Forest Pattern Discrimination using Lacunarity Analysis of High-Resolution Remote
Sensing Imagery

By

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

Master of Arts

Department of Geography and Environmental Studies

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ABSTRACT

Lacunarity analysis of remote sensing imagery was used to determine the optimal spatial extent for field-based sampling and to quantify forest canopy patterns with distance from a contamination source. Data from a boreal forest site and a hardwood forest site were utilized in two studies. The first study showed an optimal spatial extent in the hardwood forest to be 12-14m while in the boreal forest it was more varied, ranging from 8 to 18m. The scales of pattern obtained for both sites show correspondence to tree crown size. In the second study, lacunarity analysis showed canopy gap sizes were more randomly distributed closer to the mine tailings than gaps further removed. A comparison between image pattern and the standard deviation in stem size generated a correlation coefficient, $r = 0.55$. The analysis detects scales of pattern, which reflect true object sizes, and aids in optimal sample plot size determination. For these reasons, this technique has a clear advantage over other spatial pattern methods.

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CHAPTER 1- Introduction

1.1 Background

Canadian forests are a valuable resource for the nation as they provide plant and animal biodiversity, generate industrial capital and labour, and act as massive reservoirs of water and carbon for use in energy transfer to the atmosphere (Wood *et al.*, 2002). Canadian forestland stores approximately 20% of global fresh water and represents 10% of global forestland (National Forest Strategy Coalition, 2001). Temperate and boreal forests account for over 45% of the 921.5 million hectare Canadian landmass, and support a \$71.4 billion industry (Natural Resources Canada, 2001). The forestry industry generates \$31.7 billion alone in export and accounts for over 80,000 temporary and full-time jobs nation-wide (Wood *et al.*, 2002).

Forests are essential to the global carbon cycle; deforestation over the last 150 years has contributed approximately 30% to the accumulation of atmospheric CO₂ (World Resources Institute, 1998). As global concern about climate change grows, international, national and academic institutions have become crucial research contributors in programs to monitor forest productivity, patterns of growth and environmental conditions. Since forests have such a profound influence on Canadian social, economic and natural infrastructures, monitoring of the forest ecosystem is essential to ensure long-term economic resilience while minimizing stresses within the natural environment.

1.2 Forest disturbance

Forests are dynamic entities that change over time and space in response to natural forces and human disturbance. In the long-term, a forest ecosystem may go through various growth cycles, and may become dominated by only one or two species. In regions of the Canadian taiga for instance, pure spruce forests alternate spatially with pure pine forests with great regularity, each consisting of trees of similar age (Remmert, 1991). Forcier (1975) studied forest change and proposed a succession model for temperate deciduous forests in the eastern United States, based on the reproductive strategies of dominant tree species. Although natural variability, competition and succession are intrinsic parts of the forest ecosystem, severe disturbances also cause short-term and long-term change within a forest ecosystem. Extensive disturbance of the forest will affect the growth and structure of vegetation and its overall economic value. Because forests under stress are usually distinctly different than the larger healthy population, this change is easier to detect than natural change due to succession or competition since the damaging agent often induces leaf colour change, defoliation, changes in canopy gap structure or treefall. Figure 1.1 shows an example of the patchiness of aspen decline in a boreal forest due to forest tent caterpillar (FTC) defoliation.

Figure 1.1 – Aspen defoliation and mortality (Hopkin, 2002).

The grey patches in Fig. 1.1 represent aspen stands that have been defoliated or killed by FTC outbreak. The recurrence period for FTC outbreak in northern Ontario is approximately every 12 years and forecasts for the 2002-growing season are expected to reach 20 million hectares across the province (Howse, 2002).

The natural factors affecting the health of boreal forest aspen stands were outlined by Climate Change Impacts on the Health and Productivity of Aspen (CIPHA) project as: 1) changing climate conditions, 2) disease / insect outbreaks, 3) moisture and 4) fire. Hogg and Schwarz (1999) have studied tree-rings (the science of dendrochronology) to hypothesize forest stress associated with historic fire events and previous extreme weather situations. Drought also plays an important role in the productivity of boreal forest stands for forest management. “Drought is most severe in newly established timber stands and in stands weakened by overstocking or overmaturity.” (Hamilton and Johnson, 1994). Candau *et al.* (2002) highlight the use of a drought indicator to monitor forest stress and confirm correlations between years of drought and aspen decline in the Canadian boreal forest from 1960 to 2000.

The stresses outlined above are not exclusive to boreal forests. Sugar maple decline was a major concern in Ontario temperate forests during the 1980s. Decline and dieback was seen in mature maple trees, and included symptoms that could be related to insect damage, altered drainage, poor management practices or severe weather (Ontario Ministry of Natural Resources, 1995). Every forest ecosystem is

affected, at one time or another, by extreme weather phenomena. The ice storm of January 1998 was an example of a natural stress event that altered the structure of many forests in eastern Ontario and southern Quebec. It produced over 100mm of freezing rain in a 5-day period causing power outages and damaging thousands of hectares of mixed hardwood forests throughout southern Ontario and Quebec. Forest structural damage from this event is illustrated in Fig. 1.2.

Figure 1.2 – Forest structural damage in Gatineau Park after the January 1998 ice storm. Pellikka *et al.* (2000).

So far, discussion has focused on natural forest stresses and processes causing such damage. Another type of stress that has affected many natural ecosystems globally is industrial waste and contamination. Such contamination may occur suddenly due to an accident or over the long-term from gradual processes such as smelter emissions or acid mine drainage. For example, at the boreal study site of this research, a mine tailings impoundment dam was breached in the 1970's, resulting in acid mine drainage and tailings flow into the adjacent forest leading to subsequent tree mortality. Surface waste piles are also acted upon by erosional agents such as wind and water and are the subject of chemical reactions due to air and water interaction (Ripley *et al.*, 1996). Figure 1.3 shows wind blown mine tailings over a tailings pond at the study site of this research, the Kam Kotia mine near Timmins, Ontario.

Figure 1.3 – Wind blown mine tailings dust (Cosmopoulos, 2001).

1.3 Monitoring forest change

As with all living things, different forests react differently to various stresses. In order to study how forests respond to stress, several criteria must be met. Firstly, indicators must be measured which reflect the structure, productivity and vigour of the vegetation being studied. Secondly, Smith (2002) revealed that these indicators should minimize subjectivity. Thus, to measure forest structure for example, quantitative and objective approaches should be established and applied in a systematic way to allow for simple repeatability and to minimize or at least account for measurement error. For example, the Canada Centre for Remote Sensing has adopted a systematic approach to the retrieval of leaf area index (LAI) as an indicator of forest productivity from Landsat and SPOT VEGETATION imagery (Butson *et al.*, 2002; Fernandes *et al.*, 2002a) including efforts to evaluate systematic measurement errors inherent in the methodology (Fernandes *et al.*, 2002b).

Monitoring forest structure using systematic and quantitative methods provides important information for forest management strategies. Due to the large area of forestland in Canada, the use of remote sensing data is crucial for quantifying the spatial, temporal and spectral characteristics of vegetation change. With the aid of field-based statistical validation, remote sensing has proven beneficial in forest health research (Murtha, 1978; Rock *et al.* 1986), in modelling forest structure at fine spatial scales (Cohen *et al.* 1990; St. Onge and Cavayas, 1995,1997; Levesque and King,

1999) and in quantifying forest cover and LAI at coarse spatial scales, both nationally (Chen *et al.*, 2001; Fernandes *et. al.*, 2002b) and internationally (Sellers *et al.*, 1994; Myneni *et al.*, 1997). Landscape ecologists have also begun to recognize the importance of remote sensing data to identify regions of spatial heterogeneity and landscape fragmentation (Plotnick *et al.*, 1993,1996; Krummel *et al.*, 1987).

Since the statistical validation is so crucial, a linkage between the two data sources (remote sensing and field-based measurements) is dependent on the inherent variability in each of the data sets and the sampling scale in the field. Geographic data that exhibit small spatial variability are very homogeneous over a given measurement space. Conversely, data that are characterized by large spatial variation are heterogeneous, as measured quantities exhibit wide spatial fluctuations. While the two terms (homogeneous and heterogeneous) describe the extreme cases of the spatial distribution of geographic data, natural spatial heterogeneity manifests itself across a wide range of scales. “Shifts of scale may create homogeneity out of heterogeneity, and vice versa, and the information contained at one level of resolution may look like noise at another level.” (Dutilleul, 1993). Fine measurements over a relatively large study area will tend to produce a statistical distribution that is too detailed and contains random noise. In this case, the spatial variation would be too great and the amount of time to collect and analyze the data would be impractical and inefficient. Therefore, all studies that combine remote sensing and field data should consider the scale of objects under investigation and the amount of spatial variability deemed

necessary for appropriate interpretation and analysis. Both of these issues are dependent on the appropriate sample plot size on the ground.

Previous methods used to evaluate the appropriate sample plot size have failed to analyze scale effects on pattern discrimination. Also, previous research in the examination of forest structure has not analyzed the spatial patterns associated with canopy gaps. With this in mind, a technique called lacunarity was used in this research to quantify forest canopy spatial patterns in a series of remote sensing and simulated images. Lacunarity analysis is a multi-scale pattern analysis technique that can be used to quantify the size distribution of gaps in a data set and the degree of heterogeneity that exists in the spatial pattern. Previous research in landscape ecology has found lacunarity measurements useful for quantifying the scale of spatial pattern in real and simulated image patterns (Dale, 2000; Plotnick *et al.*, 1996) and to discern biological landscape function (McIntyre and Wiens, 2000). Forest ecologists have adopted the use of lacunarity measurements for systematic temporal monitoring of deforestation patterns in Amazonia (Peralta and Mather, 2000), to interpret forest cover changes in Colorado (Manier and Laven, 2002) and to detect spatial scales of pattern in boreal forest landscapes (Elkie and Rempel, 2001). Remote sensing specialists have applied lacunarity to evaluate seasonal differences in surface land cover dynamics in the Brazilian Pantanal using ERS-1 radar data (Henebry and Kux, 1995) to measure textural changes of intact Peruvian rainforests throughout the 1970s and 1980s using Landsat MSS imagery (Weishampel *et al.*, 1998) and to study the

effects of forest patterns caused by natural processes and forest management practices on radar image spatial properties (Sun and Ranson, 1998).

Lacunarity spatial analysis was applied in this research as an exploratory data analysis technique to determine the optimal spatial extent (size) of ground sample sites for a remote sensing-based analysis of forest structure. The optimal extent exists where the greatest number of object sizes can be distinguished in the data, and are contained within the smallest area in ground units. This spatial extent can provide researchers with an optimal window size at which to view, monitor and measure the objects under investigation. This pattern analysis technique was then applied to a case study in northern Ontario. As a measure of deviation from homogeneity, lacunarity was used in this case study to interpret canopy structure across a forested area contaminated by acid mine drainage and wind blown contaminants.

1.4 Research objectives

The main goal of this research was to apply lacunarity analysis of high-resolution remote sensing data for the measurement of forest canopy pattern in situations of disturbance. The work follows other research within the program of D. King at Carleton University for the long-term analysis of forest ecosystems under various levels of damage or stress (Levesque and King, 1999; Walsworth and King, 1999; Olthof and King, 2000; Pellikka *et al.*, 1999; King, 2002). More specifically, the research objectives were to:

- 1) Determine an appropriate sample plot spatial extent to optimize field-based measurements in two different forest ecosystems.
- 2) Use the lacunarity index to analyze forest canopy gap pattern dependence on distance from a source of contamination and wind stress.

1.5 Structure of Thesis

This thesis has been organized based on the following structure:

Chapter 1 – Introduction.

Chapter 2 – Forest ecosystems and geographical pattern.

Chapter 3 – Analysis methods to quantify spatial pattern.

Chapter 4 – Geographical study areas and data sets.

Chapter 5 – Lacunarity: Two Case Studies. 1) Empirical Spatial Extent Model development and analysis and, 2) Forest canopy pattern quantification.

Chapter 6 – Discussion.

Chapter 7 – Conclusions.

Chapter 2 introduces the forest as an ecological system and explains some of the terminology commonly used by foresters and ecologists in forest analysis. It also discusses geographical spatial patterns and how to assess these patterns from remote sensing data. Chapter 3 provides a literature review on a variety of techniques used to measure forest spatial patterns, describes the lacunarity algorithm in detail and how to interpret measured lacunarity functions. Chapter 4 introduces the two study areas of the research and Chapter 5 presents two applications of lacunarity analysis to evaluate forest canopy spatial pattern. Chapter 6 discusses the research significance and limitations of this study. Chapter 7 presents concluding remarks from the research.

CHAPTER 2-Forest ecosystems and geographical pattern

2.1 Forest ecosystems and measurement

Forest ecosystems are dynamic and complex environments consisting of many species of flora and fauna that are constantly interacting with one another through both time and space. Even the concept of 'ecosystem', the combination of Ecological and System, is rather ambiguous and the definition tends to vary from one researcher to another (O'Neill *et al.*, 1986). Furthermore, without a definition of the word ecosystem, characteristics of the system such as spatial and temporal scale are sure to be more ambiguous. Dale (1970) defines an ecosystem as any system open to the flow of energy and containing at least one living entity while Evans (1956) describes an ecosystem as any organizational unit of interest: organism, population or community. He also emphasizes that ecosystems facilitate "the circulation, transformation and accumulation of energy and matter through the medium of living things and their activities." For the purposes of this study, the term 'ecosystem' will reflect a local biological community and its pattern of interaction with its environment (Academic Press Inc., 1996). Although this definition is quite broad, the description itself hints of dynamic 'interactions' between distinguished biological units (flora and fauna) within an environmental framework operating over both time and space. An ecological

system dominated by a biological community of trees is then considered to be a 'forest ecosystem' (Spurr and Barnes, 1973).

To study any ecosystem, properties of the system must be properly defined and the objects of interest must be described or analyzed in terms of spatial and/or temporal scale. Ecological systems are often thought of in terms of spatial mosaics or hierarchical units in which multi-scale interactions are crucial (Remmert, 1991). In this sense, scale is an objective measure describing some physical quantity, whereas a hierarchical unit is a relative characteristic of the system. Although several researchers have studied the mosaic-cycle concept, it was renewed by Remmert (1985) and O'Neill *et al.* (1986), and a summary of applications for the concept was put forth by Remmert (1991). Such applications span a variety of disciplines and include the assessment of predictable stand-level dieback in Pacific forests (Mueller-Dombois, 1991), the isolation of growth cycles of marine benthos organisms (Reise, 1991) and the examination of neotropical forest bird distributions with respect to cyclical disturbance patterns in the surrounding ecosystem (Haffer, 1991). The mosaic-cycle concept attempts to classify various stages of growth within an ecosystem and simplifies the inter-relationships between organisms. In short, the term mosaic describes a collection of spatially associated biological unit patches that live and grow together within the larger ecosystem. Such units do not grow in unison but rather asynchronously according to resource availability creating a cyclical pattern of growth between patches. In a forest, Stage 1 typically consists of trees similar in shape, size and species. At this stage, light, temperature and humidity are regulated between canopy and understory forest components. This stage then deteriorates into one of

decay creating additional gaps in the canopy through natural tree-fall, disease or clearing. With the increase in light and temperature in these gaps, young saplings or shrubs may shoot up as the forest regenerates. In many situations these saplings are a species not part of the original primary forest, leading to a mixed structure/regeneration phase followed by a new optimal phase as the forest completes the cycle (Mueller-Dombois, 1991).

Although the cycle described above is classified statically into four stages, all forest ecosystems are open to mass and energy interactions with other ecosystems. These interactions impact the spatial and temporal characteristics of each growth stage described by the mosaic-cycle. Although ecosystems are naturally dynamic through time and space, researchers generally must study them in discrete phases by segregating data into various hierarchical levels of interest for organizational or efficiency purposes. It should be stressed that these denominations reflect the effort of specific research agendas to quantify a dynamic phenomenon. Such levels are the combined manifestation of human categorization and natural organization. O'Neill *et al.* (1986) suggest that all levels overlap and interact within the system and everything is somehow linked to everything else inside the system.

In the spatial domain, ecologists, foresters, biologists and physicists tend to dissect the representation of a forest system into a hierarchy of landscapes, consisting of patches, which are in turn made up of forest stands (Lertzman and Fall, 1998). Depending on the local geomorphology and hydrology, forest landscapes tend to

exhibit a heterogeneous pattern and are often defined as tree-dominated regions $> 10^3$ ha (Spies *et al.*, 1994; With *et al.*, 1998). Forest patches on the other hand, vary widely in size and shape (Forman and Godron, 1986; Wiens, 1976) being as small as about 1km^2 (O'Neill *et al.*, 1986). Forest stands are defined at the spatial scale between patches and canopies, while the latter are groupings of individual tree crowns (Song *et al.*, 1997). Furthermore, researchers interested in modelling energy transfers between the biosphere and the atmosphere deal with micro-level vegetation dynamics and tend to concentrate on canopy or tree-level interactions. The organism level is usually the baseline or smallest unit within the hierarchy (O'Neill *et al.*, 1986).

Given the hierarchical nature of forest ecosystems, the energy interaction between organizational units is an important consideration in many applications of earth science research. As there are connections between each of the organizational levels, the complexity and dynamics of individual trees and forest canopies have a direct influence on patch and landscape level structure and function (Norman and Campbell, 1989; Gustafson and Parker, 1992). Such complex systems can be analyzed in many ways since ecosystem behavior does not result from a single set of processes (Seixas, 2000). Fortunately, the definition of forest ecosystem defined above speaks of “local biological community and its pattern of interaction with its environment”. Therefore, if a pattern can be recorded over time or space, measurement of specific attributes of the system may be achievable. Pattern analysis is used in many applications, including biodiversity (King and DeGraaf, 2000), moose population studies (Hornberg, 2001), hydrological research (Sagar *et al.*, 2002) and a

vast number of ecological projects (Dale, 1999; Slater and Brown, 2000).

Furthermore, as the disciplines of landscape ecology and remote sensing continue to converge, such research linking the two will eventually become commonplace (Drake and Weishampel, 2000; Zenner and Hibbs, 2000; Sommerfeld *et al.*, 2000).

The forest ecosystem is a complex biological unit, organized into hierarchical levels to ensure sustainability and maintain longevity. If one or two of these levels become disturbed due to natural or anthropogenic processes, the entire system will not collapse. One of the best ways to study and describe these levels is to analyze patterns in data that have been collected over time and space. Since a hierarchy of processes form spatial and temporal patterns (Elkie and Rempel, 2001), data that reveal these patterns are often used in studies detecting forest disturbance and stress (Ripley *et al.*, 1996). The next sub-section will report on the descriptive power of spatial, spectral and temporal patterns in various data types and introduce the primary characteristics of a geographical pattern.

2.2 Perception of pattern – spatial, spectral and temporal

Human perception of anything under investigation typically begins with a visual assessment. Light interaction between the object and the eye, through absorption, transmission and scattering properties represents the transportation and

redirection of electromagnetic energy from one place to another. The human eye (like any remote sensor) is rather limited however, as the ability to discern this energy is constrained to the very narrow visible range of the electromagnetic spectrum (Ciesla, 2000). Perception of colour or analysis of specific wavelengths is representative of the first of three important characteristics of 'pattern', namely the spectral component. A spectral pattern is interpreted by the notion of spectral signatures as they describe the reflective responsivity of an object to electromagnetic energy (Ciesla, 2000). Analysis of land surface reflectance proves worthwhile in many applications for which the variability in land cover type can be discernible solely from the measured spectral characteristics. Technological developments of hyperspectral (remote sensors with high spectral resolution) imaging sensors such as CASI, TWRIS or Hyperion have proven useful in a wide range of applications in environmental monitoring (Staenz *et al.*, 2002). Spectral patterns are important components in a number of agricultural (Curran, 1994; Bowman, 1989), forestry (Roberts *et al.*, 1997) and geological applications (Van der Meer, 2001).

With reference to the human example as illustrated earlier, the advantage of using two eyes comes in the ability to distinguish the relative positions of one or various objects located in space. This can be considered the spatial component of pattern. As two eyes become focused on one object, reflected visible energy is received from multiple positions along the surface of the object. In essence, the distribution or variability in the positions of light interception by each eye is captured and quantified. These quantities are processed very quickly by optical receptors and

assumptions can be made regarding the spatial association of the object and the observer (absolute) and based on the intrinsic characteristics of the object itself (relative). Air photo interpretation is a common visual analysis technique that makes use of three-dimensional perception to discern the spatial association of objects distributed on the surface of the earth (Lillesand and Kiefer, 1999).

The distribution and spatial variability of geographic data can also be studied over time to reveal temporal patterns. Such patterns then form a way of forecasting data trends back through history or into the future. As alluded to in section 1.2, the analysis of FTC outbreak patterns in northern Ontario since 1950 reveals a 12-year period of reoccurrence. Cooke (2002) has taken the research further by correlating temporal aspen decline to forest spatial heterogeneity since 1950. It was concluded that greater forest fragmentation ($\uparrow$ variability in forest size) leads to a prolonged outbreak duration. Temporal data are usually integrated with either spectral or spatial data to enhance understanding or description of the system. Peralta and Mather (2000) analyze deforestation patterns in Acre, Amazonia both temporally (data for years 1975-1989) and spatially (data derived from socio-economic trends throughout the study area). They conclude that the occurrence of smaller, irregular deforestation patches pre-1975 was the result of family groups that dominated both the economy and the exploitation of natural resources in the region. Post-1985, the presence of larger, more regular deforestation patches tended to dominate the system as the economy began to grow both regionally and globally.

In essence, pattern is a specific property (or characteristic) describing a system and is governed by either the spectral, temporal or spatial constraints of the data under investigation (Seixas, 2000). For determination purposes of this thesis research on optimal plot size determination and pattern scale analysis, spatial pattern will be given precedence over temporal and spectral patterns as the relevant geographic descriptor. This spatial analysis was thought to be an important starting point for the examination of forest structure and extensions of this work could then use the results from this spatial analysis in conjunction with other temporal or spectral data sets.

2.3 Spatial pattern in forests

Spatial pattern is defined in ecological terms as the arrangement of objects in space that characterize a certain amount of predictability (Dale, 1999). Seixas (2000) uses the term 'organization' as a substitute for 'arrangement' in the definition above, for a more concrete understanding of how a group of objects exhibits an observed spatial pattern. If a group of objects is organized in space, it is assumed to be predictable, which can be quantified in terms of spatial pattern. The study of quantitative patterns in geographical data allow scientists to infer ideas as to how populations are organized, and may allow them to estimate the development of such organization. A forest for instance, may contain many different tree species of various shapes and sizes, all of which operate in an organized fashion. This forest would show a visually different spatial pattern than a forest containing only one tree species. In

fact, there is increasing evidence that uneven-aged mixed forests are ecologically and economically more stable (resilient to disturbance) than even-aged single species populations (Larsen, 1997; Thorsen, 1999) and less susceptible to massive insect outbreaks. “Even-aged forest monocultures that often produce uniform microclimate and food-resource conditions are the forest systems that most favour the performance of pests” (Puhe and Ulrich, 2001). Furthermore, other biological communities are affected by the overall amount and pattern of vegetation in forest ecosystems (Schieck *et al.*, 2000).

Spatial patterns that dominate forest ecosystems can be characterized in one of three ideal ways: dispersed, random or clustered. Trees that are dispersed exhibit a regular pattern and are distributed with spatial uniformity across the earth’s surface (McGrew and Monroe, 1993). This may occur in a forest plantation where all the trees are planted systematically at once. They will mature at the same time and even spacing will ensure consistent structural characteristics over the occupied space. When there is no dominant trend or spatial pattern in the observed data, the arrangement of trees is random. The spatial distribution of trees in an undisturbed natural forest tends towards randomness when each tree is in competition with others for sunlight (at the canopy level) and nutrients (in subsurface zones). Furthermore, natural forests may contain many species of trees and shrubs, all which have different growth rates. A clustered forest exists when the spatial arrangement of trees is explained by dense groupings. Spatially fragmented forests have large canopy gaps and clumped patches of vegetation. In a natural setting, tree clustering varies by

species and surface environmental conditions at the stand level (Zoladeski and Maycock, 1990).

When forests are examined at the individual tree level, no two samples are alike in size, shape or form and their position and pattern of growth is determined by several important factors. Dale (1999) outlines three distinct natural determinants of spatial pattern in landscape ecology. Firstly, vegetation morphology influences object position and organization throughout a plant community. Tree size, growth and structure are aspects of morphology and influence the observed pattern in a forest system. Since all plants tend to grow depending on nutrient and resource availability, the more sun shining through the forest canopy in one location will allow saplings there to grow into that location. Young beech trees for example, need a lot of light and cannot mature in shady conditions (Remmert, 1991). Secondly, environmental factors influence how vegetation patterns develop in a natural system and vice-versa (Hogg *et al.*, 2000; Puhe and Ulrich, 2001). For example, Hansen *et al.* (2000) used both vegetation morphology and environmental factors of soil texture, topography and cover type to map and further analyze the aboveground net primary productivity (NPP) spatial pattern in the greater Yellowstone ecosystem. Lastly, the sociological interactions between the plants themselves tend to influence pattern development, as competition between rival species is always an important forest process. Williams (1996) developed a simulation model for defining competitive interactions in temperate forests, while Opio *et al.* (2000) created a competition index based on integrated values of tree height and diameter.

Another factor that influences forest pattern is stress and disturbance. Such factors alter the observed spatial pattern in a forest by causing structural damage or mortality. Canopy gaps due to tree mortality are a common feature in forest environments and are readily apparent in the observed pattern (Sommerfeld *et al.*, 2000). Such pattern variability from foliage to non-foliage is shown in Fig. 1.1.

Pattern analysis techniques allow the detection of forest canopy gaps, which are interpreted as the surface area directly under a canopy opening (Runkle, 1985). The spatial analysis of gaps in the forest canopy is important since a gap presents a response to a disturbance and a means of regeneration (Sun and Ranson, 1998). Quantification of size and extent of such canopy gaps helps to develop understanding of historical forest dynamics (Axelsson and Ostlund, 2001) and to interpret structural differences within the forest (Elkie and Rempel, 2001). The spatial analysis of canopy gaps using remote sensing imagery is a useful means for development of understanding of the forest patterns linked to structural variations. It can show areas of spatial fragmentation and highlight areas characterized by structural damage. Integration with spectral and temporal analyses can aid in the development of an effective methodology for mapping and monitoring forest structural condition and change.

Although many patterns are easy to discern, such as vegetation damage or mortality, the process (es) that created the pattern is often not as simplistic. Since

ecological relationships beneath a forest canopy are spatially related to the pattern of gaps and sunlight penetration (Silbernagel and Moeur, 2001), the study of natural spatial patterns in a forest ecosystem tends to provide inferences about the occurrence and magnitude of natural processes. Of course, more than one pattern or process could be dominant at any one time in such a system, so inferential conclusions should be taken with caution. Extreme variations in the normally observed pattern of a forest system could be linked to natural processes such as establishment, growth, competition, reproduction, senescence or even mortality. Other processes that act to modify the pattern of a forest ecosystem involve both natural and anthropogenic disturbance. NASA has recently established phase three of the Forest Ecosystem Dynamics (FED) project to address the influence of spatial heterogeneity on multi-scaled processes in the boreal forest (Ranson *et al.*, 2000).

Geographic spatial patterns are usually the result of the combined relationship between object characteristics (vegetation structure and sociology within the community) and their inherent interactions with resources and environmental conditions operating within the system. Such patterns and processes need to be clearly defined and quantified to improve the understanding of the system as a whole (Tischendorf, 2001). The next sub-section will present three examples of how geographic spatial patterns can be used to infer processes over spatial and temporal scales.

2.4 Linking spatial pattern to spatial process

To understand vegetation communities as natural systems, we must describe and quantify their natural characteristics both spatially and temporally. Space and time provide the framework linking pattern and process, however as discussed above, neither is comprehensible without the notion of scale, which will be discussed in greater detail in the following section. The current section introduces ecological pattern and process in general terms and provides three useful examples describing how spatial pattern and process are linked in nature. The first example illustrates hydrological patterns and associated spatial and temporal processes. The second example shows how researchers in forestry interpret historical processes from tree-ring data collected in the field. Finally, the last example illustrates how spatial land use patterns influence thunderstorm development patterns across a landscape.

Fig. 2.1 presents an image subset from Landsat ETM+. The patterns depicted in the scene are representative of current and past processes.

Figure 2.1 – Patterns revealing historical hydrological processes detected from Landsat ETM+. Red, green and blue represent reflective spectral wavelengths centred at 1600nm, 830nm, and 660nm, respectively.

The Landsat ETM+ scene (false colour composite, see figure caption) illustrated in Fig. 2.1 reveals historic meanders that are now bare soil (bright pink) and active meanders in dark blue. A meandering stream exhibits both erosional and depositional properties and alters its route based on energy fluctuations. Energy expenditure becomes minimized as it meanders since the length of the river increases while the gradient (i.e. slope) decreases (Whittow, 1984). The results of the processes described above are illustrated in the landscape patterns presented in Fig. 2.1.

The relationship between pattern and process is presented in Figure 2.2. The example graphic demonstrates how past processes can be interpreted by patterns observed in the present.

Figure 2.2 – CIPHA research methodology, interprets past processes from present pattern (Canadian Forest Service, 2002).

Dendrochronology is the science of dating and analysis of past events (processes) through the study of tree ring growth (patterns) (Fritts, 1976). This analysis gives researchers the ability to combine elements of both pattern and process into a comprehensible, yet complex model similar to that occurring in nature. In Fig. 2.2, the CIPHA project uses data collected in the present to infer past processes (insect defoliation) and to help explain future trends in aspen forest health. The diagram specifically shows years of prosperous growth (thick bands up to 1978), years of slow growth as narrow growth rings (white, highlighted with arrows) and finally, years of recovery (medium thickness) in which the growth rate increasingly approaches the pre-disturbance growth rate (Hogg, 2002). In this case, growth rate patterns can be used to interpret processes from the past and interpolate these rates for the future.

The final example of the relationship between spatial pattern and process is presented in Fig.2.3. This figure is based on a Regional Atmospheric Modeling System (RAMS) developed and applied by Pielke *et al.* (1997). It illustrates the impact of landscape-level spatial pattern feedback on regional weather processes.

Figure 2.3 – Landscape pattern and its influence on thunderstorm development. The simulation scale is 156km. Reproduced from Pielke *et al.* (1997).

The image on the left of Fig.2.3 shows a heterogeneous land use pattern and a simulated thunderstorm formation over the landscape. This scenario is meant to simulate present day mesoscale meteorology over a highly fragmented landscape. The right image shows a more homogeneous land use pattern and the thunderstorm formation associated with it. Such a landscape pattern illustrates pre-colonial settlement in the southern USA. Although the results presented above are based on simulations using real data, such research is becoming important for monitoring interactions between the atmosphere and the biosphere and how landscape patterns influence these processes over time and space.

Linked ecological units, each of which follows a specific growth cycle, characterize the forest ecosystem. Each unit is characterized by an observable pattern that can be quantified and modeled over time and space. Between-unit cycles are often offset from one another, a key component to the mosaic-cycle concept of ecosystems (Remmert, 1991). The pattern-process examples (Figs. 2.1 – 2.3) are influenced by a variety of system characteristics operating throughout the system. The erosional capability of a meandering river for example, depends not only on the energy of the water but also on the soil texture, the amount of vegetation on the banks of the river and also on the local topography. The spatial patterns of a system may provide insight into processes that influence the growth and productivity of the vegetation, especially in complex and dynamic natural forest environments.

The next sub-section will describe the important factors of spatial pattern (including scale) that one must consider when applying such perceptions to data derived from any natural phenomenon.

2.5 Scale as a characteristic of pattern

2.5.1 Scale

The notion of scale can be thought of as a quantitative characteristic of an object. Turner and Gardner (1991), define scale as “the spatial or temporal dimension of an object or process, characterized by both grain and extent.” Grain is the spatial or temporal resolution whereas extent is the size of the study area over which the data are collected (Wiens, 1989). O’Neill and King (1998) define scale as the “physical dimensions of observed entities and phenomena” while Marceau (1998) describes it as “operational and refers to a practical, standard system used to partition geographical space into operational units.” Informally, she defines it as “the window through which the investigator chooses to view the world.” Goodwin and Fahrig (1998) dissect scale into two components, namely spatial scale of the experiment and scaling of the population. While the observer subjectively chooses the former, the latter describes the spatial structure of the population. Although the meaning of scale is

varied, there is a wealth of research documenting its importance in all earth science disciplines. Early ecological studies revealed the presence of natural scales representing ecological processes and physical patterns over the landscape (Kershaw, 1957; O'Neill *et al.*, 1988). These methods tended to be empirical procedures where the scale of observation was changed to detect the range of patterns and processes within the population. Many authors have used this approach when choosing appropriate sample plot size (Atkinson and Curran, 1997; Atkinson, 1993; Trietz and Howarth, 2000).

2.5.2 *Scaling, up and down*

Much attention has been given to transferring scaling models developed at one particular organizational unit to another. A pattern of data points is usually collected at one scale across time or space and models are developed to relate a pattern observed at this measurement scale to another. Such methods are used to extrapolate precise, yet spatially sparse sample measurement data over larger geographical areas. Williams (1991) for instance, measured the reflectance of various forest canopy components (leaves, branches and stems) within several conifer stands and one deciduous stand. Each of these component reflectances were separated relative to the overall canopy reflectance measured from a helicopter. Song *et al.* (1997) analyzed forest canopy characteristics by simulating point patterns of stems together with 3-

dimensional crown shapes. Luther *et al.* (2002) are developing a strategy to map forest biomass using data measured at the tree-level and aggregated to stand-level estimates for subsequent correlation to Landsat imagery. Such scaling efforts are clearly mandatory as it would be a tedious job to measure any canopy or stand-level attribute let alone something larger such as a patch metric or landscape measure. In short, scientists "...have a limited ability to make representative measurements on larger canopy scales" and must therefore "apply small-scale short-term measurements to make large-scale, long-term inferences" (Norman, 1993). Such methods are referred to as bottom-up analysis procedures since they extrapolate precise field-based measurements of the objects making up the system to form more generalized characteristics of the system as a whole. These approaches have the advantage of starting with first principles and clearly defined variables (Hinckley *et al.*, 1998). Jarvis (1993) presents the advantages and disadvantages of bottom-up scaling methods in vegetation models while Waring and Running (1998) prove their utility for multi-scale analysis of forest ecosystems.

The opposite approach to the bottom-up method is the top-down procedure. Price (1993) presents such a technique to model leaf area index from satellite data while Mukai and Hasegawa (2000) extract forest damage areas from Landsat TM data to estimate the amount of windfall trees. Aerial sketch mapping is also a common method of obtaining areal polygon estimates of forest decline and stress in the boreal forest (Hopkin, 2002). These methods often utilize Geographic Information System (GIS) technologies and incorporate remote sensing data as a tool that accurately

measures reflected energy over large portions of the earth, linking and integrating data across spatial and temporal scales (Castle, 1998).

2.5.3 The importance of pattern, scale and extent

This section is meant to present graphical examples illustrating the spatial characteristics of a given pattern, namely scale, extent and grain size. Fig. 2.4 (from Hay *et al.*, 2001) illustrates the relationship between pattern and characteristics of scale, grain and extent. The grain size increases vertically in this figure whereas, the spatial extent increases horizontally from the centre of the figure. The right portion of Fig. 2.4 illustrates a series of remote sensing patterns and how an increase in grain size affects the observed pattern.

Figure 2.4 – The relationship between pattern and scale, and aspects of scale: grain size and spatial extent. From Hay *et al.* (2001).

The next example illustrates how a spatial pattern may appear homogeneous at one scale of observation yet heterogeneous at another. In Fig. 2.5, the grain size is assumed to be equal to the size of the dots. When everything contained within the green square is observed, the groups (or clusters) of points appear as clumps of data. The distance between clusters is variable and their position within the square is not regular. At this extent (green), the data groups exhibit a clumped spatial pattern. As the spatial extent changes to the red square, the focus becomes set on the single data points and the groupings are no longer a concern as they appear outside the measured extent. Throughout the red spatial extent, the data exhibit a random pattern since the distance between clusters is variable, though the data points are well distributed throughout the study area. Such data tend to be distributed more homogeneously throughout this extent as opposed to the larger (green) extent.

Figure 2.5. The relationship between pattern and characteristics such as scale, heterogeneity, grain size and spatial extent. From Dale (2000).

CHAPTER 3 - Analysis methods to quantify spatial pattern

The following chapter presents a literature review describing historical and current methods used to quantify spatial pattern for ecological applications.

3.1 Literature review of pattern analysis methods in ecology

Quantifying the spatial characteristics of the forest canopy using remote sensing data often facilitates data exploration and understanding of spatial processes without the need for extensive ground-based sampling. Such spatial data measured at multiple scales could extend analysis from relatively localized study areas to more broad-scale landscapes. Since much of remote sensing research is related to the scale of interest (Woodcock and Strahler, 1987; Marceau *et al.*, 1994; Marceau, 1998), measuring data at one scale can provide insight to data at other scales. Fernandes *et al.* (2002b) for instance, use in-situ measurements of LAI to remotely map this parameter at scales of 30m to 1000m. By modelling forest spatial pattern over several scales, the analyst can describe and identify dominant scaling regions in the data. These regions often reflect the size of the inherent objects in ground units. Since it is widely recognized that natural systems operate over many scales (Mandelbrot, 1983) fractal and other multi-scale spatial analysis methods are currently being applied by

foresters (DeCola, 1989), geologists (Sim and Agterberg, 1999) and landscape ecologists (With *et al.*, 1998) to characterize surface patterns at a wide range of spatial resolutions and describe how the identified patterns change with the observed scale. The following describes some of the typical approaches used to quantify spatial pattern within a forest environment.

To date, researchers in remote sensing, forestry and landscape ecology have adopted a wide variety of spatial analysis techniques to quantify spatial vegetation patterns. Measures of spatial clumping or fragmentation may be based on quadrat sampling, nearest-neighbour point process sampling, semivariance, grey level co-occurrence texture algorithms or wavelets. The following discussion will reveal the degree to which these methods are comparable to lacunarity analysis and why one method may be more useful than another in modelling forest structure.

Quadrat sampling techniques have been used extensively in past research to determine the variance-to-mean ratio between particular quadrats (Pielou, 1969; Woodcock and Strahler, 1987; Hyppanen, 1996). The limitation of such a technique is that it fails to interpret the pattern of organization within the sample quadrat. Furthermore, the derived index (measure of dispersion) does not identify differences of mean density or the degree of aggregation (data arrangement) within a sample (Plotnick *et al.*, 1993).

Nearest-neighbour point process sampling is another useful technique for determining the degree of aggregation of a data set. A number of authors have used this procedure to quantify tree clustering in natural forests (Getis and Franklin, 1987)

and simulated landscape dynamics (Gardner and O'Neill, 1991). In the point process methodology, an initial starting point is assigned to the data and the proportion of data points within a given distance of the start point is recorded. This proportion of points is then compared to a random distribution for statistical significance. The problem with this method is the sensitivity of the algorithm to the boundaries of the map. Although corrections have been proposed (Getis and Franklin, 1987), it seems quite restrictive to incorporate such assumptions into the analysis.

Semivariance analysis was originally introduced as a geostatistical tool to describe the grouping of variables over space (Matheron, 1963). It represents a stochastic analytical model because it derives both deterministic values (range and sill) and the degree of randomness (nugget) in the data. Such a model has been used extensively in remote sensing (Curran, 1988; Lacaze *et al.*, 1994; Woodcock *et al.*, 1988) to determine an optimal spatial resolution (Hyppanen, 1996; Atkinson and Curran, 1997; Atkinson, 1993; Butson and King, 1999), to derive forest structural estimates (St. Onge and Cavayas, 1995, 1997; Cohen *et al.*, 1990; Levesque and King, 1999) and to quantify the spatial structure of other vegetation types (Goodin and Henebry, 1998). The semivariance of an image can be measured either in a square matrix or from data collected along a transect. Derived statistics of the range, sill and nugget can then be analyzed to determine the region where the data points are more similar to each other than points further removed. This is described as the region of spatial dependence (Curran, 1988). Although such a method is easy to comprehend conceptually and perform mathematically, it has several limitations. The first limitation is the assumption that the input data are stationary (the statistical properties

of the data are held constant over the entire sampling space). No matter how large the area of interest is, semivariance measures the input data with reference to global mean and variance values. Since the semivariogram (average semivariance curve) does not account for localized mean and variance values in the semivariance calculation, high spatial variance in these values could produce unreliable estimates of spatial dependence (Rossi *et al.*, 1992). Furthermore, the method has limited capabilities for the detection of local features that deviate from the mean (Cohen *et al.*, 1990) or object size variance within a scene. For gap analysis studies, the semivariogram would either calculate the spatial dependence (range) of the small gap sizes (with small lag), or the large gap sizes (with large lag), but not both simultaneously.

A similar problem to that given above can be stated for texture measures derived from the grey level co-occurrence matrix. Using the 'gliding box' technique, a window of specified size surveys the image for a variety of statistical quantities. Such measures in remote sensing analysis include, entropy (Franklin and Peddle, 1989), angular second moment, inverse distance moment (Peddle and Franklin, 1991), dissimilarity, contrast (Barber and Le Drew, 1991; Olthof and King, 1997) and a variety of others summarized in Haralick *et al.* (1973). Many of these algorithms assess the data based on spatial proximity for one specific lag or neighbourhood distance (Henebry and Kux, 1995). This methodology is very useful to assess objects at one particular scale but has not been successfully applied in multi-scale analysis (Plotnick *et al.*, 1993; Henebry and Kux, 1995). Several researchers have attempted to resolve the multi-scale aggregation problem by plotting texture measures over a range of window sizes (e.g. Musick and Grover, 1991), but the results were unsatisfactory

for two reasons. Firstly, the analysis incorporated non-overlapping windows, which failed to count co-occurrences across the window boundaries. Secondly, although the results did quantify the arrangement of objects within a given window, it did not isolate object sizes inherent in the spatial pattern.

The wavelet transform is considered an alternative to lacunarity and any of the methods mentioned above. Briefly, a wavelet is described as any mathematical function that is characterized by oscillation and decay (Young, 1993). Therefore, "wave" -oscillate and "let" -little or rapid decay. This transform can essentially take on any 2 or 3 dimensional shapes and can be scaled to coincide with the observed data for a multi-scale analysis. Several authors have found wavelets useful for increasing the classification accuracy of a remotely sensed image (Zhu and Yang, 1998), multi-spatial resolution studies (Ranchin and Wald, 1993) and characterizing forest canopy gap structure (Bradshaw and Spies, 1992). The latter authors reveal a two-scenario outcome for the calculated high wavelet variance on which the results are based. They state (pg. 214), " Because the wavelet variance is both proportional to the number and intensity of a feature of a given scale, a peak in the wavelet variance may indicate either a large number of small gaps and/or the presence of a small number of large (very open) gaps." In such a situation, it is clearly difficult for the analyst to quantify what the wavelet variance is indicating based on forest structure alone. Also, because many wavelet shapes can be defined, it is quite difficult to determine the most appropriate ones (s) for a given data type. Simply having the choice between many of these curves would characterize an inefficient use of time in seeking out the 'best'.

3.2 Lacunarity

The following section describes lacunarity analysis and provides details on the algorithm and interpretation of results.

3.2.1 Background

The word lacunarity was first coined by Mandelbrot (1983) to describe the texture of a fractal, with its origin in the Latin term for gap, *lacuna*. Lacunarity was first introduced to measure the deviation of a fractal from translational invariance (object appears invariant as observation scale changes, same as self-similar), as some fractals were found to have the same fractal dimension (D) for visually different textures (Mandelbrot, 1983; Gefen *et al.*, 1983). Lacunarity is a measure of fractal geometry as it represents the prefactor in the general power-law equation where the exponent is the fractal dimension (D) (Henebry and Kux, 1995). In the formula,

$$F(x) = \lambda(x)^{(D-E)} \quad [1]$$

Where $F(x)$ is the function, $\lambda(x)$ represents the lacunarity, D is the fractal (fractional dimension) and E is the Euclidean dimension of the function.

The lacunarity parameter [λ], describes the degree of heterogeneity of the fractal set. In a true fractal set, when $\lambda \rightarrow 1$, the variation in gap size is minimal and the pattern is self-similar. Self-similarity in a pattern refers to a fractal data set that looks the same (homogeneous) across all observable scales. As $\lambda \rightarrow \infty$, a wide range of gap sizes is evident in the structure of the fractal producing a visually different texture. Thus, lacunarity arose from the problem of differentiating two objects defined by the same fractal dimension but presenting visually different textural patterns. The most common method in current literature has used the following equation [2] describing lacunarity (λ) as a function of window size (r) for which the data were extracted (Henebry and Kux, 1995):

$$\lambda(r) = 1 + \text{Variance} / (\text{Mean})^2 \quad [2]$$

This is the relative variance equation derived from the first and second moments of the mean-probability distribution function calculated at the specified box size (r). The relative variance ratio is preferred over other measures of dispersion since it usually follows a consistent pattern with scale and is therefore an important analysis tool for many ecological properties (Waring and Running, 1998).

The most common form of the relative variance equation that is related to lacunarity is calculated as the coefficient of variation (CV) given as:

$$CV = \text{Standard Deviation} / \text{Mean} \quad [3]$$

These two indices measure similar characteristics of a given data set, however the lacunarity index tends to emphasize the tails of the frequency distribution through the squaring of both numerator and denominator in [3]. The derivation of the lacunarity equation [2] using the "gliding box" method, originally introduced by Allain and Cloitre (1991) is presented in the next section.

3.2.2 Gliding box method

The gliding box method requires that the data be positioned with reference to an underlying square lattice, or arrangement of grid cells. For remote sensing data, this would be the pixel structure of the image. It is assumed for this section that a binary image is used. Each pixel has dimension (Δ) on one of its sides and the linear size of the set (L), represents the linear dimension across the image. A gliding box with size ($r \times r$) is placed directly over the square lattice, and moves as a sample window that

collects the lacunarity data at all possible locations throughout the image. For each box size (r), the box mass (M) at a given position is determined by adding the total number of active sites. The frequency distribution $[n(M,r)]$ is then calculated from all box masses (M) determined by passing the box through the image. Next, the probability distribution function $[Q(M,r)]$ is calculated by dividing $n(M,r)$ by the total number of boxes of size (r). The sum of each $M*Q(M,r)$ derives the mean probability distribution function and the sum of $M^2*Q(M,r)$ derives the variance probability distribution function. The mean and variance values representing the first and second moments of the probability distribution are determined. Therefore, the lacunarity value for box size (r) is;

$$\lambda(r) = 1 + M^2Q(M,r) / [MQ(M,r)]^2 \quad [4]$$

The mean and variance represent the mass statistics measured for each box size. A double-log curve of lacunarity versus box size is plotted to show the spatial response function identifying (i) the change in spatial pattern across scales, and (ii) scales of pattern (object sizes) depicted in the image (Elkie and Rempel, 2001). The shape of the response function depends only on the aggregation of objects within a given spatial pattern (Plotnick *et al.*, 1993). For the objectives of this research, the primary concern was the relative shape of the lacunarity curve as it reflects the inherent spatial pattern and pattern fluctuations with reference to the box size range. Hence, changes

in absolute lacunarity values with respect to variable-sized spatial extents were less important than the relative nature of the curve.

3.2.3 Interpretation of distribution

As shown in Fig. 3.1c, the lacunarity curve reveals a graphical representation of the scale-dependent spatial non-stationarity in this example dataset (Henebry and Kux, 1995). A function calculated for a random pattern, as in Fig. 3.1a, shows a rapid decay in lacunarity with increasing box size. A clumped pattern like the one in Fig. 3.1b, produces a lacunarity function that declines more gradually to a break point, which approximates the average object scale in the data (in this example, the average tree size). After the break point, the function shows a swift decay characterized by a more homogeneous pattern at larger box sizes. Both random and clumped patterns reach a lacunarity of 1.0 at large box sizes as they become homogeneous with respect to the observation scale.

Figure 3.1. Example a. random map, b. clumped map, c. lacunarity function and d. lacunarity slope function. Black is zero (0) and white is one (1). Original images were 21 X 21pixels but expanded for presentation.

To analyze the fluctuation points in the lacunarity function with a greater degree of certainty, the first derivative of the curve may be plotted against the box size (Dale, 2000). As shown in Fig. 3.1d, the lacunarity slope curve for a random spatial pattern begins with negative slopes that increase consistently throughout the curve. The curve plotted for the clumped pattern starts at a relatively modest negative slope, decays to the steepest slope at the break point (6m), and then increases towards zero at larger box sizes. The trough width exhibited by the lacunarity slope curve indicates the rate of change in object sizes over the range of measured box sizes. A narrow trough indicates discrete break points in the pattern, whereas a wider trough reveals a more continuous change in object sizes. In this case, the object in the clumped pattern is irregular in shape and the deviation around the break point represents a more gradual change of object sizes.

3.2.4 Forest gaps or tree crowns

Since lacunarity is a measure of gap pattern and gap size, the objects of interest are the gaps or holes in the pattern. Take for example, a map containing all ones (1's). The map would be homogeneously occupied no matter which box size was

used. Every individual grain (or pixel) would be occupied and there would be no holes in the pattern. If the same analysis were done on a map containing all zeros (0's), the resultant lacunarity at $r=1$ would approach infinity, as there are an infinite number of gap sizes inherent in the scene. Hence, for a lacunarity analysis of a spatial pattern to be successful, the objects of interest within a given spatial pattern must always have a value of zero whereas, the background pattern itself contains 1's. It is only within these bounds that the texture of the pattern can then be evaluated. The influence of such an effect is illustrated in Fig.3.2.

Figure 3.2 – Example of various random and clumped patterns in comparison to inverse patterns. Total spatial extent is 25m. Black is zero (0) and white is one (1).

a. Random 30:70 **b. Inverse** **c. Lacunarity Slope Functions**

d. Random 50:50 **e. Inverse** **f. Lacunarity Slope Functions**

g. Clump 30:70 **h. Inverse** **i. Lacunarity Slope Functions**

j. Clump 50:50 **k. Inverse** **l. Lacunarity Slope Functions**

The lacunarity slope functions shown in Fig. 3.2c, f, i and l illustrate how lacunarity scales of pattern are measured for different map population sizes. In this case, Fig.3.2a presents a randomly generated pattern consisting of a more sparsely populated map (30% population), a wide range of gap sizes ($\uparrow$ lacunarity) and one scale of pattern (11m). Furthermore, since the lacunarity is large, the magnitude of the slope function is also large. Fig. 3.2b is the inverse of A. This map contains fewer gaps overall (now 70% population), the pattern is less lacunar and the slope function fails to identify any scales of pattern in this map. The effect of inverting a random map with a population probability of 50% is illustrated in Fig.3.2d-f. The lacunarity slope functions for these two maps are extremely similar and no scales of pattern are recognized. Hence, a randomly generated map having a population of 50% contains very similar gap size distributions in both the original and inverse scenarios. Fig. 3.2g-i show the original and inverse results for a clumped spatial pattern. The black curve in Fig.3.2i shows a scale of pattern at 2.5m representing the outer black border surrounding Fig.3.2g. The red curve in Fig.3.2i on the other hand, depicts a scale of pattern equal to 21.5m representative of the large black box in the center of Fig.3.2h. The final example, presented in Fig.3.2j-l shows the lacunarity results for a clumped spatial pattern containing a population of 50%. The black box depicted in Fig.3.2j has a smaller range of gap sizes and the pattern is dominated by one scale of pattern at 3.5m. The inverse map shown in Fig.3.2k has a similar pattern to that in Fig.3.2i, however the population is larger now (50% occupation) so the scale of pattern exhibited by this map is reduced to only 18m.

The examples presented in this section show the influence of zero values (gaps) within the observed spatial pattern and how the lacunarity metric attempts to quantify these zero values compared to the observed pattern overall. These examples also illustrate the importance of populated pixels in a spatial pattern as this population affects the overall magnitude of lacunarity values. Since absolute lacunarity will vary with the occupied population size, it is useless to compare lacunarity results between maps with varying population sizes. Although population size in a forest canopy is dependent on canopy density, this parameter was held constant in the second study of this thesis so the results would highlight object size variability and arrangement within the structure of the canopy. In summary, the results derived from a lacunarity analysis of a spatial pattern are dependent on the:

- 1) Grain size and Extent (this governs the sampling space and the range of box sizes)
- 2) Proportion of occupied pixels (population size)
- 3) Texture of non-occupied pixels (gaps)

The next chapter describes the study areas under investigation in this research and Chapter 5 presents two applications of lacunarity analysis to assess forest pattern with remote sensing data.

CHAPTER 4 – Study areas and data sets

Two distinctly different study sites were selected for this research in order to study the forest canopy spatial patterns characterized in different regions. Within the two regions, two different data sets involving both field measurements and remote sensing data were analyzed. Throughout this paper, for simplicity, any reference to Data Set #1 will correspond to field and image data collected in the mixed hardwood forest of Gatineau Park, Quebec. Data Set #2 represents the data collected in the boreal forest at the Kam Kotia mine, near Timmins, Ontario. The locations of these data sets are highlighted in Fig. 4.1.

Figure 4.1 – Locations of Data Set #1 and Data Set #2.

This chapter describes each region in detail with sub-sections outlining; a) region characteristics, b) field measurements and, c) remote sensing data acquisition.

4.1 Gatineau Park, Quebec – Region characteristics

This study region is located in the temperate hardwood forest of Gatineau Park, Quebec. The approximate coordinates of the centre of the park are 46°30' N latitude and 76°00' W longitude. Climatological data recorded for the region between 1927-1990 (Environment Canada, 2002) indicate an average daily temperature during the summer months (June, July and August) of approximately 19.1° C and mean precipitation for the same time period of about 87.7 mm. The underlying bedrock is representative of the metamorphosed igneous and sedimentary rock base in the southern portion of the Canadian Shield. The region is dominated by syenite, marble and striated gneiss all formed during the Precambrian era. The topography in the area consists of rolling hills and isolated flatlands interconnected with bare rock escarpments and a vast number of marshes, small lakes and streams. Beaver activity is very prominent in the area and tends to constantly modify the hydrological and vegetation patterns over the rugged terrain.

The forest is dominated by overstory deciduous trees such as sugar maple (*Acer saccharum*), basswood (*Tilia americana*) and red oak (*Quercus rubra*). Isolated

conifer patches of eastern white pine (*Pinus strobus*) and eastern hemlock (*Tsuga canadensis*) are also sparsely distributed across the region. Forest understory vegetation in the region consists of white ash (*Fraxinus americana*), ironwood (*Ostrya virginiana*), beech (*Fagus grandifolia*) and white birch (*Betula papyrifera*).

4.1.1 Field measurements

The study site consists of two 100m X 50m forest sample plots. Referred to as #701 and #702, the sites were established in 1987 and 1988 respectively, for long-term study by the Quebec Ministry of Natural Resources (QMNR). Since their establishment, intensive field campaigns have been conducted every five years to measure and document forest structure and mensuration changes at each site. Both sites (shown as Site #701 and #702 in Fig. 4.2) are similar in species composition, although the former is situated in a well-drained elevated portion of the forest along the Eardley escarpment. The average elevation at this site is <300m above sea level.

Figure 4.2 – Gatineau Park, Quebec, red square inset from Fig. 4.1. Contour interval is 50m.

As Fig. 4.2 illustrates, site #702 is located in a lowland area of the park that tends to be poorly drained. Although both sample sites were initially established to monitor broadleaf vegetation, conifer patches tend to be more prominent around #702 where the average elevation is about 200m ASL. Each study site is further divided into sub-plots measuring 10m X 10m. Within each sub-plot, forest structural characteristics were measured by the QMNR in 1997 and 1998. The data set includes variables such as diameter at breast height (DBH), tree height, crown height, crown size, leaf area index (LAI), crown closure and a visual estimate of tree crown vigour. For enhanced spatial analysis, tree stem mapping was conducted at each site using distance measurements recorded in centimetres.

The forest is currently undergoing a recovery process from the effects of a severe ice storm. The QMNR noted that site #701 was the most severely damaged, with 50 to 75% crown loss in dominant trees. Site #702 was classified as having moderate damage, with 25 to 50% crown loss (QMNR, 1998). Forest health research at the same sites has confirmed these damage estimates through the application of remote sensing-based models to predict forest structural characteristics in the field (Pellikka *et al.*, 1999).

4.1.2 Remote sensing data

The remotely sensed data were collected on August 18, 1998 using a Vinten 70mm camera with Kodak 2443 CIR film flown at two altitudes. The high altitude photographs were acquired at 3200m above ground level, whereas the low altitude data were flown at 1240m above ground. The photographs were scanned using the Kodak Photo CD process to a variety of resolutions up to 6144 x 4096, approximately equivalent to a 0.64m ground pixel size for the high altitude data and a 0.25m pixel size for the low altitude data. Georeferencing of the imagery was performed using a series of ortho-rectified photographs that were made available for the entire study area in 1994 (National Capital Commission, *per. comm.*). In each case, the image rectification process yielded a root mean square (RMS - the square root of the mean squared deviation of a signal from a given baseline) error of less than two pixels. The minimum-bounding rectangle for each sample plot was then extracted from the image based on the GPS coordinates obtained in the field. Since the ground plots did not align to true north, a null-value mask (ancillary map layer containing null values) had to be applied to the offsite values contained within the minimum-bounding rectangle.

4.2 Kamiskotia, Ontario – Region characteristics

The second study site consists of a forest area 1.4km by 1km located approximately 60km northwest of Timmins, Ontario in the small community of Kamiskotia. The site is located at 48°35' N latitude and 81°36' W longitude. Climate data measured in the region between 1955 and 1990 (Environment Canada, 2002) reveal a summer (June, July and August) mean daily temperature of 15.7° C and an average rainfall of 94.9 mm during the same months. The underlying geology of the area is mainly comprised of mafic volcanic rocks dispersed with a lesser concentration of intermediate to felsic volcanics representative of the Archean Superior Province within the Canadian Shield (Ministry of Northern Development and Mines, 2002). Within the study area, fine-textured glacial deposits of clay and silt dominate the surface (Natural Resources Canada, 2002). Well-developed clay-loam soils dominate the western and central portions of the site, whereas sandy-loams are characteristic in the eastern areas. A regional map showing the community of Kamiskotia is presented in Fig. 4.3.

Figure 4.3 - Kamiskotia study site, cyan square inset from Fig.4.1.

The entire study site is situated on very flat topography and all plots are dominated by Boreal forest vegetation such as trembling aspen (*Populus tremuloides*) in the upper canopy and fewer numbers of white birch (*Betula papyrifera*), black spruce (*Picea mariana*) and balsam fir (*Abies balsamea*) in the understory. Due to the presence of fine-textured clay soil overlain by a thick (>30cm) organic layer and the presence of sphagnum moss (*Sphagnum* spp.), black spruce and competition shrubs such as speckled alder (*Alnus rugosa*) and red raspberry (*Rubus idaeus*) dominate poorly drained bogs located in the central portion of the site.

The study area has been affected by wind-blown and acid drainage contaminants from the north unimpounded mine tailings pond directly adjacent to the study site. From the period 1942 to 1972, the Kam Kotia mine was in operation and produced over 6 million tons of ore and 200,000 tons of waste rock (Ferguson, 1993). After the closure of the mine in 1972, three large tailings deposits were left that contaminated an area of approximately 350 ha. These deposits and the surrounding area are highlighted in Fig. 4.3. Although attempts have been made to contain the waste rock and the associated acid mine drainage through installment of dams and containment berms (Gibson, 1976), little has been done to preserve the surrounding environment up to the present. In September 1999, the Ontario Ministry of Northern Development and Mines announced a new restoration program aimed at containment of the unimpounded tailings under the Abandoned Mine Rehabilitation Program. The

rehabilitation will occur over the next 5 years at a cost of \$28 million (MacKinnon, 2002).

Previous field research in the forested area affected by the contaminants has shown the soil pH to vary from 1.4-2.0 in the creeks delimiting the site and relatively high concentrations of heavy metals such as aluminum, zinc and chromium have accumulated within the first 200m of the forest-tailings (F/T) boundary (Levesque and King, 1999). Research by Olthof and King (2000), found relations between forest structural parameters of leaf area, canopy closure and stem size with image texture. The authors also concluded that greater tree windfall was associated with sandy soils and less soil organic matter. The dynamics of vegetation growth and succession at the site have been documented in temporal studies by Walsworth and King (1999) and Cosmopoulos and King (2001).

4.2.1 Field measurements

Two different sets of sample plots were established at the site throughout the 1990's each of which was remeasured during the 1999-growing season to coincide with the remote sensing data acquisition presented in the next section. The first set (referred to herein as Data Set #2a) consisting of six, 50m by 50m plots was established in 1993 in initial research on image semivariance and spectral unmixing relations with forest health and structure (Levesque and King, 1999; 2002). The plots were systematically placed at specific distance intervals from the edge of the mine

tailings. They are numbered from 1-6. Forest inventory data such as DBH, tree height, crown closure, canopy openness and tree health were measured in each of the six plots every two years since their establishment. During an intensive field campaign for this thesis research in the summer of 1999, field measurements were replicated at each of the six plots to form the single-season forest structural database for this research. These sample plots are dominated by overstory trembling aspen (*Populus tremuloides*) approximately 70 years in age.

The second set of forest sample plots (referred to herein as Data Set #2b) was established in 1997 to develop a multivariate forest health index and to analyze a spatial gradient of forest health with respect to the distance from the F/T boundary (Olthof and King, 2000). Six previously established transects were used to place 10m-radius plots in a systematic fashion at various distance intervals away from the tailings edge. The first plot along each transect was placed at a distance of 10m from the F/T boundary. Sample plots were initially placed at intervals of 25m up to a distance of 110m at which the interval changed to 50m between plots. Beyond a distance of 510m from the tailings edge, the between-plot distance interval increased to 100m. The farthest plot from the tailings edge was determined by the northern site boundary (north creek), generally located at a distance of 810m for the western half of the site and 610m to 310m for the eastern half of the site. In the summer of 1997, forest structural data were collected at each of these sites (Olthof, 1999). These measurements were replicated for this research in 1999 and form the field data component used in this study.

4.2.2 Remote sensing data

The remotely sensed data were collected on August 20, 1999 using a Kodak Megaplug 1.4 digital camera with 8-band filter wheel (King, 1995). The imagery was acquired at three altitudes resulting in pixel spatial resolutions of 0.25m, 0.5m and 0.8m. The view angle of the lens was 14° and the shutter speed of the camera was fast enough to allow three spectral bands to be acquired at the lowest altitude, four bands at the medium altitude and all eight spectral bands at the highest altitude. To locate the four sample plots in the imagery, ground targets measuring approximately two square metres, were placed before flight at the start and end of each transect and on the tailings. After image acquisition, real-time differential GPS techniques were used to record ground target locations and sample field locations to within ± 0.5 m. Band to band image registration was performed followed by a frame-to-frame mosaicking process which produced an overview of the entire study site. In each case, the image rectification process yielded a RMS error of less than two pixels. For this particular study only the near-infrared band (750nm $\pm$ 10nm) at a spatial resolution of 0.5m was used, as this wavelength was best at distinguishing between vegetation overstory and understory.

CHAPTER 5 -Forest pattern discrimination using lacunarity analysis

5.1 Introduction

The following chapter describes the methods and results of two studies of lacunarity analysis in remote sensing. Subsection 5.2 presents the data and methods that were used to develop an Empirical Spatial Extent Model (ESEM) and the results that were obtained from application of this model to high-resolution imagery of both the hardwood and boreal sites. Subsection 5.3 presents a lacunarity analysis of forest pattern changes with distance from the contaminated mine at the boreal site.

5.2 Study 1: Empirical Spatial Extent Model

Remote sensing imagery covering sample plots from the two study sites described in Chapter 4 were analyzed to determine scales of pattern and an optimal spatial extent for sampling to capture these patterns. The optimal extent exists in this case, where one or more object scales can be distinguished in the data, and the objects are contained within the smallest areal unit. Upon retrieval of the optimal spatial extent in each forest type, a description of object sizes is presented and compared to ground measurements of tree crown size to validate the image model.

Thus, the derived model (ESEM) produces two output variables; 1) *The optimal spatial extent in ground units* and, 2) *Specific object sizes within the spatial extent that make up the image spatial pattern.*

The main goal of this study was to determine an optimal spatial extent in ground units which best depicts a distribution of multiple object sizes in two unique natural forest environments. The specific objectives were to:

- 1) Develop an image-based model to determine an optimal spatial extent in two forested regions.
- 2) Compare the resultant optimal spatial extents for each forest type.
- 3) Compare the output of the model (measured scales of forest pattern) against tree crown measurements.

5.2.1 Field and image data

To develop the ESEM, high-resolution remote sensing imagery was used at each of the two study sites introduced in the previous chapter. To validate the object sizes derived from the model, field measurements of tree crown diameter were used. This section outlines the field and image data that were used in each forest type.

5.2.1.1 Mixed hardwood forest data

Since it was assumed that the remote sensor could only provide a reliable estimate of the upper forest canopy, only the QMNR average crown size measurements for dominant and intermediate trees were compared to the model. The average crown size was calculated based on the mean value of north-south and east-west crown measurements.

Lacunarity analysis was conducted using the near-infrared spectral band from Data Set #1, as it provided the greatest contrast between tree crowns and canopy shadows. This spectral band also contained the most information since the Kodak photographic scanning procedure tended to maximize the spectral variance in the near-infrared band and gradually minimized the spectral variance in the visible wavelengths. To ensure a comparison could be made between forest regions (mixed and boreal), the fine resolution data for this site was aggregated using a 2 X 2 pixel local averaging filter to a pixel size of 0.5m. This spatial resolution (grain size) was used throughout the research as it captures forest canopy spatial characteristics at the individual tree level and falls within the guidelines set forth by O'Neill *et al.* (1996), suggesting a grain size of 2-5 times smaller than the spatial features of interest be used. The two study plots at this site are shown in Fig. 5.1. Each of the sample plots were cropped from the original imagery so they were representative of square sections of forest measuring 50m X 50m generated from the centre of each site.

Figure 5.1 – Gatineau Park images of Site 701(a.) and 702(b.). Pixel spatial resolution was originally 0.25m but aggregated to 0.5m using a 2 X 2 local averaging filter.

5.2.1.2 Northern boreal forest data

The field data at the boreal site was collected in August, 1999 in six 50m X 50m plots and forms a portion of Data Set #2a (shown as red squares in Fig. 5.2 below). To validate the scales of pattern detected through the lacunarity technique, field-based measurements of crown size were made in tandem with the remote sensing data acquisition. For all of the dominant trees within a plot, each crown was measured with a tape in two directions, north-south and east-west. Due to time constraints, no intermediate tree crowns were measured in this field campaign.

The lacunarity analysis was conducted using the near-infrared spectral imagery from Data Set #2a. This spectral band seemed to capture the forest canopy variability best. The plots are illustrated by the red squares in Fig. 5.2 (Cosmopoulos, 2001).

Figure 5.2 – Kamiskotia image mosaic (near-infrared spectral band). Pixel spatial resolution is 0.5m. Red squares indicate Data Set 2a plot locations. Green lines show the forest transition transects representative of Data Set 2b.

5.2.2 ESEM methodology

The following section describes the procedure used to develop the Empirical Spatial Extent Model (ESEM). Since the goal of ESEM was to provide a preliminary description of the forest canopy spatial pattern at each study site, only a small number of large sample plots was used in the model development. The use of large plots was mandatory to provide a wide range of spatial extents and box sizes for analysis. The methodology outlined in Fig. 5.3 below, illustrates the generic analysis procedure independent of site characteristics.

Figure 5.3 – ESEM development procedure.

The grey-scale images of the plots (Fig. 5.1 and plots 1-6 in Fig. 5.2) were converted into 1-bit binary images (Fig. 5.4 and Fig. 5.5) based on the mean digital number value. Image digital numbers (DN) equal to, or above the mean were assigned a value of 1; DN below the mean were assigned a value of 0. Although this can be quite an arbitrary methodology, it does provide repeatability when using a variety of input data sources. When inverted a value of 0 was given to upper canopy dominant trees while a value of 1 was assigned to gaps or spaces in the forest canopy. To reiterate from Chapter 4, this inversion allows the lacunarity of the tree crowns to be measured rather than the reciprocal. The binary images for the plots in Gatineau Park are presented in Fig. 5.4 and the plots in Kamiskotia are shown in Fig. 5.5.

Figure 5.4 – Binary images of plots 701(a.) and 702(b.). Tree crowns are displayed as black (0) and canopy gaps are displayed as white (1). Total spatial extent is 50m. Green square shows the largest extent measured at 40m, red square indicates the smallest extent at 7m.

Lacunarity distributions were then calculated for variable-sized input images ranging from the largest (40m X 40m – green square in Fig. 5.4a.) down to the smallest (7m X 7m – red square in Fig. 5.4a.). The 40m extent was chosen as the upper limit since it was felt that beyond this, site characteristics would cause increased variability in the structure of the forest canopy. The 7m extent was selected as the lower limit since below this, image spatial variability would be due more to within crown structure. As shown in Fig. 5.4a, the variable-sized extents were all centred about the middle point of the image. The lacunarity functions were plotted on log-log graphs and then converted to first-derivative slope curves similar to the example in Chapter 3, Fig. 3.1.

Figure 5.5 – Kamiskotia images, original and binary thresholded based on mean digital number. Tree crowns are black (0) and canopy gaps are white (1). Total spatial extent is 50m (or 100 pixels).

a. Plot 1 **b. Plot 1-Binary** **c. Plot 2** **d. Plot 2-Binary** **e. Plot 3** **f. Plot 3-Binary** **g. Plot 4** **h. Plot 4-Binary** **i. Plot 5** **j. Plot 5-Binary**

k. Plot 6

l. Plot 6-Binary

The resultant lacunarity distributions are separated into four groupings for presentation purposes. Group 1 shows extent sizes from 7m to 10m, Group 2 from 12m to 16m, Group 3 from 18m to 25m and Group 4 from 30m to 40m. All groups for Data Set #1 and only the 'optimal' group for each plot in Data Set #2a are shown in the results section. For brevity, the non-optimal groups for Data Set #2a are presented in Appendix A. The form of each distribution was interpreted to obtain an optimal spatial extent in the forest. The criteria for spatial extent optimization were:

- 1) The smallest extent that contains multiple scales of pattern.
- 2) If only one scale of pattern is present over all measured spatial extents, then the smallest extent that captures this quality was deemed optimal.
- 3) If the next extent grouping larger than the one under assessment contains more unique scales of pattern, then one of the extents in the next grouping was chosen.

The results obtained for each of the two different forest environments were assessed and a comparative discussion is given based on visible similarities and differences for the optimal spatial extent that was obtained in each case.

5.2.3 ESEM results

The following section describes the results obtained from the spatial extent model analysis. This section has been organized primarily based on objective, and secondly, by forest cover type.

5.2.3.1 Objective #1- Optimal sample plot spatial extent in two distinct forests

The results for each of the lacunarity analyses of the temperate hardwood data are presented in Fig. 5.6 and 5.7. Figure 5.6 shows the lacunarity slope curves for Site #701.

Figure 5.6 – Lacunarity slope functions for #701. The functions show the identified scales of pattern for the tested spatial extents. Optimal extent is the bold green line depicted in b.

c.

d.

The 8m and 9m spatial extents in Fig. 5.6a show two scales of pattern, one at 2.5m and the other (more subtle) at 5.0m. As the spatial extent is reduced, the pattern scale at 2.5m tends to dominate. The 7m extent (blue line in Fig. 5.6a.) detected one scale of pattern at 2.5m. The 16m-extent plotted as the black line in Fig. 5.6b shows two unique scales of pattern. The gradual trough between 5.5m-7.0m depicts the smallest pattern scale and the second pattern scale is centered at 13m. Recall from section 3.2, that a wide trough characterizes a broad range of continuous scales of pattern, whereas a narrow trough shows more discrete scales. As the extent is reduced to 12m, three scales of pattern become apparent at 2.5m, 5.5m and 9m (more subtle). The smallest scale, centred at 2.5m, tends to capture the brightest pixels of the smallest trees in this plot. These objects show up well when there is little or no interference from the dominant tree crowns in the imagery. The intermediate scale captured in this spatial extent occurs at 5.5m. It reflects the average size of the dominant tree crowns in the data but also includes intermediate canopy trees that are clustered together. The third scale found at this spatial extent occurred at 9m. In this type of forest, this scale of pattern may be reserved for very large crowns or clustering of the dominant tree crowns in the imagery. This spatial extent is the most appropriate extent for this site. The 14m extent also shows 3 object scales but not as distinctly as 12m. The 18m extent shown in green (Fig.5.6c) depicts two scales of pattern, one shown over a broad range between 6m-8m and the second at 14m. The 20m extent also captures the broad scale of pattern between 6m-8m but the larger scale is no longer evident as the red curve plateaus beyond 14m. The curves presented in Fig. 5.6d show that at larger

spatial extents, the plot pattern tends to be more homogeneous and the scales of pattern evident in Fig. 5.6 a-c become increasingly generalized. Figure 5.7 shows the lacunarity graphs for Site #702.

Figure 5.7– Lacunarity slope curves for #702. The functions represent the influence of spatial extent on scales of pattern. Optimal extent is the bold red line in b.

a.

b.

The slope function for the 7m extent presented in blue (Fig. 5.7a) reveals only one unique scale of pattern at 3m. The 8m and 9m extents exhibit two scales of pattern, the smallest between 2m-2.5m and the largest at 3.5m-4m. The black curve indicating an extent of 10m also captures two scales of pattern at 2.5m and 4.5m. As seen in Fig. 5.7b spatial extents of 14m and 16m (red and black lines, respectively) capture three unique pattern scales. The first scale is centered between 4m-5m, the second at 7.5m – 8.5m and the third between 12m-12.5m. The 14m spatial extent is optimal for this site as it is the smaller of the two. The smallest scale of pattern captured at this extent was 4m, which closely approximates the average crown size of intermediate trees (4.9m). The second scale captured was 7.5m, approximately equivalent to the average size of dominant trees. The largest scale of pattern detected was 12m, which could be related to the spatial clustering of dominant and intermediate tree crowns in the forest. The 12m extent only captures two scales of pattern at 3m and 6.5m. At spatial extents 18m – 25m, three scales begin to emerge from the pattern as shown in Fig. 5.7c. The red curve representing a 20m extent separates two smaller scale patterns out, one at 2.5m and the other at 6.5m. The third scale of pattern illustrated in this curve is centred at 11m, however crown sizes up to 14m are influencing this pattern as shown by the wide trough and gradual increase in slope after a ground distance greater than 12m. The black curve (25m extent) in Fig. 5.7c maintains the smallest scale pattern at 4.5m, while presenting another scale at 9.5m and one at 13.5m. Figure 5.7c also shows how the observed scales of pattern change with extent. At large extents, troughs are usually wider and tend to generalize the size

of objects within a pattern. Conversely, small extents tend to focus on specific objects that dominate the spatial pattern and measure object sizes with more specificity. At the 30m spatial extent, three scales of pattern are still observed. The second trough in the green line displays a broad range of scales indicating that object sizes are 12m-16m. Spatial extents greater than 30m tend to characterize two generalized scales of pattern centred at approximately 2m and 15m-17m, respectively.

The graphs presented in Fig. 5.8 are the results from the lacunarity analysis of boreal forest images characteristic of Data Set #2a. Instead of presenting results for all six plots multiplied by 13 extents, only the optimal spatial extent group is presented for each plot.

Figure 5.8 – Lacunarity slope curves for Kamiskotia plots 1-6 (a-f, respectively). The functions represent the influence of spatial extent on scales of pattern. Optimal extent is the bold line in each graph.

c.

d.

e.

f.

As shown in Fig. 5.8a, the optimal spatial extent derived for plot 1 was 14m with three scales of pattern at 4m, 6m and 7.5m. An extent larger than this would essentially retain two unique scales of pattern at the expense of sampling a larger area. An object size of 4m can be indicative of small intermediate deciduous trees or larger conifers that would be seen by the digital camera through the dominant forest canopy. These smaller tree crowns tend to dominate the grey-scale image. The average dominant tree crown size in this plot is 5.6m, which closely resembles the second scale of pattern measuring 6m. A spatial extent of 18m is optimal for plot 2 as revealed by the green curve in Fig. 5.8b. A spatial extent smaller than this optimum value would tend to generalize the smaller scaled objects. The two unique scales of pattern exhibited by this image occur at 4.5m and 9m on the ground although the trough of the green line extends up to 10.5m. According to the field measurements (Table 2), the tree crowns are larger and the image seems to exhibit a more clumped pattern than for plot 1. The two scales of pattern detected at 4.5m and 9m represent both intermediate tree crown sizes and intermediate-dominant tree cluster sizes, respectively. The results in Fig. 5.8c show an optimal spatial extent occurring at 18m in the image data for plot 3. The distinct break point at 3m would be generalized and rather undetectable at spatial extents larger than 18m as illustrated by the black line. The second scale of pattern indicative of this plot is centered at 10m. The smallest scale (3m) approximates the size of intermediate tree crowns in the image whereas the larger (10m) is again due to aggregation of intermediate-dominant tree crowns in the upper canopy. Figure 5.8d shows an optimal extent of 18m exists for plot 4. This image depicts three scales of pattern that were captured in the lacunarity analysis at

2.5m, 7m and 12.5m. A visual analysis of this plot reveals a large variability in crown size and this extent detected three scales of pattern at 2.5m, 7m and 12.5m, respectively. The intermediate scale of pattern measured in this plot overestimated the mean size of the tree crowns by 1.2m, whereas, the largest scale of pattern represented the clustering of these large tree crowns. Plot 5 showing an optimal spatial extent of 14m is presented in Fig. 5.8e. Three scales of pattern were captured in this image at 2.5m, 7m and 8.5m, respectively. Figure 5.8f shows the smallest spatial extent documented in this study, captured at 8m for plot 6. Two scales of pattern were found at 2m and 5m, the former characterizes individual tree crowns and the latter may be an underestimate attributed to intermediate tree clusters or dominant tree crowns.

5.2.3.2 Objective #2 - Comparison of spatial extent in two distinct forests

This section presents a summary of the optimal spatial extents derived for each forest cover type. The optimal spatial extents measured in the mixed forest of Gatineau Park ranged from 12-14m for both plots. These plots were dominated by sugar maple with scales of pattern ranging in size from 2.5m to 12m.

A larger range was determined in the boreal forest sites. Plots 2-4 characterized relatively large spatial extents at 18m, while plots 1,5 and 6 showed smaller extents ranging from 8m to 14m. Aspen trees ranging in size from 2m up to 12.5m dominated these plots. Table 5.1 shows the most appropriate spatial extent measured in Plot 6 was 8m, which is located furthest from the mine tailings pond. As one moves into the forest from the tailings/ forest boundary optimal spatial extents generally increase and decrease again with distance. This pattern could be caused by factors such as tree morphology, age or within-plot spatial association may account for the optimal spatial extent and scale of pattern differences calculated for each forest type. As older, dominant trees in the Kamiskotia site die off, large gaps are produced which in turn cause a clumped pattern at larger spatial extents. In most cases, understory tree crowns tend to add variability to the measured scales of pattern as they grow into and occupy these gaps. The smaller extents derived for the mixed hardwood site are due to the grouping of variable-sized tree crowns in a smaller space. This effect tends to minimize the importance of the understory component to the overall

spatial pattern. Also note that only three out of the six plots in the boreal forest revealed three scales of pattern (plots 1,4 and 5). Referring back to Fig.5.5g, plot 4 shows the presence of understory crowns growing into a large gap in the central portion of this plot. This figure also shows both medium crown sizes and dominant crown clusters surrounding the large gap. The small gap in the upper-left portion of this image also enhances the clumped pattern illustrated by this plot. A wide range of crown sizes is also illustrated in the Gatineau plots as they each show three unique scales of pattern. The Gatineau plots also showed more discrete object sizes when comparing the trough widths to the Kamiskotia plots. This could indicate a less amount of crown overlap at the canopy level or lesser contributions of understory to the observed spatial pattern. In summary, the optimal spatial extent seems to be dependent on the size of tree crowns and their arrangement in space. A larger spatial extent is needed to study the plots characterizing a clumped canopy pattern over the plots characterizing a more distributed spatial pattern. This is readily observed upon visual comparison of Fig. 5.5c to i.

Site	Optimal Extent	Pattern Scale
Gatineau		
701	12m	2.5m, 5.5m, 9m
702	14m	4m, 7.5m, 12m
Kamiskotia		
Plot 1	14m	4m, 6m, 7.5m
Plot 2	18m	4.5m, 9m
Plot 3	18m	3m, 10m
Plot 4	18m	2.5m, 7m, 12.5m
Plot 5	14m	2m, 6.5m, 8.5m
Plot 6	8m	2m, 5m

Table 5.1- Comparison of optimal spatial extents and scales of pattern determined for each forest type based on lacunarity analysis of remote sensing data.

5.2.3.3 Objective #3- Comparison of ESEM pattern scales with tree crown size measurements

Table 5.2 presents the comparison results of model pattern scales to ground-based measurements of tree crown size. No data were collected for intermediate tree crowns in the study sites located at Kamiskotia. The results in Gatineau Park show that the scales of pattern interpreted through lacunarity analysis have the ability to detect crown size in the forest although there is some mixing between ecological entities. Dominant tree crowns in plot #701 were detected from the remote sensing data as 9.0m, whereas in the field these crowns were measured at 7.8m. The intermediate scale of pattern recorded at 5.5m seems to reflect the size of intermediate crowns that were measured in the field at 5.0m.

Site	Image Data	Field Data	
	Pattern Scale	Mean Crown Diameter {St. Dev.}	
		Dominant	Intermediate
Gatineau			
701	2.5m, 5.5m, 9m	7.8m {2.3m}	5.0m {1.3m}
702	4m, 7.5m, 12m	7.2m {2.2m}	4.9m {1.4m}
Kamiskotia			
Plot 1	4m, 6m, 7.5m	5.6m {1.5m}	N/A
Plot 2	4.5m, 9m	7.1m {1.9m}	N/A
Plot 3	3m, 10m	7.2m {2.1m}	N/A
Plot 4	2.5m, 7m, 12.5m	5.8m {2.0m}	N/A
Plot 5	2m, 6.5m, 8.5m	5.1m {1.5m}	N/A
Plot 6	2m, 5m	6.4m {2.3m}	N/A

Table 5.2 - ESEM pattern scale with ground-based tree crown measurements.

The intermediate scale of pattern determined for plot #702 at 7.5m seems to coincide with dominant tree crown measurements on the ground (7.2m). The other scales of pattern approximate intermediate tree crowns (approximately 4m-5m) as well as mixed clusters of dominant and intermediate tree members (approximately 12m).

The lacunarity results over the six Kamiskotia sites show variable scales of pattern. The finest scales of pattern at these sites underestimate the dominant tree crown size measured on the ground. The largest scales of pattern that were identified in the lacunarity analysis were larger than the crown sizes. Again this could be due to crown mixing and overlap at the canopy level. In future study, more sample plots would be needed to separate out this influence.

5.2.4 Summary of ESEM

The results show that the ESEM would be useful as a preliminary step in a research project to obtain a basic description of the surface patterns that exist in the study area or to describe the approximate range of object sizes that comprise the pattern. The lacunarity results obtained for each forest type show differences in relative pattern homogeneity and in their determined scales of pattern. The results for both forests tended towards homogeneous spatial patterns at larger extents, particularly in the hardwood forest. The largest extents obtained in this analysis

captured a wider range of crown sizes. Upon visual inspection, there was also a noticeable influence of smaller sized trees where large gaps occurred in the upper canopy. The image data for Site #701 presented an optimal spatial extent of 12m. A sample window larger or smaller than this extent would lead to the analysis of a more homogeneous spatial pattern. There were three unique scales of pattern detected in this plot. The image data for Site #702 showed an optimal spatial extent at a window size of 14m where three unique scales of pattern at 4m, 7.5m and 12m were detected. The spatial extents obtained in the lacunarity analysis of the sample plots located in the boreal forest are quite variable from plot to plot. In plot 1, the optimal extent was 14m and captured three distinct object sizes of 4m, 6m and 7.5m. The optimal extents in plots 2-4 were all determined to be 18m. Plot 5 demonstrated how the grouping of smaller trees could form a relatively smaller spatial extent at 14m. This plot had the lowest average crown diameter and the grey-scale image shows many small tree crowns throughout. The scales of pattern for this plot were determined to be 2m, 6.5m and 8.5m. The last plot in the boreal forest analysis provided an optimal spatial extent of 8m. The average tree crown size measured 6.5m in this plot.

5.3 Study 2: Forest canopy pattern quantification

The second study assessed the usefulness of lacunarity to quantify forest canopy spatial pattern along a gradient of environmental disturbance. The research questions for this application was as follows:

Are there noticeable differences in canopy pattern with increasing distance from the tailings edge? Can these differences be quantified?

This was accomplished by comparing lacunarity analysis at a variety of distances from the Kam Kotia mine tailings to a homogeneous baseline pattern. This technique is commonly applied to test the usefulness of a certain metric for identifying variations in one pattern from another. Most methods are purely qualitative (Plotnick *et al.*, 1993), while others are quantitative (Zenner *et al.*, 2000). A measure of lacunarity deviation from homogeneity was determined for each of the plots based on the maximum difference in lacunarity over all measured box sizes.

The specific objectives of this study are to:

- 1) Compare lacunarity analysis of forest canopy spatial patterns to a randomly generated homogeneous pattern in order to assess the degree of heterogeneity with respect to distance from a contaminated mine tailings deposit.

- 2) Determine the direction and strength of association between lacunarity deviation from homogeneity and the standard deviation of tree stem size.

5.3.1 Field data

To test objective 2, tree stem diameter at breast height (DBH) was measured for each tree over 2m in height in each of the 40 sample plots representing Data Set #2b (see Section 4.2). The standard deviation in DBH was computed for each plot and compared to the deviation from homogeneity lacunarity measurements describing the forest canopy spatial pattern. A parameter such as DBH describes the structure of vegetation and should be related to the spatial pattern measured from a remote sensor. A plot showing a low standard deviation in DBH would contain similar sized trees, presenting a more homogeneous distribution of gaps throughout the forest canopy. Conversely, a plot exhibiting a large standard deviation in DBH would be more heterogeneous as the objects are more variable in size. In contrast to Study 1, no comparison between crown size and pattern scales was made in this study, since no tree crown measurements were available for Data Set #2b.

5.3.2 Image data

To develop an image-based approach to measure forest canopy spatial patterns, high-resolution remote sensing imagery was used from the boreal forest study site at

Kamiskotia, Ontario. Only the near-infrared reflective channel was analyzed and each plot was cropped covering a ground area of 20 X 20m (or 40 pixels) from the larger mosaic presented in Fig. 5.2. This spatial extent was larger than all the optimal extents (ranged 8m-18m) determined from Study 1 and although this size may contain a certain amount of data redundancy, it was considered to be an appropriate size to examine in this study. Scenes were cropped about the geo-referenced centre point defining each plot. A total of 40 sample plots were assessed in this work spanning all six transects. Transect A was sampled in 8 plots (10m, 85m, 110m, 210m, 310m, 410m, 510m, 710m), B and C in 8 plots each (10m, 60m, 110m, 210m, 310m, 410m, 510m, 710m), and D in only four plots (10m, 410m, 510m, 710m). Transect E was sampled in a similar manner to B without a plot at 710m and F consisted of 5 plots (10m, 60m, 110m, 210m, 310m).

5.3.3 Methodology to quantify forest canopy pattern

The methodology for this application was separated into two parts; 1) The preparation of 40 sample plot images and, 2) The creation of a template random homogeneous map. The first part begins on the left side of Fig. 5.9. The sample plots were extracted from the study site mosaic shown in Fig.5.2.

Figure 5.9 – Flow chart describing the methods to quantify canopy pattern.

In this study, the mean digital number could not be used to threshold the images (as in the last study) because the resultant maps would contain different occupational probabilities making it impossible to compare lacunarity measurements between them. So an alternative approach had to be considered. First, the mean and percentile were determined based on the histogram of digital numbers for each plot, as shown in Fig. 5.10. This figure shows the percentile of occurrence on the y-axis and the mean digital number plotted on the x-axis. Next, the maximum and minimum histogram percentiles (shown by the red and blue vectors, respectively) were determined as shown in Fig. 5.10. To ensure that the threshold value chosen was representative of all 40 plots, the middle value (54%) between the minimum and maximum percentiles was chosen. Binary maps were then generated for each plot representing 54% gaps and 46% tree crowns. Since the main goal of this study was to quantify forest canopy spatial patterns (both gaps and trees) against one homogeneous case, binary inverse images were not generated as they were for Study 1. In this study, the gaps were given a value of zero (0) and the tree crowns were assigned a value of one (1). For simplicity these maps are referred to as 'slaves'.

Figure 5.10 - Scatterplot of mean digital number versus percentile of occurrence for 40 sample plots.

The second part of the analysis is shown on the right side of Fig. 5.9. One rectilinear random map showing a homogeneous distribution of objects was created containing a 46% population of tree crowns. A perfectly homogeneous map could not be used since the population ratio must be consistent across samples to ensure that a comparison could be made on a plot-by-plot basis for all 40 sample plots. This homogeneous map is referred to as 'master'.

The lacunarity gliding-box technique was then implemented on all images. In all cases, the box size ranged from 2-28 pixels while holding the spatial extent constant at 40 pixels. The output of the lacunarity algorithm in this experiment is a gap size distribution based on an index, where a value of 1.0 is produced for a homogeneous (narrow) distribution of gap sizes and a value that deviates from 1.0 relates to a wider range of gap sizes. A high lacunarity will also result if the dataset contains large, heterogeneously distributed gaps.

5.3.3.1 Lacunarity: Deviation from homogeneity

To assess the degree to which the spatial pattern of each slave deviated from the master, a deviation from homogeneity metric was calculated. The lacunarity curve representing the forest canopy pattern from each slave was compared to the same

curve generated from the master. This comparison is illustrated in Fig. 5.11 using data from Plot A10.

Figure 5.11 – Deviation from homogeneity. a is the master and b is the slave. Black represents gaps in the forest canopy and the objects of interest in this study. White indicates trees.

This method measures the maximum difference between two points along each of the lacunarity curves as shown by the green arrow in Fig. 5.11. The master is shown in 5.11a and the slave is shown in 5.11b. After the maximum deviation from homogeneity was calculated over all slaves, this value was plotted against the corresponding ground distance from the mine tailings to infer forest patterns over the entire study site. The second part of the analysis attempted to relate the deviation from homogeneity metric to the standard deviation in tree stem size on the ground. Firstly, the standard deviation in diameter at breast height was calculated for each plot and graphed against distance from the mine tailings edge. Next, a scatterplot was generated to visually describe the relative correspondence between these two data sets.

5.3.4 Results

The results from this analysis are presented in the order of the objectives listed in section 5.3.1.

5.3.4.1 – Objective #1- Comparison between forest canopy spatial pattern and homogeneous pattern

Fig.5.12 illustrates the results for all six transects, representing 40 samples overall. Each point represents the maximum deviation in homogeneity in each slave pattern with respect to the master image.

Figure 5.12 – Comparison of measured maximum deviation from homogeneity versus distance from the tailings edge.

The distribution of points starts with a moderate deviation from homogeneity and increase very sharply as the distance approaches 110m. The plots located at 110m show a relatively high deviation from homogeneity indicative of dominant tree crown clumping and large gaps in the canopy. From 210m to 410m the points illustrate a gradual decline revealing a decrease in deviation from homogeneity at 410m. A relatively small range of gap sizes characterizes the plots located in this zone and the image patterns are quite homogeneous. The data after a distance of 410m reveal the presence of larger and more variable-sized forest canopy gaps with increased distance from the mine tailings. Clearly, there is an edge effect of the tailings but after 110m, the forest patterns fluctuate in degree of homogeneity about a line of zero slope.

5.3.4.2 – Objective 2- Comparison between forest canopy homogeneity and tree stem size

In an effort to link canopy gap size distributions to actual field data, this section presents the results obtained from the comparison between field-based measurements of DBH versus the deviation from homogeneity quantities derived from remote sensing data discussed in the previous section. Fig. 5.13 illustrates the mean (a.) and standard deviation (b.) in DBH measurements with distance from the mine

tailings for each plot. The mean DBH values generally increase with distance from the tailings as shown in Fig. 5.13a. All plots located between 10m-210m from the F/T boundary show an increase in mean DBH. Within this distance the standard deviation in DBH generally decreases and increases again as the distance from the tailings approaches 310m. Past 310m, mean DBH increases along several transects and decreases for others. The decrease may be due to the small, dense vegetation that occupies the wetland area in the centre of the study site. This region along Transects C and D, for instance, tends to be poorly drained and black spruce and understory trees such as balsam fir sparsely dominate the plots. All show an increased mean and standard deviation in DBH from 510m-710m.

Figure 5.13 – Mean (a.) and standard deviation (b.) in diameter at breast height (DBH) in relation to distance from the mine tailings.

To compare image pattern deviation from homogeneity to DBH deviation from homogeneity, a scatterplot of the standard deviation in DBH versus the maximum deviation from homogeneity is presented in Fig. 5.14.

Figure 5.14 – Scatterplot showing the relation between field-based measurements of tree stem size and the maximum deviation from homogeneity.

Although there is a significant positive relation between these two data sets, the strength of association is weak. The Pearson's r -value for this correlation is 0.55 ($p < 0.001$) indicating that although there are commonalities between data sets, the deviation from heterogeneity index fails to explain much of the variability (only 30%) inherent in the standard deviation in DBH on the ground.

5.3.5 Summary of forest canopy pattern quantification

The second objective of this thesis was to measure the spatial pattern of a forest canopy and how this pattern deviates from a homogeneous case based on distance from a mine tailings pond. The image-based lacunarity results were then compared to the homogeneity of tree stem size measurements on the ground. The results show a general trend towards increased heterogeneity with distance from the mine tailings. The sites located adjacent to the tailings (10m) showed spatial patterns that deviated moderately from the homogeneous image. Many small tree crowns and shrub vegetation dominate this boundary. The overstory is quite open resulting in a thick layer of shrub and ground vegetation, which leads to a more homogeneous spatial pattern at this close proximity to the tailings. These results also show the presence of an edge effect at the F/T boundary. At distances greater than 500m from the tailings edge, the forest canopy generally becomes more heterogeneous, as the variable-sized tree crowns compete for light and other essential nutrients at the canopy

level. Although DBH statistics showed similar correspondence to the trends described above, the forest canopy deviation from homogeneity captured only 30% of the variance in the standard deviation in DBH.

CHAPTER 6 - Discussion

This chapter presents a discussion of the significant findings obtained from this research and highlights some limitations inherent in the procedure.

6.1 The significant findings of this research

The significant findings of this research are threefold:

- 1) Development of an empirical spatial extent optimization tool using remote sensing data.
- 2) The detection of various scales of pattern within a natural forest canopy.
- 3) Forest canopy spatial pattern quantification for multi-spatial / temporal analysis.

The development of an empirical spatial extent optimization tool using remote sensing data has utility in a wide range of earth science applications from the mapping of biological communities to aiding in forest management practices. In forestry alone, spatial extent optimizations for field-based studies are still not considered in great detail and sample plots are often established without explicit consideration of the inherent variability of the phenomenon under investigation. In this research, it was found that a plot size of 18m X 18m would capture at least three scales of pattern in a

highly variable boreal forest, while a plot size of 12m-14m was sufficient to capture three scales of pattern in a less variable temperate hardwood forest. In both forest types, it was more efficient to choose a smaller spatial extent that captured most of the spatial variability in the plot rather than a larger one that would capture literally the same amount of information but at the expense of including much data redundancy. In essence, these results have true physical meaning (they can be interpreted in metres on the ground) and are representative of the forest types for which they were derived. Furthermore, the results obtained for the temperate hardwood site correspond well to an earlier study using semivariance analysis, in which optimal plot sizes ranged from 9m to 12m (Butson and King, 1999). Although semivariance and lacunarity analyses may yield similar results, the latter has the advantage of isolating one or more object scales.

Lacunarity spatial analysis has the ability to detect various information hierarchies inherent in a remote sensing pattern. As a natural system is composed of many, variable sized objects, such an analysis tool is useful for highlighting spatial scales that dominate a particular pattern. In this study, the scales of pattern detected in both forests added a dimension to the spatial analysis of forest canopies that is related to individual tree crown and crown cluster sizes.

Lastly, a technique to quantify forest canopy heterogeneity has been proposed using lacunarity analysis of high-resolution remote sensing data. Often the first step in modelling natural systems is to try to discern and quantify visually different spatial

patterns. The terms homogeneous and heterogeneous are often used in a qualitative sense, and have little meaning outside the main context for which they were proposed. By quantifying these terms, increased knowledge can be gained based on relative associations that exist within the data set under investigation. In this research, methods were developed for evaluating the deviation from homogeneity of canopy spatial patterns with respect to distance from a mine tailings deposit. Plots directly adjacent to the tailings generally exhibited a lower deviation from homogeneity than plots farther away. This was indicative of the variation from highly damaged, open forest near the tailings, which had a larger, younger understory component, to undamaged, more closed forest of older trees farther from the tailings. The deviation from homogeneity index can also be linked to physical parameters of the forest such as the variability in tree stem size. Measured over 40 samples, the correlation coefficient between the maximum deviation from homogeneity to standard deviation in DBH equaled 0.55.

6.2 Research limitations

Although several research limitations have been documented in various sections of this thesis, this section highlights the main assumptions incorporated into the lacunarity analyses performed in this study and provides suggestions for future research. Three of the most important limitations were:

- 1) Robust thresholding techniques.

- 2) Scale comparisons using a variety of hierarchically generated random maps.
- 3) The need for more ground-based validation data representative of forest canopy structural characteristics.

Image digital number thresholding is a science in its own right and the fundamental idea behind most image segmentation techniques (Pal and Pal, 1993). A major limitation in the first lacunarity analysis (to determine optimal spatial extent) was the use of a global mean digital number as the threshold to segment forest canopy trees from gaps. Since lacunarity is dependent on the density of the observed pattern, the mean digital number was used to separate the pattern effects from canopy density. Since the mean digital number varied for each plot, this value was thought to be representative of the intrinsic variability that exists at each plot. The second lacunarity analysis also incorporated a rather arbitrary threshold level for all scenes based on the middle percentile (54% gaps, 46% trees). This decision was made after initially testing of various threshold levels. Therefore, any extension of this work should consider the analysis of various threshold levels and the influence that such variations have on the final outcome of the work. For example, one approach would be to use ground-based measurements of tree crown size in a bottom-up framework matching them with lacunarity scales of pattern derived empirically for many threshold levels. When the lacunarity scales of pattern matched those values measured on the ground, the given threshold would be used.

The second limitation to the analysis presented in this thesis deals with the construction of a randomly generated, homogeneous map. Ideally, maps should have been generated in a multi-scaled fashion for each plot instead of using just one master homogeneous image to which all plots were compared. The advantage of using a hierarchical master map would be to examine at what specific scales the slave pattern deviated most from the homogeneous master pattern. Such information was not within the scope of the current study but may be useful in an extension of this work.

The third constraint in this work was in the limited amount of ground data that were available and coincident with the remote sensing coverage. At the outset of this research design, leaf area index and canopy clumping were to be the main field variables. However, data collection of these parameters during the field campaign failed due to a combination of human and instrument error. Only DBH data were available for Data Set #2b and intermediate tree crown sizes could not be a part of Data Set #2a due to time constraints.

In essence, the methods and results of this study represent new research and thus, much development and work was required. The scope of testing and evaluation was therefore limited to relatively small patches of forest in 2 different forest types. The procedures developed should be tested over a wider range of forest conditions and land cover types to add greater reliability to the methods and enhance the results obtained in this study.

CHAPTER 7 – Conclusions

With increasing use of remote sensing in monitoring of forest ecosystems, very little consideration has been given to spatial pattern analysis and the validation of such patterns in the field. Also, the use of spatial pattern characteristics to aid research design, including sampling, spatial resolution and coverage is still in exploratory stages. Both of these aspects have been addressed in this thesis using spatial pattern analysis of high-resolution remote sensing data over two forested areas in Canada.

The first objective of the thesis developed methods for the determination of optimal sampling spatial extent in natural forest systems. This is an important aspect of research design, as it becomes increasingly inefficient to sample over larger and larger areas. Over sampling in a study area produces data redundancy, wastes time and is costly. To determine optimal sampling spatial extents in a natural forest, lacunarity analysis was performed on two high-resolution remote sensing data sets over previously established sample sites. Using an empirical approach, spatial extents from 7m to 40m were examined and the optimal spatial extent was determined to be the smallest extent characterizing multiple scales of pattern. A subsequent analysis was then done to compare the observed scales of pattern to measurements of tree crown size collected in a ground-based inventory campaign during the same growing season. The results showed an optimal spatial extent in a mixed hardwood forest to be 12-14m while in the boreal forest it was more varied, 8-18m. The larger extents found

in the boreal forest are caused by a wider range of crown sizes and the arrangement of these crowns in the plot. The scales of pattern calculated for the mixed forest scenario show good correspondence to the dominant and intermediate measurements of tree crown size. The calculated scales of pattern often overestimated the tree crown size measured in the field and instead represented clumps of dominant and intermediate trees.

The second objective in this thesis addressed the need to quantify forest canopy spatial pattern and relate image patterns to forest structure. Lacunarity analysis was used to quantify the image spatial patterns of the boreal forest under stress from mining activities. The forest adjacent to a large tailings deposit had undergone extensive degradation since the 1970's. It was assumed that a forest canopy pattern analysis would reveal spatial characteristics of the degradation based on distance away from the contaminated source. The results show canopy gap sizes to be more homogeneously distributed closer to the mine tailings than the canopy gaps further removed. However, a comparison between deviation from homogeneity and the standard deviation in DBH of dominant trees led to only a moderate correlation.

Lacunarity analysis of high-resolution remote sensing imagery has provided insight into boreal and temperate hardwood forest spatial patterns. The analysis can not only isolate unique scales of pattern, which reflect object sizes in the field, but it can also aid in optimal sample plot size determination in a forest system for which

field data may not be available. For these reasons, such a technique has a clear advantage over other spatial pattern methods.

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APPENDIX A - Sub-optimal spatial extent groups for the Kamiskotia study site**PLOT 1**

PLOT 2

PLOT 3

PLOT 4

PLOT 5

PLOT 6

APPENDIX B - Lacunarity source code written in C++

```

int CMac2Dlg::process(int ROWS, int COLS, int RMIN, int RMAX, int data_type)
{
    // load array with image pixel values from binary file pointer 'BIN_in2'
    for (i=0;i<=(ROWS-1);i++) {
        //initialize counter
        for (j=0;j<=(COLS-1);j++) {
            z = fgetc(BIN_in2);    //48 = 0 in ASCII code

            Array[i][j]=z; //create matrix of pixel values
        }
    }
    Rmin=RMIN;
    Rmax=RMAX;

    for (r=Rmin;r<=Rmax;r++) {    ///start of big for loop of box sizes (r)

        count=0;
        funROWS = ROWS;
        funCOLS = COLS;
        boxsize=r;
        ///over a range of box sizes

        unsigned long int max = (funROWS-boxsize);

        for (x=0;x<=max;x++) { ///move the box along i and j
            for (y=0;y<=max;y++) {

                m=0;    ///initialize m counter
                for (i=x;i<=x+boxsize-1;i++) { ///assign box
                    for (j=y;j<=y+boxsize-1;j++) {

                        linematrix[m]=Array[i][j]; ///output window in 1-D

                        m++;
                    }
                }
            }
        }
    }
}

```

```

unsigned long int first=0, last=m-1;

/////if to process variable data_types(1==binary, 2==8-bit)
/////
if(data_type==1) {/////for binary data
unsigned long int s = sum(first, last, linematrix);
LACsum[r][count] = s;      ///collect sum of each particular box (counted with
                           'count', ///for r box sizes
}

count++;

}
}      ///end of x loop

} ///end of r loop

///start interactive lacunarity analysis for the range of box sizes/////

for (r=Rmin;r<=Rmax;r++) {      ///start of big for loop of box sizes (r)

    ///Mking 1-D matrix/////
    m=0;
    unsigned long int square = (ROWS*COLS);

    unsigned long int MAXcount = (ROWS-r+1)*(ROWS-r+1);

    ///*****ZERO ALL INTERACTIVE MATRICES*****/////////
    n = square;
    zero(linematrix, n);  ///zero linematrix

    ///*****CREATE 1-D MATRIX*****/////////

    LINE( r, MAXcount, linematrix, LACsum); ///1-D linematrix using LACsum array

    ///SORTING 1-D MATRIX/////

    n = MAXcount;
    sort_fun(linematrix, n);  ///sort linematrix

    /// Generating HISTOGRAM/////////

```

```

n = MAX;

zero(value, n); ///zero histo matrices
zero(cnt, n);

unsigned long int max= MAXcount;
////////////////////
unsigned long int NEWmax = Histogram(max, linematrix); ///get histogram of
linematrix
////////////////////
///function returns m counter and two filtered matrices....NEWvalue[], NEWcnt
////////////////////
first = 0, last = NEWmax-1;    ///get sum of NEWcnt[] for future use
unsigned long int freq = sum(first, last, cnt);
m=0;

unsigned long int MAX1=last;

////////*****LACUNARITY CALCULATION*****////////
n=MAX;
zero3(PROB, n);    ///call to float zero function
zero3(LACMEAN, n);
zero3(LACVAR, n);

m=0;
k=0;
kk = freq;
/**get probability matrix**/
for (i=0;i<=MAX1;i++) {
    q = cnt[i];
    PROB[i] = (q)/(kk);    ///generate prob
}

m=0;
k=0;
/**get first moment matrix**/

for (i=0;i<=MAX1;i++) {
    k = value[i];

    LACMEAN[i] = (k * PROB[i]);

```

```

}
m=0;

/**get second moment matrix**/

for (i=0;i<=MAX1;i++) {

    qq = ((value[i])*(value[i]));

    LACVAR[i] = (qq * PROB[i]);

}

////////*****get SUMMATIONS for LACMEAN and LACVAR*****////////
first = 0, last = (MAX1);
double mean = sum2( first, last, LACMEAN);
double variance = sum2(first, last, LACVAR);

double mean2 = mean * mean;

LACUNARITY = 1+ (variance/mean2);

}////end of R interactive

}///end of process

```