown size (m)</i>	0.268	<u>0.000</u>	0.081	<u>0.003</u>	<u>0.000</u>	<u>0.035</u>
<i>Tree height (m)</i>	0.638	<u>0.016</u>	0.211	0.107	<u>0.003</u>	0.085
<i>Tree crown closure (%)</i>	0.107	0.104	0.487	0.107	<u>0.043</u>	0.153
<i>Tree stress index (1 to 5)</i>	<u>0.028</u>	<u>0.004</u>	<u>0.002</u>	<u>0.000</u>	<u>0.002</u>	<u>0.001</u>
 (b) Individual tree-scale						
	0.25 m	0.50 m			0.25 m	0.50 m
	<u>0.000</u>	<u>0.000</u>			<u>0.000</u>	<u>0.000</u>
<i>Tree height (m)</i>	<u>0.000</u>	<u>0.000</u>			<u>0.000</u>	<u>0.000</u>
<i>Tree crown closure (%)</i>	<u>0.000</u>	<u>0.000</u>			<u>0.000</u>	<u>0.000</u>
<i>Tree stress index (1 to 5)</i>	0.194	<u>0.037</u>			<u>0.047</u>	<u>0.037</u>

Table 33. Significance level (P) of models using DN variables and models using IF variables or a combination of DN and IF variables at (a) canopy-scale and (b) tree-scale.

Table 33 shows the significance level (P) of models using only DN variables and models produced using IF variables or a combination of DN and IF variables. At the forest canopy-scale, 14 out of 18 models are improved by using IF variables or a combination of DN and IF variables (Table 33a). At the individual tree crown-scale only the tree

height model is improved (Table 33b) which indicate that complex image transformation are not necessary at this scale of study.

8.4 CONCLUSIONS

DN and IF variables are complementary since they often mix to produce the most significant models. IF variables or a combination of both DN and IF variables improve 14 models out of 18 at the forest canopy-scale when compared to the use of DN variables alone.

It is the spatially transformed variables (texture, semivariogram) of DN and IF that produce the most significant models at both forest canopy and individual tree crown scales. Semivariogram variables were the most often entered into models at the canopy-scale and texture variables are the most entered at the tree crown-scale.

Canopy closure, tree crown size, and stress index measures can be predicted at all three spatial resolutions. The 0.5 m and 1.0 m resolutions are better predictors of forest stem density than the 0.25 m resolution. Both tree height and tree crown closure are only predicted significantly using the 0.5 m resolution. If only one spatial resolution must be used to model the six forest measures, the 0.5 m resolution is the best choice since it produces similar or better models than those using the 0.25 or 1.0 m resolutions.

The individual tree crown-scale analysis improved significantly the prediction of individual tree crown closure. All other variables are best predicted at the canopy-scale.

9. DISCUSSION

9.1 INTRODUCTION

The main goal of this research was to develop image-based models of forest structure and health from spectral and spatial information sensitive to forest structural variation. The classical approach typically uses raw spectral information or spectral transformations such as vegetation indices (e.g. band ratios, NDVI). More recently, advances in sensor technology have provided multiple to many spectral bands of narrow bandwidth. Analysis techniques such as spectral unmixing to determine image fractions have demonstrated potential in forest modeling. Image fractions are spatial measures of the within-pixel areal proportions of spectral (radiometric) objects. They are typically linked to the components of land cover types present in the scene (e.g. in this study: vegetation and wood) but they may also include purely radiometric elements (e.g. shadow). Other spatial transformations such as image texture and semivariance measures have also demonstrated strong potential in modeling of forest structure. Research in all of the above has typically involved assessment of spectral variables or image fractions alone, and has occasionally included spatial analysis of raw spectral data. This thesis has introduced analysis of the spatial characteristics of image fractions using both fractional textures and semivariance measures. No studies of this kind have been found in the literature to-date. In addition, most research is conducted using: 1. a pre-determined image resolution that often depends on the sensor capabilities, 2. canopy-scale sampling (image samples extracted from whole plots), and 3. spatial analysis of only one spectral

band. In this thesis, analyses were conducted at the canopy-scale and at the individual tree crown-scale (samples taken only from tree crowns), using imagery of three resolutions (0.2 m, 0.5 m, 1.0 m) in three 10 nm bandwidth spectral bands (550 nm, 670 nm, 800 nm). This comprehensive analysis was designed to provide answers to the questions: ‘What is the most appropriate type of sampling?’, ‘What is the most appropriate image resolution?’, ‘What is the most appropriate spectral band?’ and, most importantly, ‘What is the best combination of complementary image variables?’ in modeling of the forest structure and health variables considered. This provided more insight into the information contained in the spectral/spatial data and allowed a better understanding of the relationships between image data at sub-metre resolution and forest ground measurements.

In this chapter, issues raised throughout the thesis are discussed to provide a focussed context for development of conclusions to the research and recommendations for further work.

9.2 SIGNIFICANT FINDINGS OF THIS RESEARCH

9.2.1 Image brightness and image fractions

As determined in section 6.3.4, image fractions (IF) were not often significantly correlated with image brightness (DN). Thus, image fractions derived from image brightness represent different and perhaps complementary image information that can

enhance models with forest measures. Image fractions provide spatial information about the radiometric structure of the image and are related to the percentage ground cover within each pixel, whereas raw image brightness is a measure of the average radiance (or reflectance) of the pixel. This complementarity was borne out in the multiple regression forest models (Chapter 8) where there were similar numbers of DN and IF variables in the best model for each forest variable (48% and 52% of the available variables respectively) at the forest canopy-scale and more IF variables at the individual tree crown-scale (33% DN variables and 67% IF variables). However, in some cases image fractions were the only image variables that produced significant relationships with the forest measures. For example, in modeling of tree height, the shadow fraction is higher for smaller trees due to the shading effect produced by taller trees on smaller trees.

9.2.2 Spatially transformed image brightness and image fractions

Total brightness and image fraction variables are static and do not incorporate the spatial dynamic that is produced by their variation over the forest canopy or tree crowns. This spatial variation can be as good or better than DN or IF information at indicating the state of health of the forest. This is particularly evident in open damaged canopies with significant amounts of ground vegetation. For example, a higher image wood fraction could be due to either a couple of dead trees in a healthy canopy or to small defoliated branches spread over a damaged canopy. These two states cannot be distinguished without spatial analysis of the wood fraction, which informs on how they are distributed and arranged over the canopy and relates better to the canopy condition. A second

example that was found in this research is that higher shadow fraction and lower vegetation fraction may result from a few large openings in the canopy (which otherwise may be healthy) or from many small gaps spread over an open damaged canopy. The spatial patterns of these image fractions provide a better means to identify these two conditions. Thus, spatial measures were found to be complementary to DN and IF variables, and in cases such as those described above, to provide more significant information in modeling forest structure and health. Figure 52 illustrates a situation where two plots have a similar average wood fraction and different texture of wood fraction.

Figure 52. Average wood fraction for Plot 3 and 4 at 0.25 m resolution and their respective contrast measure.

The modeling results from Chapter 8 showed that spatial measures of image brightness can also be considered complementary to spatial measures of image fractions. For example, in Model 3 of Table 19, the 670 nm band texture was combined with texture of

the wood fraction. This improved the relationship with stem density from an R^2 of 0.69 to 0.98.

Complementarity was also evident between semivariogram range and image texture at the forest canopy-scale. The range improved structural forest models (canopy closure, stem density, tree crown size, tree height) as it is a measure that indicates the size of forest canopy features (e.g. vegetation gaps, vegetation clusters such as tree crowns). However, it also incorporates some textural aspects since a homogeneous texture is more likely to produce a large range than a heterogeneous texture. It was not found to be useful at the individual tree crown-scale because the large contrast between trees and deep shadows is not present within individual tree crowns. Spatial variation of crown image samples is better defined using image texture. Image texture variables appeared in each of the best models at both scales of analysis, with the exception of tree crown size at the forest canopy-scale. In some cases, such as forest canopy closure, the range of the image semivariograms and image texture variables combined together to provide the size component of the structural objects (e.g. gaps) and their spatial arrangement and variability. Thus, it is possible to detect complex patterns involving object size in relation to spatial variability when combining texture and range.

9.2.3 Spatial resolution

In general, the image variables extracted at the 1.0 m and 0.5 m resolutions relate better to forest canopy-scale measures than those from the 0.25 m resolution. Of all resolutions,

the 0.5 m models were most often the most significant (see Table 31a). At the individual tree crown-scale, both 0.25 m and 0.5 m resolutions produced similar results. Thus, if both scales of study are conducted at the same time and only one spatial resolution can be used, 0.5 m is the best choice.

Even though the three spatial resolutions used in this study are among the highest available by any sensor at this time, the results of these analyses indicate that high spatial detail is very useful in forest modeling. In fact, the wood endmember, which was found to be very significant in this study, was resolved because there was a large dead standing tree in the image scene. Because it still had a dense network of branches, a wide area of pixels were composed of significant wood fractions. The linear morphology of branches and stems as seen from above does not produce pure wood pixels at the 0.5 and 1.0 m resolutions. For such high detail related to tree stress, the 0.25 m is more suited. Even smaller pixels may be required to detect the wood fraction if a large single occurrence of wood such as this dead tree does not exist.

9.2.4 Scale of study

Spatial variables such as texture and the semivariogram variables were not found to be significant in bi-variate modeling of the forest variables at the individual tree crown-scale. However, in multiple regression analysis, texture measures become the dominant variables and appear as primary variables in all but one of the models (see Table 30a). These models incorporated more image variables than those at the forest canopy-scale.

This indicates that the interaction between the image variables is more complex, and makes the interpretation more difficult.

Sampling individual tree crowns is useful for understanding how trees manifest stress, and the extracted measures can be aggregated over the canopy. However, they do not relate directly to forest canopy stress as tree spacing and gaps, which respond to long term stress, are not represented in individual tree sampling. Image measures of the spectral, structural and textural variations over a forest canopy involve areas beyond the individual tree crowns. For this reason the tree crown-scale analysis misses important parts of the crowns, such as their edges, which may be better indicators of their state of health. In fact, an unhealthy tree may appear dense at the centre (thickest part) of its crown because of the contribution of multiple leaf layers. However, at crown edges the number of leaf layers is reduced, thus providing a better distinction between open and less open tree crowns.

Both individual tree and forest canopy scales of study are, however, useful in practical application. For example, image analysis of individual tree crowns may aid decision making for selective cutting or be combined with semi-automatic individual tree crown delineation techniques such as the one developed by Gougeon (1997). Automated forest inventory could be enhanced by the addition of spectral and spatial variations that are indicative of stress level within individual tree crowns. In areas of mixed species, sampling individual tree crowns could be done on a species basis. One way to accomplish this would be to perform a “hierarchical” spectral unmixing. The data would first undergo

an initial unmixing. Then the areas where there are no vegetation fractions (or below a threshold fraction) would be masked and the remaining data unmixed again. The endmembers in this case would be related to vegetation attributes such as species. Such a method has not been reported yet in literature and warrants investigation. It might require the use of more spectral bands to resolve closely related species although three bands would be sufficient to distinguish between deciduous and coniferous trees since they behave very differently in the near infrared (much higher reflectance from deciduous trees). Image analysis at the forest canopy scale, on the other hand, provides more insight about the structure and state of health of the forest. As pointed out by Curtiss and Maecher (1991), reflectance over a forest canopy is a better indicator of canopy stress since the variation introduced by branch spectra at tree crown level is averaged out over many individual tree crowns. The forest canopy scale of study can provide information about the forest state of health, its yield, and its state of growth.

9.3 RESEARCH LIMITATIONS

9.3.1 Number of study plots

As stated in 4.2.1, the plots were initially designed to be large for analysis of a statistically valid number of trees in each. The canopy-scale analysis was adopted later in order to study the spatial effects of variations in gaps, tree density and size. Because of the restricted number of sample plots, results of the canopy-scale analyses must be interpreted with care. The approach taken was of 'relative comparison' between models

and methods without concluding on the absolute value or significance of any one model. Only significant relationships were analyzed. However, in many cases, the relationships were close to being significant. Increasing the number of plots may produce additional significant relationships. It would also be possible with more plots to investigate other statistical methods such as canonical analysis as in Olthof and King (2000) and Cosmopoulos (2000).

9.3.2 Number of spectral bands

The number of spectral bands determines the spectral detail that can be resolved. More bands would produce more endmembers that relate to more detailed features on the ground. Examples of endmembers that could possibly be resolved with more bands include: the sunlit and skylit (diffusely lit) parts of tree crowns, different species, and understory, especially in gaps where shadow predominates when using three bands. Using a small number of spectral bands is, however, not necessarily a limitation (Lévesque *et al.*, 2000). In fact, fewer bands focus on fewer spectral details and the endmember spectra represent broader mixtures of cover types. In this research using very high spatial resolution, the four well-defined endmembers (vegetation, shadow, soil/tailings, wood) were sufficient to assess forest damage. Adding more bands, and therefore more endmembers, may result in more complicated relationships with ground forest measures that are difficult to explain. For example, the vegetation fraction would not represent an aggregate measure such as LAI as well since it would be separated into more constituents (sunlit, skylit, species). This research therefore represents an early step

in development of an understanding of the relationship between image constituents and ground forest parameters. In the near future, research will begin to combine high spectral and high spatial (< 1 m) data. More important, when using multispectral data is to ensure that the bands are positioned according to physical spectral properties.

9.3.3 Sampling individual trees

As shown in 6.2.2 the individual tree crown extraction method was found appropriate for total image brightness. In fact, as long as the pixels are extracted from the crown, they statistically represent the tree crown. This is not the case when using spatial data. Since it is difficult to determine visually the exact crown limits, this important crown information is probably missing. Information near the crown boundary incorporates the variation from the contrast between the high shadow values of the gaps between trees and the less dense leaf area at the edge of tree crowns. Seed and King (1997), using three spectral shadow fractions, found that such crown-edge information ("transitional shadow") was significant in models of LAI.

Trees were selected that were easy to delineate visually, i.e., their crown limits appeared clearly in the image. However, for this reason smaller trees were generally avoided. These trees may lie in shadows of surrounding taller trees and could contribute to a positive relation with shadow fraction as with canopy-scale sampling. Another example of the effect of the sampling bias is that the image wood fraction at the tree-scale cannot be used in this study to properly assess tree health. According to field notes, 90% of the

sampled tree crowns do not display dead branches on the top of their crown. Instead, 85% display small dead branches in the intermediate crown and 48% displays large dead branches in the lower part of their crown. By choosing the best delineated tree crowns from the image, it is more likely that the more damaged trees (open with dead branches) will be avoided.

9.3.4 Image quality

The 1993 image data were acquired with the multispectral camera system in prototype state and the exposure was not optimized. However, inflight histogram analysis allowed the optimization of the dynamic range of the 1995 data, and subsequent imagery acquired for other projects, resulting in an improved radiometric quality. The shutter speed of 1/300s resulted in image motion of less than 0.4 pixels in all data. However, during this exposure time, high and variable wind may have introduced some image blurring of the tree crowns.

BRDF was shown not to be significant (see 6.2.1). However, little research has been conducted on the geometric effects on spatial measures and image fractions. Shadow changes from being largest when viewed at nadir to smaller when viewed off-nadir. Although the camera view angle was small ($\pm 9.2 \times 7.2$ degrees), these geometric effects may be present.

9.4 RECOMMENDATIONS FOR FURTHER RESEARCH

The following recommendations are made with the aim to improve the methods and results of the present research and to provide ideas for future research:

- For further research, it is recommended to have a greater number of study plots to allow the validation of the models. It may be necessary to improve time-consuming field sampling techniques to enable the sampling of a greater number of plots.
- This method should be adapted to accommodate the monitoring needs of the Ontario Ministry of Northern Development and Mines rehabilitation program. For this purpose, research should be conducted to test these models in temporal monitoring throughout the site using plots installed by Olthof (1999).
- In 1997, the spectral capability of the multispectral camera system was improved to allow the acquisition of data in 8 user selected bands. Using the same spatial resolution range, the method should be investigated using these 8 bands. In this case, more endmembers could be resolved such as the sunlit and skylit (diffusely lit) parts of tree crowns, different species, and understory. The spatial variation of these new endmembers in relation to forest measures could be assessed through texture and semivariance analyses used in this research.

- BRDF effects are currently being analysed in a different research project at Carleton University using larger view angles. This analysis should also include the BRDF effects on spatially transformed image data (fraction, texture, semivariogram).
- To further develop the methodology for temporal monitoring, sensor calibration and atmospheric correction will be required.
- As mentioned in 9.2.4, the individual tree crown analysis method could be combined with an automated tree crown delineation method. Forest inventory could also be enhanced by the addition of spectral, structural and textural variations that are indicative of stress within individual tree crowns.
- Research should be carried on to determine the real effects of open and closed forest canopies on spectral and textural canopy-scale variables. This will aid in distinguishing between the low texture-low damage case and the low texture-high damage case.

10. CONCLUSIONS

The main goal of this research was to develop image-based models of forest structure and health from spectral and spatial information indicative of forest structural change. This was accomplished at two scales of study (forest canopy and individual tree) using high spatial resolution multispectral imagery (0.25 m, 0.5 m, 1.0 m) acquired in three 10nm spectral bands (550 nm, 670 nm, 800 nm). Traditional methods use raw spectral variables and their basic spectral (e.g. band ratio, vegetation index) and spatial (image texture) transformations. For this study, spectral unmixing was conducted and spatial transforms of the resulting image fractions were derived. Analysis of such fractional texture and fractional semivariogram range and sill variables has not been reported in the literature. Their evaluation in modelling of forest structure using two scales of sampling and three image resolutions forms the major contribution of this research.

The KamKotia mine site was selected because of its known acid mine drainage problem. Field research at the site found a spatial gradient in soil metal concentrations but variations in tree leaf spectral data and forest tree structure and health were not directly linked to soil chemistry. Other factors such as wind contamination and blowdown appeared to be impacting the forest. For these reasons, mapping of AMD effects on the forest was not pursued. Instead, the site served as an excellent laboratory for combined analysis of forest structure in general (which has application in forest management and ecology) and net forest health impacts of mining.

The results of this study contribute to a better understanding of how image spectral and spatial characteristics relate to forest structure and health conditions. The spatial detail from each of the two image variable types (image brightness, image fraction) provides different information about the forest canopy or individual trees, hence these image variables can be complementary when modeling forest structure and health. However, it is their spatial transformations (texture, semivariogram range) that contribute most to the best forest-canopy and tree-crown models since spatial data incorporates the spatial dynamic produced by the variation of forest canopy and tree crowns. This spatial dynamic cannot be seen when using static image variables such as raw image brightness and image fraction variables.

Sampling was done at two scales: (1) forest canopy-scale where image measures were extracted from a sample taken over the whole plot and (2) individual tree-scale where image measures were extracted from individual tree crowns. Forest canopy-scale measures are best expressed at the 0.5 m and 1.0 m resolutions whereas individual tree-scale measures relate best to 0.5 m and the 0.25 m. Hence, if only one spectral band is to be used for both canopy and individual tree-scale studies, then 0.5 m is the best choice.

The canopy-scale study provides more insights about the structure and state of health of the forest canopy around the KamKotia mine site than does the individual tree scale study. As pointed out by Curtiss and Maecher (1991), the measured reflectance over a forest canopy is often a better indicator of stress since the variation introduced by the spectra of branches at tree crown level is averaged out over many individual tree crowns.

Furthermore, the tree-scale study does not relate to the overall canopy condition since it misses important parts of the canopy that may be related to the stress condition (e.g. gaps between trees, tree crown edges). However, prediction of tree characteristics using the individual tree-scale of study is useful in understanding how trees manifest stress.

The results of the present study demonstrate that when the right image variables are used, forest structural characteristics can be successfully modeled. Models used here are empirical but the method can be adapted to different forest canopy ecosystems. Such methods are applicable to other mine sites and to recovery programs such as the Ontario Abandoned Mine Rehabilitation Program, as well as other aspects of forestry and ecology including habitat monitoring and forest structure and health assessment related to climate change.

As image spatial and spectral resolutions increase, as remote sensing technology evolves, and as integration of diverse data sources becomes more feasible, these results will aid in forest inventory, management and monitoring.

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APPENDIX 1: SUMMARY OF PROCEDURE FOR ACID DIGESTION OF SOILS

Aqua regia (HCl / HNO₃: 3:1)

1. Record the exact weight of approx. 3 g of crushed material placed in a 100 ml beaker.
Wet the sample with a small amount of d.i. (distilled, deionized) water. Add 15 ml of hydrochloric acid in 5 ml aliquots, swirling samples between each aliquot. Let stand for 30 minutes.
2. Add 10 ml of nitric acid in 2 ml aliquots, swirl and let stand 10 minutes between each addition to avoid foaming. Let stand for an additional 30 minutes after last addition.
3. Place samples on hot plate and heat at low (90°C) for approx. 2 hours. Increase heat to evaporate to dryness. Dissolve salts with 3 ml of HCl and 15 ml of d.i. water. Transfer solution to 30 ml volumetric flask, rinsing residues with 3% HCl and take to volume.

Aqua regia dissolves the noble metals as well as metal oxides. Silicates are only partially decomposed. If the HCl is added first, sulphur is released from sulphide minerals, avoiding their subsequent oxidation and precipitation as insoluble sulphates (Fletcher, W.K., 1981; Dolezal, J. et al., 1968).

APPENDIX 2: RESULTS OF THE SOIL CHEMICAL ANALYSIS

1992 soil samples: Al (%)

Horizon: Month:	A		B		C	
	August		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	3.42	0.45	2.78	0.63	2.34	0.24
Plot 2	1.64	0.75	1.37	0.44	1.41	0.44
Plot 3	2.58	1.24	2.01	0.90	2.03	0.77
Plot 4	0.91	0.17	0.79	0.32	1.06	0.26
Plot 5	0.72	0.38	0.93	0.23	1.06	0.39
Control plot	0.16	0.05	0.46	0.07	0.42	0.13

1993 soil samples: Al (%)

Horizon: Month:	B				C			
	May		August		May		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	8.52	3.97	8.29	6.56	10.05	3.97	11.20	1.89
Plot 2	4.45	0.15	7.24	2.07	6.56	3.62	9.34	1.54
Plot 3	8.09	4.08	6.74	1.18	6.76	2.81	9.26	3.63
Plot 4	4.11	0.55	3.47	0.94	4.02	1.00	4.97	0.56
Plot 5	1.85	0.11	3.56	2.01	5.39	0.97	4.46	0.45
Control plot	1.13	0.62	2.41	1.11	2.45	0.50	2.61	0.84

TAILINGS	
August	
mean	std. dev.
3.25	2.74

1994 soil samples: Al (%)

Horizon: Month:	B		C	
	August		August	
	mean	std. dev.	mean	std. dev.
Plot 1	3.17	0.53	3.04	0.34
Plot 2	1.33	0.47	2.20	0.55
Plot 3	1.45	0.26	1.77	0.48
Plot 4	0.66	0.23	0.87	0.24
Plot 5	0.66	0.15	0.68	0.06
Control plot	0.25	0.22	0.43	0.10

ICPES detection limit for AL: 0.1%

Precision for 1992 data : NA

Precision for 1993 data based on 5 repeats: 0.078%

Precision for 1994 data based on 2 repeats: 0.062%

1992 soil samples: Cr (ppm)

Horizon: Month:	A		B		C	
	August		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	76.26	9.06	65.68	11.43	54.96	5.35
Plot 2	34.63	13.60	36.05	9.39	37.58	7.94
Plot 3	57.09	21.68	55.22	18.48	54.50	15.93
Plot 4	25.74	5.62	22.83	5.18	32.39	13.00
Plot 5	21.87	14.55	32.32	9.08	35.08	9.13
Control plot	6.32	3.18	18.52	5.29	19.11	1.80

1993 soil samples: Cr (ppm)

Horizon: Month:	B				C				TAILINGS	
	May		August		May		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	121.40	59.08	105.70	71.06	132.20	39.71	170.90	43.32	20.14	9.81
Plot 2	67.32	2.54	102.00	34.73	101.40	61.82	117.90	18.22		
Plot 3	106.80	44.14	124.30	52.09	82.81	11.51	121.80	48.65		
Plot 4	66.97	9.51	43.80	21.58	63.80	16.17	60.03	6.45		
Plot 5	24.34	3.25	43.65	25.07	81.57	7.05	56.48	7.07		
Control plot	10.69	10.08	32.90	19.77	32.05	1.77	43.34	12.77		

1994 soil samples: Cr (ppm)

Horizon: Month:	B		C	
	August		August	
	mean	std. dev.	mean	std. dev.
Plot 1	156.00	16.72	147.60	11.77
Plot 2	87.96	31.21	120.90	25.39
Plot 3	93.63	14.92	108.90	32.95
Plot 4	46.80	18.60	52.55	36.67
Plot 5	54.59	12.30	52.54	14.76
Control plot	7.45	18.41	52.54	11.75

ICPES detection limit for Cr: 0.1 ppm

Precision for 1992 data: NA

Precision for 1993 data based on 5 repeats: 0.052 ppm

Precision for 1994 data based on 2 repeats: 0.020 ppm

1992 soil samples: Cu (ppm)

Horizon:	A		B		C	
Month:	August		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	31.04	15.21	26.58	2.87	31.65	0.74
Plot 2	25.37	10.86	12.93	6.96	20.29	4.50
Plot 3	29.64	15.33	20.52	10.09	30.76	10.09
Plot 4	13.25	0.97	8.38	3.87	14.66	3.25
Plot 5	11.26	7.30	7.81	3.03	13.54	7.23
Control plot	0.97	0.41	1.75	0.83	2.53	1.32

1993 soil samples: Cu(ppm)

Horizon:	B				C				TAILINGS	
Month:	May		August		May		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	19.82	10.63	13.71	12.35	31.87	16.94	38.05	4.54	941.30	811.50
Plot 2	10.79	2.12	14.72	3.67	29.34	15.48	31.13	7.66		
Plot 3	24.10	15.68	14.65	5.17	20.95	7.95	29.89	15.05		
Plot 4	10.18	1.66	7.27	3.13	12.15	1.79	14.84	1.94		
Plot 5	2.78	0.48	5.02	3.10	12.15	0.72	12.52	0.75		
Control plot	0.88	1.07	5.78	6.30	2.86	0.96	7.78	4.37		

1994 soil samples: Cu (ppm)

Horizon:	B		C	
Month:	August		August	
	mean	std. dev.	mean	std. dev.
Plot 1	26.90	6.03	41.60	4.14
Plot 2	11.83	6.80	30.02	8.44
Plot 3	16.63	4.94	25.32	7.17
Plot 4	7.81	3.13	12.53	2.47
Plot 5	11.23	3.73	13.26	3.75
Control plot	2.20	3.08	6.06	3.08

ICPES detection limit for Cu: 0.01 ppm

Precision for 1992 data: NA

Precision for 1993 data based on 5 repeats: 0.055 ppm

Precision for 1994 data based on 2 repeats: 0.027 ppm

1992 soil samples: Fe (%)

Horizon:	A		B		C	
Month:	August		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	4.15	0.39	3.54	0.45	3.01	0.27
Plot 2	2.19	0.60	2.25	0.47	2.11	0.50
Plot 3	3.28	0.86	2.88	0.98	2.77	0.91
Plot 4	1.62	0.20	1.41	0.50	1.80	0.34
Plot 5	1.17	0.57	1.57	0.28	1.58	0.29
Control plot	0.09	0.04	0.73	0.23	0.65	0.12

1993 soil samples: Fe(%)

Horizon:	B				C				TAILINGS	
Month:	May		August		May		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	3.30	1.04	2.81	1.17	3.56	0.77	4.00	0.73	11.00	1.67
Plot 2	2.36	0.06	2.77	0.54	2.53	1.23	3.10	0.31		
Plot 3	3.11	0.82	2.76	0.42	2.42	0.53	3.20	0.92		
Plot 4	2.12	0.21	1.72	0.23	1.87	0.50	1.87	0.08		
Plot 5	1.01	0.00	1.43	0.72	2.29	0.19	1.60	0.24		
Control plot	0.41	0.35	0.92	0.44	1.12	0.13	1.22	0.24		

1994 soil samples: Fe(%)

Horizon:	B		C	
Month:	August		August	
	mean	std. dev.	mean	std. dev.
Plot 1	1.66	0.15	1.53	0.23
Plot 2	1.16	0.28	1.33	0.28
Plot 3	1.37	0.16	1.35	0.35
Plot 4	0.83	0.22	0.75	0.19
Plot 5	0.85	0.13	0.71	0.13
Control plot	0.28	0.33	0.59	0.07

ICPES detection limit for Fe: 0.05%

Precision for 1992 data: NA

Precision for 1993 data based on 5 repeats: 0.089%

Precision for 1994 data based on 2 repeats: 0.055%

1992 soil samples: Mn (ppm)

Horizon:	A		B		C	
Month:	August		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	724.67	231.43	503.56	76.27	493.20	113.93
Plot 2	742.17	296.04	569.15	162.03	467.30	137.44
Plot 3	772.12	156.59	702.47	192.26	510.22	114.02
Plot 4	500.58	43.91	353.29	154.84	417.98	93.72
Plot 5	932.74	990.53	522.33	174.11	672.49	417.80
Control plot	7.90	3.13	55.23	24.54	90.16	59.72

1993 soil samples: Mn(ppm)

Horizon:	B				C				TAILINGS	
Month:	May		August		May		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	561.94	213.57	582.65	334.85	712.54	180.58	781.92	194.76	326.53	314.01
Plot 2	476.72	38.87	620.43	208.16	445.86	182.82	575.25	47.24		
Plot 3	1066.88	660.69	795.38	307.33	508.27	68.81	646.93	120.03		
Plot 4	472.22	44.02	325.51	129.02	512.56	225.49	500.59	34.37		
Plot 5	114.21	73.83	249.45	164.11	497.77	15.28	446.78	91.71		
Control plot	25.30	17.36	117.13	117.37	58.27	2.31	226.51	151.29		

1994 soil samples: Mn(ppm)

Horizon:	B		C	
Month:	August		August	
	mean	std. dev.	mean	std. dev.
Plot 1	591.13	169.05	495.72	105.63
Plot 2	497.28	138.21	471.97	103.04
Plot 3	634.66	117.14	502.18	134.16
Plot 4	389.94	219.34	367.43	74.42
Plot 5	473.25	198.06	385.57	98.47
Control plot	36.53	53.39	174.25	105.62

ICPES detection limit for Mn: 0.01 ppm

Precision for 1992 data: NA

Precision for 1993 data based on 5 repeats: 0.134 ppm

Precision for 1994 data based on 2 repeats: 0.091 ppm

1992 soil samples: Ni (ppm)

Horizon:	A		B		C	
Month:	August		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	45.27	6.80	40.73	5.62	35.44	3.57
Plot 2	20.98	6.80	23.17	7.26	25.12	5.52
Plot 3	37.50	14.38	34.89	10.53	34.26	9.20
Plot 4	16.93	4.05	14.02	4.09	15.82	6.86
Plot 5	13.20	9.78	19.15	7.26	23.79	8.94
Control plot	1.90	0.84	8.80	3.12	9.95	1.49

1993 soil samples: Ni (ppm)

Horizon:	B				C				TAILINGS	
Month:	May		August		May		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	36.00	17.11	30.19	21.55	47.69	18.40	52.30	11.09	8.14	6.99
Plot 2	18.28	0.62	29.40	8.24	31.03	18.78	37.72	4.50		
Plot 3	32.90	17.63	31.85	7.10	31.15	14.82	38.28	14.02		
Plot 4	18.67	2.64	13.10	5.65	18.54	4.22	19.82	1.18		
Plot 5	5.71	1.80	11.85	7.24	21.56	3.44	18.15	2.80		
Control plot	1.69	2.47	8.93	6.13	7.79	1.34	12.70	3.70		

1994 soil samples: Ni (ppm)

Horizon:	B		C	
Month:	August		August	
	mean	std. dev.	mean	std. dev.
Plot 1	67.89	7.01	67.98	9.16
Plot 2	37.12	10.06	55.69	13.95
Plot 3	44.01	5.43	52.87	16.39
Plot 4	20.94	7.28	24.73	7.20
Plot 5	21.17	6.02	22.07	6.15
Control plot	1.98	7.74	12.37	3.41

ICPES detection limit for Ni: 0.1 ppm

Precision for 1992 data: NA

Precision for 1993 data based on 5 repeats: 0.083 ppm

Precision for 1994 data based on 2 repeats: 0.022 ppm

1992 soil samples: Pb (ppm)

Horizon:	A		B		C	
Month:	August		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	17.32	1.69	13.33	2.54	11.37	1.40
Plot 2	31.84	16.18	11.13	1.53	8.84	1.67
Plot 3	16.51	2.19	12.46	4.09	11.97	3.54
Plot 4	14.20	9.33	8.01	1.74	8.83	1.15
Plot 5	10.21	3.77	7.98	1.30	7.51	1.72
Control plot	3.54	1.36	2.64	0.63	1.87	1.00

1993 soil samples: Pb (ppm)

Horizon:	B				C				TAILINGS	
Month:	May		August		May		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	15.62	8.57	9.92	4.61	12.07	9.62	15.00	5.95	107.10	38.07
Plot 2	8.69	1.11	8.13	5.61	5.14	10.10	8.67	2.19		
Plot 3	16.87	10.98	8.59	4.79	8.31	1.09	6.25	3.60		
Plot 4	6.58	3.15	5.35	2.10	3.54	5.81	5.77	3.02		
Plot 5	4.03	1.19	6.32	2.34	5.92	0.50	5.66	1.75		
Control plot	0.92	0.83	2.13	1.09	0.11	0.89	3.60	2.53		

1994 soil samples: Pb (ppm)

Horizon:	B		C	
Month:	August		August	
	mean	std. dev.	mean	std. dev.
Plot 1	12.40	11.94	11.99	4.11
Plot 2	9.68	4.74	7.83	4.34
Plot 3	10.01	5.30	4.67	4.47
Plot 4	6.71	4.27	4.42	2.81
Plot 5	5.62	2.25	2.73	3.12
Control plot	2.40	2.25	2.73	3.12

ICPES detection limit for Pb: 0.1 ppm

Precision for 1992 data: NA

Precision for 1993 data based on 5 repeats: 0.471 ppm

Precision for 1994 data based on 2 repeats: 0.485 ppm

1992 soil samples: Ti (ppm)

Horizon: Month:	A		B		C	
	August		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1	728.23	174.15	930.18	103.39	926.74	157.03
Plot 2	318.86	114.37	572.41	147.33	541.52	151.17
Plot 3	489.77	201.14	815.35	320.48	752.86	228.79
Plot 4	382.61	76.73	345.06	132.89	483.44	127.26
Plot 5	113.32	37.05	238.66	95.40	336.63	92.67
Control plot	47.51	39.56	209.80	50.76	161.11	56.30

1993 soil samples: Ti (ppm)

Horizon: Month:	B				C				TAILINGS	
	May		August		May		August		August	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Plot 1										
Plot 2										
Plot 3										
Plot 4										
Plot 5										
Control plot										

1994 soil samples: Ti (ppm)

Horizon: Month:	B		C	
	August		August	
	mean	std. dev.	mean	std. dev.
Plot 1	456.36	127.50	479.83	140.08
Plot 2	365.47	84.35	515.32	185.39
Plot 3	425.46	97.54	593.78	133.22
Plot 4	217.28	77.44	308.17	73.53
Plot 5	201.03	66.80	223.31	27.67
Control plot	99.22	51.40	182.50	44.91

ICPES detection limit for Ti: 0.05 ppm

Precision for 1992 data: NA

Precision for 1993 data: NA

Precision for 1994 data based on 2 repeats: 0.143 ppm