FOREST CHANGE DETECTION AND MAPPING IN GATINEAU PARK, QUÉBEC,
1987 TO 2010 USING LANDSAT IMAGERY

By

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Abstract

Remotely sensed observations can be used to infer landscape dynamics, however the reliability of detected change depends on the spatial and temporal resolution of the data. The goal of this research was to detect both abrupt and subtle change within the forests of Gatineau Park, Québec, by integrating ground-based measurements with Landsat imagery. Thirty three 1 ha field plots were surveyed with respect to vegetation quantity and health during the growth season of 2010, and thirteen near-anniversary Landsat TM 5 images from 1987 to 2010 were assembled into a relatively calibrated image time series. Regression of 2010 Landsat derived vegetation indices against the field data helped aid interpretation of the spectral trends extracted from the image time series. Results show distinct localized spectral trajectories due to gradual forest deterioration or regrowth. Mapping the timing, location, magnitude, and duration of forest change will help inform land management policy and actions within Gatineau Park and other similar landscapes.

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1.0 Introduction

Forest landscapes are constantly changing as a result of natural and human-induced disturbances, as well as seasonal and successional dynamics (Spies, 1998). A disturbance event interrupts forest succession; depending on the type, magnitude and duration of the event, structural and compositional forest change can occur at a range of scales in space and time (He et al., 2011). For example, distinct and abrupt changes are often associated with a forest fire or clear-cut, while more subtle changes occur as a result of decay, minor damage, natural succession and progressive growth following a disturbance (Gomez et al., 2011).

Forest recovery rates are often site- and species-specific. The resulting forest can be quite similar to prior conditions; however some change may permanently alter local habitat characteristics and ecosystem function. With sustainability as a primary goal for resource and environmental managers, improved monitoring methods are in high demand, especially for large tracts of land that require informed decision making. Understanding forest patterns, trends and rates is essential for their preservation and may help to assess the effectiveness of different management approaches (Paolini et al., 2006).

Monitoring to detect change is a process whereby a difference in the state of an object or phenomenon is identified through observations made at different points in time (Singh, 1989). At regional or global scales this can be a difficult task, especially if ground-based observations are the only data source available. At these spatial extents, remotely sensed data are generally preferred. Compared to ground-based data, they are spatially extensive and can be frequently obtained (Innes and Koch, 1998).

Measurements made on the ground, however, continue to provide invaluable information, and are often integrated with remote sensing techniques for model development, validation, and quality control. This integration helps to reduce on-the-ground sampling requirements. In addition, if ground-based data are available, physically meaningful interpretations of the remotely sensed data can be achieved through empirical methods (He et al., 2011).

The focus of this research was to integrate field data with remote sensing techniques to identify gradients of forest ecosystem change in Gatineau Park, Québec using a Landsat Thematic Mapper (TM) 5 image time series. This remote sensor is commonly used to detect and monitor human activity and community-level vegetation dynamics (Coppin et al., 2004).

Abrupt changes within a landscape are often referred to as land cover conversions, and can be detected with acceptable accuracy using imagery before and after the event. Detecting subtle land cover modifications, however, continues to challenge the remote sensing community (Lu et al., 2004). This is because variability within the atmosphere, as well as errors related to image alignment, make it difficult to distinguish between spectral image characteristics related to ecologically relevant change and noise from the sensor, environmental effects (atmospheric, topographic) and data processing (Song et al., 2001; Schroeder et al., 2006).

Persistent and cumulative subtle changes, taking place across consecutive growth seasons, may progress towards a land cover conversion. Therefore, the ability to remotely detect and map subtle change trajectories in addition to abrupt changes would help to

inform the decisions made by environmental and resource managers. Use of image time series has been suggested in the literature as a means to improve the precision in which change can be detected (He et al., 2011). This is because multiple remotely sensed image acquisitions of the same region across time can be used to identify trends within a landscape that would likely be undetectable using two image dates.

The main premise for optical remote sensing as a tool for monitoring forested landscapes is that a change in forest composition, structure and health can be represented by a change in spectral reflectance or image texture (Lu et al., 2004). Using information from different wavelengths, the spectral reflectance of a particular location can be used to infer the type of land cover, and its state, during the time of image acquisition (Vogelmann et al., 2009). Texture variables describe signal variations across space, and can be used as spatial indicators of horizontal variations in canopy architecture or species composition (Wulder et al., 1998). A spectral or spatial change between image dates can be used to quantify forest change, but the precision with which change can be detected is largely dependent on the ability to remove radiometric errors from the imagery (Coppin et al., 2004).

Atmospheric effects represent one of the most significant radiometric errors in change detection (Chavez, 1996). Research efforts are working towards developing effective and operational procedures to remove them. The goal is to derive reliable estimates of surface reflectance across space, but for an image time series, a ‘common’ radiometric scale is most important (Schott et al., 1988; Song et al., 2001; Schroeder et al., 2006). Each image date should appear as though it was acquired using “the exact same camera settings” (Coppin et al., 2004); day-to-day variability within the atmosphere

makes this difficult. As radiant energy travels through the atmosphere, gases and aerosols scatter, refract or absorb it; this modifies the signal received by a sensor, and therefore, reducing atmospheric effects is generally a mandatory step for most change detection applications.

A wide range of remote sensing change detection techniques exist, but opinions vary with respect to which are most effective. Depending on the scale and the objective of a particular application, certain techniques or sensors may be more appropriate. Coppin et al. (2004) and Lu et al. (2004) both provide comprehensive reviews of the techniques commonly used to 2004. Comparing their work to a similar review published by Singh (1989) indicates that the techniques used in the early 1980s were quite similar. Until recently, data availability and imagery costs often limited research to detecting change using two near-anniversary dates. These bi-temporal change detection techniques are emphasized in the literature, and have been reported as being effective for detecting abrupt land cover conversions, or reporting on the overall net change within a landscape across a given time period (Coppin et al., 2004).

Now that the Landsat satellite archive is freely available, community-level forest monitoring has become increasingly feasible. Cohen et al. (2010) states that dense Landsat image time series (LTS), composed of multiple image dates, are expected to become the norm. The Landsat archive, which began in 1972, provides near-global coverage every 16 days and is the longest running remotely sensed data archive available (Xie et al., 2008). Since the opening of the Landsat archive, in January 2009, a few studies (Vogelmann et al., 2009; Powell et al., 2010; Cohen et al., 2010) have confirmed that a LTS is capable of detecting the spatial distribution of subtle and abrupt inter-annual

forest changes, however they suggest that field data are necessary to corroborate evidence of change and understand how a particular image variable can be used to interpret a particular landscape (Gomez et al., 2011). This movement towards temporal trend analyses, largely facilitated by the Landsat archive, will certainly lead to an improved understanding of ecosystem dynamics and management strategies. It formed the foundation of this thesis research.

1.1 Objectives

The goal of this research was to detect a gradient of changes within Gatineau Park's forested ecosystems and to determine causal factors responsible for the detected changes. A change in vegetation quantity is considered to include changes in live green biomass, and is assumed to be a result of anthropogenic or natural factors. Sudden or gradual differences across time may be related to changes in vegetation quantity or ecosystem health. The specific research objectives were to determine:

- 1) statistically significant relationships between ground-based estimates of vegetation quantity and Landsat TM 5 satellite imagery;
- 2) the location, direction, timing, and magnitude of spectral change within Gatineau Park's forests;
- 3) the vegetation communities being impacted, the magnitude of the impacts in terms of vegetation change (based on the relationships developed in Objective 1) and the causal agents of vegetation change.

2.0 Background and Theory

Forested ecosystems are dynamic, and changes occur as a result of natural and human-induced processes. Monitoring a forest requires repeat observations, and therefore efficient and effective methods are necessary. Ground-based observations can be very precise, but also time consuming, whereas Earth observations are spatially extensive, but can be associated with high levels of uncertainty. Both data sources have advantages, so integrating them together is a primary objective of this research. This chapter describes how the structure of a forest can be used to infer its state at a particular moment in time, and discusses the main premise for optical remote sensing as a tool for forest monitoring. A summary of the remote sensing techniques relevant to this research is also provided.

2.1 The dynamics of a vegetated surface: process-form relationships

From the perspective of a remote sensor, a forested landscape appears as a mosaic of unique forest patches that can be characterized by composition and structure. The current state of a patch influences the spectral radiance received by a remote sensor (Lu et al., 2004), and is considered to be a product and driver of ecosystem function, and largely a result of the historical disturbance regime (Odum, 1974; Spies, 1998; Zenner and Hibbs, 2000). While the composition of a forest patch refers to the diversity of its species, the three-dimensional arrangement of biomass defines its structure. These forest characteristics are highly interconnected; a structural change caused by a disturbance event for, example, may alter functional processes that eventually lead to a shift in species composition (Oliver, 1981).

This natural phenomenon is widely referred to as ecological succession, but it is not a straightforward or linear process. Successional changes involve stochastic disturbance events and a complex interaction of processes (Oliver, 1981). Species-specific tolerances to temperature, nutrient levels, light and moisture are frequently reported as the main controls on vegetation dynamics. More specifically, temporal shifts in species dominance are strongly associated with a change in the availability of light as a resource, whereas spatial transitions in species composition often relate to the moisture gradient of a landscape (Smith and Huston, 1989).

Smith and Huston (1989) modeled vegetation dynamics using the general principles of a cost-benefit analysis. Their model ignores reproduction and focuses on productivity as the main currency. They state that a trade-off exists for species capable of tolerating areas where resource availability is low. While many species thrive where resource availability is high, some species prefer reduced exposure. Herein lies the trade-off: as a result of competition many species are forced to grow in less than optimal conditions, the species that are tolerant of a range of conditions have a competitive advantage.

Oliver (1981) summarized the progression of events that occur after an abrupt disturbance, which they refer to as an event that essentially clears all living trees from an area. In terms of forest succession, such an event can be viewed as a 'starting point'. Following an abrupt disturbance, the development of a forest can be divided into four progressive seral stages: stand initiation, stem exclusion, understory reinitiation, and an old growth stage. Figure 1 illustrates the compositional and structural changes that occur between each stage. It should be noted that an abrupt event, as defined by Oliver (1981),

may force an area into the stand initiation stage, however, less severe events may also cause a setback to the natural progression of forest succession. Following a disturbance, if persistent/resistant trees remain, they influence future forest development.

Figure 1: Schematic diagram of stand development following a major disturbance (Oliver, 1981).

During the 'stand initiation stage', pioneer tree species compete for growing space. They colonize a relatively vacant area by sprouting from existing roots and stems, and from buried or dispersed seed. Certain species are better suited to the initial environment, or exhibit fast early growth rates; these species are expected to become the first dominant overstory species (Species 'A' in Figure 1). Persistent understory species may eventually become the new dominant species (B) if their growth rates exceed that of the first overstory species. If species 'A' is intolerant of shade, local extinction is inevitable and eventually they become competitively excluded from the stand. The slower growing shade tolerant species (C and D) persist within the understory, and eventually form a distinct sub-canopy layer.

Over time, conditions may support entry of new shade tolerant recruits. This 'understory reinitiation' stage is characterized by a forest structure with three distinct canopy layers (as seen in Figure 1). Available light is low for this new cohort, and as a result, its growth rates are often suppressed. Local disturbances, however, may create canopy gaps that change the light conditions, and promote the release of a single, or a few understory trees into the top layers of the canopy. These successional dynamics and stochastic changes eventually lead to 'old growth' conditions, which are distinctive in that compositional and structural characteristics remain relatively stable over both space and time. This dynamic equilibrium persists until another destructive disturbance event occurs.

Not all forest disturbances, however, are considered destructive and abrupt. Some forest change is temporary and may occur as a result of seasonal anomalies related to weather, storm damage or insect defoliation, amongst other processes. These changes

alter forest structure during a single growth season, but recovery is often observed the following year. Cumulative perturbations as a result of insects, pollution, climate change, recreation and overuse, however, may gradually lead to significant long term changes in forest structure and composition. Initially these changes may not be noticeable, but in some cases they become irreversible. Early detection for some forest changes may be necessary to successfully mitigate them.

Given the spatial and temporal variability of most disturbance regimes and environmental controls, forested landscapes are inevitably dynamic. Changes may be associated with an abrupt or gradual change in vegetation quantity or health, and some forms of change may not be obvious on the ground or from remotely sensed imagery (Vogelmann et al., 2009). This research was intended to evaluate the utility of a Landsat image time series, for detecting structural changes related to vegetation quantity within a temperate forest environment.

2.1.1 Inferring the state of a forest using structure as an indicator

Mapping and monitoring forest structure is an important remote sensing application, and is commonly conducted using visible and infrared imagery combined with field data. Powell et al. (2009) modelled aboveground forest biomass using a Landsat time series and field data, and compared several empirical modelling approaches. Eklundh et al. (2003) investigated the utility of Landsat TM data for estimating leaf area index (LAI); and Pasher and King (2011) used high resolution airborne imagery to develop a multivariate representation of structure that they refer to as ‘forest complexity’.

Forest structure has also been modelled using other remotely sensed data sources such as LiDAR (Light Detection and Ranging), or RADAR, however these data are comparatively expensive. For example, Hopkinson and Chasmer (2007) modeled canopy gap fraction using LiDAR, and Frazer et al. (2011) investigated the accuracy and uncertainty of LiDAR-based estimates of forest stand biomass. Hyde et al. (2006) used LiDAR, RADAR and optical data to map forest structure for wildlife habitat analysis.

The space occupied by biomass defines the structure of a forest and can be broken down into several structural attributes. McElhinny et al. (2005) provide a detailed list and discuss the ecological importance of each one. Structural attributes can be defined at a range of scales, and are often measured in terms of abundance, richness, size and variation. For medium to coarse resolution remote sensors, structural attributes should be considered at the community-level; it would be difficult to meaningfully integrate ground-based data obtained at finer scales. Given the resolution of the imagery used in this research, fine-scale structural attributes that describe tree branch characteristics or leaf shape, as examples, will not be discussed. Spies (1998) outlined four particularly important community-level categories that can be used to infer forest structure as it relates to vegetation quantity and health:

- 1) live tree size and age distribution
- 2) vertical foliage distribution
- 3) horizontal canopy distribution, and
- 4) dead wood or coarse wood debris (CWD)

The heights as well as the diameter at breast height (DBH) of each species included within a forest inventory are commonly used to estimate tree size. DBH data are

often preferred since they can be acquired through relatively reliable and efficient methods, and through allometric models can often be used to estimate the height and age of a forest (Ritson and Sochaki, 2003). For even-aged stands, diameter distributions follow a narrow bell-curve, especially when compared to older uneven-aged forests. An old growth forest exhibits a relatively wider distribution and often reveals a few peaks that correspond to the cohort of an understory re-initiation event (Figure 1). So, unique distributions can be used to objectively determine the seral stage of a forest (Spies, 1998). The main assumption is that the variability in diameter data reflects the variability in height and age; however these relationships are site-specific, and require local knowledge of the growth rates and vegetation dynamics typical of an area (Lahde, 1999).

Latham et al. (1998) demonstrate that DBH variance can also be used to indicate vertical canopy layering. This helps to emphasize the strength of diameter data as a structural indicator, and illustrates the notion that many attributes of a forest are well correlated.

Given its ecological importance, assessing the foliage distribution of a forest has become a distinct research interest. Early research by MacArthur and MacArthur (1961) showed that a structural attribute, which they referred to as foliage height diversity (FHD), was an important predictor of bird species diversity. The underlying notion is that the arrangement of foliage controls the availability of light, temperature and moisture. A forest with a diverse arrangement of foliage also provides a variety of habitats, and is therefore capable of supporting a diversity of species.

Unfortunately, for most studies, inferring a foliage distribution requires more detail than provided by DBH data alone (Pasher et al., 2007). Since the idea of FHD was

initiated, its ecological meaning has been reconceptualised by many authors (McElhinny et al., 2005). There seems to be no standard methodology for its measurement, but, it is widely agreed that structural attributes related to the distribution of foliage serve as surrogates for many biophysical processes, and can be used to infer vegetation quantity.

Changes in vegetation quantity can occur in both vertical and horizontal directions, and may indicate deteriorating or growing conditions. As ecological succession progresses, the vertical foliage distribution tends to increase in height and evenness, horizontal canopy gaps become larger and close more slowly (Spies, 1998). In the absence of a disturbance, a forest stand tends to accumulate live biomass; but following a disturbance event, a decrease generally occurs in vegetation quantity that is proportionate to the magnitude and duration of the event.

Coarse woody debris (CWD) has also been cited in the literature as an important community-level structural attribute (McElhinny et al., 2005). This is because CWD, found standing or lying on the ground, serves as important habitat for both birds and invertebrates. It also contributes to ecosystem functions such as soil development, water storage, and nutrient cycling. Its role as habitat, however, is more thoroughly understood (Spies, 1998). The presence of CWD and its relative abundance can be used as an indicator of past disturbance events. Harmon et al. (1986) points out that the distribution of CWD represents a balance between additions and losses. While tree mortality or damage increases the amount of CWD, losses occur through decay, fragmentation, and transport. The density of CWD often increases as a forest ages, but the highest amounts are often found in young forests recovering from an abrupt disturbance (Spies, 1998).

In combination, characterizing a forest with respect to its tree size distribution, vertical and horizontal foliage distribution, as well as the arrangement of CWD can help to compare between different forest patches. These forest traits may also help to identify the seral stage of a forest and can be used as indicators of growing or deteriorating conditions. Objective estimates of forest structure are preferred, however for most remote sensing studies a balance between sampling time and the level of detail required are important considerations. Depending on the research question and available timeframe for data collection, certain methods are more feasible than others.

2.1.2 Direct and indirect measurement of forest structure

The ability to measure forest structure accurately, efficiently and close to the time of acquisition of remotely sensed data is crucial if the goal is to correlate ground-based observations with remotely sensed data. Direct methods provide accurate and precise data, however, they are time consuming and difficult to implement for large scale applications. In addition, depending on the research question and the level of detail required, direct estimates may not be necessary. Indirect methods are becoming increasingly popular since they provide a rapid and non-destructive means to assess forest structure (Breda, 2003; Jonckheere et al., 2004).

Rhoads et al. (2004) state that visually estimating forest damage or vegetation quantity may be adequate for broad-scale applications, but these techniques are subjective, biased, and difficult to compare between studies. Leaf area index (LAI) is commonly used as a ground-based estimate of vegetation quantity, and can be used to interpret the distribution of foliage within a forest. It is a unit-less index defined as the

total one-sided area of all photosynthetic tissue per horizontal unit area of ground (Jonckheere et al., 2004).

Traditionally, direct estimates of LAI were acquired through measurement of leaves following harvesting or litter trapping. Assuming lateral homogeneity, representative forest patches, or single trees, are strategically selected and estimates of LAI are interpolated across space. Although these techniques are considered accurate, they are not compatible for large area applications, or seasonal monitoring. Research continues to make use of direct estimates, but for the purpose of calibrating indirect methods.

Indirect estimates of LAI are commonly inferred by measuring the amount of light that transmits through the canopy of a forest (Leblanc et al., 2005). Because leaf orientation is highly variable, and the leaves of most tree species are not perfectly flat, LAI estimates derived through optical methods are defined as half the total one-sided area of all leafy material per unit area of ground. This definition is based on the mean angle of a spherical canopy surface. Optical methods use the Beer-Lambert law to model canopy transmittance as:

$$P(\theta) = e^{-G(\theta)PAI / \cos(\theta)} \quad (1)$$

where θ is the zenith angle of view (generally between 0 and 60°), $P(\theta)$ is the canopy gap fraction (percent (%) sky), $G(\theta)$ is the mean projection of foliage perpendicular to θ , and finally PAI (plant area index), is a measure of both leafy and woody tissue (i.e. $PAI = LAI +$

WAI). Techniques are now available to estimate $P(\theta)$, and allow for the inversion of Equation 1 to estimate PAI (Chen, 1991):

$$PAI = (P(\theta)\cos(\theta)/G(\theta)) \quad (2)$$

Unfortunately, this inversion technique assumes a Poisson distribution, and therefore a random arrangement of foliage elements. This assumption violates reality, and in addition, true LAI estimates are not represented by Equation 2 since woody tissues are included. For these reasons, Chen and Black (1992) redefined PAI as effective LAI (LAI_e), a term that recognizes that inversion models ignore the non-random components of a forest canopy, and are incapable of differentiating between leafy and woody tissue. Correction parameters have been developed to compensate, but only a few instruments are capable of collecting the required data (Breda, 2003). Regardless, optical techniques provide meaningful and rapid proxies of vegetation quantity.

Nilson (1971) introduced a correction parameter known as the clumping index (Ω_c), which describes non-random canopy components and is based on the canopy gap size frequency distribution. Chen (1996) showed that when combined with a clumping index, indirect methods can be just as reliable as direct methods. The TRAC (Tracing Radiation and Architecture of Canopies) device (Chen and Cihlar, 1995) and hemispherical photography are both capable of retrieving the necessary data to derive the clumping index of a forest stand. A revised version of Equation 2 incorporates this clumping index for improved estimates of LAI_e (Leblanc et al., 2005):

$$LAI_e = \ln(P(\theta)\cos(\theta)/G(\theta)\Omega_c) \quad (3)$$

Leblanc et al. (2005) summarizes three widely used clumping indices known as the LX, CC, and CLX methods. Each one is based on different assumptions about a forest canopy. Lang and Xiang (1986) were the first to propose a clumping index that uses logarithmic averages for LAI, which they refer to as the LX method. This index assumes that a forest canopy contains gaps and that vegetation components are locally random (Gonsamo and Pellikka, 2009). The CC method was developed by Chen and Cihlar (1995) and later modified by Leblanc (2002a). It relies on gap size and gap fraction information which are applicable to most types of plant canopies. The CLX method combines the concepts of both the CC and LX methods (Leblanc et al., 2005).

For coniferous species in particular, foliage elements are inherently clumped since needles are clumped on shoots, and shoots are clumped on branches. Authors commonly use a species-specific needle-to-shoot ratio (y_e) to refine LAI estimates of coniferous forests, as seen in Equation 4 (for broad leaf species, $y_e = 1$):

$$\text{LAI} = \text{PAI}(y_e) \quad (4)$$

Chen and Cihlar (1996) showed that if the intention is to calibrate a remotely sensed model using indirect estimates of LAI_e , correction parameters such as Nilson's Ω_c , or y_e are not mandatory. Instead, a strategic field survey is the most important. Using sample regions of the Boreal forest, they demonstrated that PAI estimates showed the strongest correlations with Landsat image data. King et al. (2005) showed that PAI estimates within the southern parts of Gatineau Park also demonstrated the best regression-based relationships with high resolution multispectral aerial photography. Since PAI is based on canopy gap fraction, it is

also a good estimate of canopy interception, corresponding well to the underlying theory of a remotely sensed vegetation index, which is the focus of the next section.

2.2 Mapping vegetation quantity using multispectral imagery

Early research by authors such as Jordan (1969) demonstrated a strong and positive correlation between vegetation quantity measured on the ground and the ratio between red and near-infrared reflectance from the same surface. This relationship is based on the principle that green biomass absorbs relatively more red than infrared energy, and based on this research was initiated on what are now known as spectral vegetation indices (SVIs).

Deriving a SVI from remotely sensed data provides a spatially continuous interpretation of a landscape, so many authors use empirical modelling techniques to map forest distributions in physically quantifiable terms. Using both field and Landsat image data, Hall et al. (2006) mapped above ground biomass and stand volume using a multivariate regression analysis. Powell et al. (2010) compared three different empirical methods to model aboveground biomass as a continuous variable. They found that the results of each model were quite similar, and recommended linear regression analysis due to its simplicity.

While such calibration is necessary for national resource inventories, for some applications they can be avoided by simply viewing a remotely sensed SVI as a surrogate for vegetation quantity. Sections 2.2.1 to 2.2.3 summarize some of the more commonly used methods to derive SVI data from multispectral imagery.

2.2.1 Reflectance theory based spectral vegetation indices

Many SVIs consider the interaction between photosynthetically active radiation (PAR) and the surface of a leaf (Jiang et al., 2008). Green biomass absorbs PAR selectively, and the proportion that is not absorbed, is either transmitted, or reflected back into space (Chen and Cihlar, 1996). The visible (VIS) portion (0.4 - 0.7 μm) of PAR is highly absorbed by a leaf because chlorophyll pigments utilize energy at these wavelengths in photosynthesis, particularly in the red portion of the spectrum. The opposite is true for near infrared (NIR) wavelengths (0.7-1.4 μm); a healthy leaf is adapted to reflect NIR energy since it overwhelms photosynthetic function. Finally, shortwave infrared (SWIR) wavelengths (1.4 - 3 μm) are highly absorbed by water; an increase in reflectance may indicate a decrease in vegetation health or moisture content (Lillesand et al., 2004).

Figure 2 shows hypothetical spectral reflectance curves for bare soil, green vegetation and water across the VIS to SWIR range. It can be seen that each land cover has a unique spectral signature (spectral curve shape), although variations for a given land cover type are a result of a number of factors. For a vegetated surface, reflectance is largely related to health, quantity, and structure and differences across space and time can be used to infer forest dynamics.

Figure 2: Hypothetical spectral signatures for bare soil, vegetation and water (Lillesand et al., 2004).

In forest remote sensing, leaf-scale reflectance theories are extrapolated to the canopy scale. Reflectance information about a landscape, for two or more bands can be used to infer vegetation quantity and health, the simplest SVI taking the form of a ratio (Jordan 1969). Common examples include the normalized difference vegetation index (NDVI), the simple ratio (SR), and the moisture stress index (MSI). These indices are based on the notion that for a given increase in vegetation health or biomass, reflectance in NIR wavelengths increases, and conversely decreases in red and SWIR wavelengths (denoted as p_n , p_r and p_s , respectively) (Lillesand et al., 2004):

$$NDVI = (p_n - p_r) / (p_n + p_r) \quad (5)$$

$$SR = p_n / p_r \quad (6)$$

$$MSI = p_s / p_n \quad (7)$$

These SVIs are often well correlated with ground-based estimates of vegetation quantity (Turner et al., 1999). Empirical relationships between NDVI and LAI, for example, can be used to map the spatial variability of a vegetated surface (Chen and Cihlar, 1996). Since remotely sensed images are spatially extensive and frequently retrieved, SVIs are often used to monitor changes in ecosystem structure and function (Alcaraz-Segura et al., 2010), detect changes in phenology (Julien and Sabrino, 2009), and are frequently used as an input for many biophysical models (Cao et al., 2004). Pettorelli et al. (2005) discuss how NDVI in particular has become one of the most powerful tools for interpreting environmental change.

The utility of NDVI has been demonstrated in many ecological applications. Given that it is a ratio, errors in image derived reflectance caused by topography, sun angle variations and the atmosphere are reduced (Matsushita et al., 2007). However, some authors have found that ratio indices can be limiting if used as a single predictor variable (Turner et al., 1999). This is because canopy structure, background reflectance, and certain atmospheric constituents can make them susceptible to error and uncertainty (Matsushita et al., 2007). Over a range of vegetation densities the relationship between NDVI and live green biomass strongly increases, however, after an LAI of about 5, asymptotic behaviour is commonly observed. This is largely because incident radiation is attenuated by a dense forest canopy. Therefore, where biomass and canopy layering are high, NDVI estimates may not be representative (Pettorelli et al., 2005).

For applications focused on overstory LAI, and where canopy openness is greater than 20%, understory vegetation may contribute a strong background signal. Within Canada's Boreal region, Chen and Cihlar (1996) selected sample sites that captured a

range of structural conditions with varying degrees of canopy openness. For each site, optical estimates of LAI were acquired at different stages of the same growth season. Correlating Landsat derived SVI data with ground-based estimates of LAI showed that spring (leaf-off) data had the strongest correlations. They concluded that during spring conditions, deciduous understory species have the least affect on the signal retrieved by a sensor, and therefore, overstory conifer LAI estimates were more closely related to the SVI data representing the same time.

Where vegetation is sparse ($LAI < 2$), the energy reflected from exposed soil can also mix with vegetation radiance. To compensate, the soil-adjusted vegetation index (SAVI) was proposed by Huete (1988) for agriculture and semi-arid environments. Essentially this transformation shifts the origin of reflectance data plotted in red and NIR spectral space, and has been seen to reduce the effects of soil brightness over a wide range of vegetation densities. The choice of SVI is often dependent on the research objective; for empirical modelling, the best proxy is often determined based on comparisons between model parameters. The goal is to determine the image variables that are sensitive to high biomass regions, and optimize the vegetation signal (Jiang et al., 2008).

The Enhanced Vegetation Index (EVI) has been proposed as a SVI that not only incorporates an adjustment for background noise, but is also resistant to atmospheric influences and the effects of different forest structures. EVI was first proposed for MODIS (Moderate Resolution Imaging Spectroradiometer) imagery to optimize the vegetation signal in high biomass regions, but it can be used for other sensors. It

incorporates a similar linear transformation as SAVI, and uses the blue band to reduce atmospheric signal noise and uncertainties (Jiang et al., 2008):

$$EVI = G \frac{P_n - P_r}{P_n + C_1 P_r - C_2 P_b + L} \quad (8)$$

where p_b represents blue surface reflectance and G is a gain factor. C_1 and C_2 are aerosol resistance terms. L is the same soil-adjustment factor derived from SAVI, however, Jiang et al. (2008) state its value is different because of the interaction and feedbacks between the soil adjustment factor and the aerosol resistance terms (C_1 and C_2). Studies focusing on a range of environments have adopted the coefficients used in the MODIS EVI algorithm: G as 2.5, C_1 and C_2 as 6 and 7.5, respectively, and L as 1 (Jiang et al., 2008). Chen et al. (2004) applied this algorithm to Landsat data.

For sensors without a blue-band, Jiang et al. (2008) developed a modified 2-band EVI, referred to as EVI2. Justification for this model was based on the notion that red and blue surface reflectance are highly correlated, which is especially true when atmospheric effects are low. Jiang et al. (2008) determined the optimal linear adjustment factors that achieved the most similar results between EVI and EVI2:

$$EVI2 = 2.5 \frac{p_n - p_r}{p_n + 2.4 p_r + L} \quad (9)$$

Other transformations that produce SVIs are derived using orthogonalization techniques similar to a principal components analysis. Landsat data are commonly transformed using the tasseled-cap transformation (Crist, 1985; Jin and Sader, 2005), which reduces six reflectance bands to three orthogonal indices called brightness, greenness and wetness (TCB, TCG, and TCW, respectively) (Healey et al., 2005). TCB

is often associated with overall or soil reflectance, TCG with vegetation, and TCW with soil or canopy moisture (Crist and Cicone, 1984).

These indices are created using a linear combination of sensor-specific weightings for each band (Table 1 in the Appendix), and are frequently used to highlight meaningful vegetation change in forested environments as they generally account for most of the variability within a single image date. The tasseled-cap transform was named by Kauth and Thomas (1976) who found that the distribution of red and near infrared pixel values representing a wheat field formed a shape similar to that of a tasseled cap (Figure 3).

Figure 3: Example tasseled-cap pixel distribution in NIR and Red reflectance space. Image modified from Kauth and Thomas (1976).

2.2.2 Spectral mixture analysis to infer vegetation quantity

Given the heterogeneity of most surfaces, the spectral reflectance value of an individual pixel is likely influenced by a combination of land cover types. It is well known that background signals from soil surfaces for example, can influence a SVI and

confuse empirical relationships. For relatively coarse resolution sensors, sub-pixel information is often necessary (Simic et al., 2004). Spectral mixture analysis (SMA) is a technique, originally developed for hyperspectral imagery, which can be used to derive fractional images of different surface components referred to as endmembers, which are considered to be pure pixels, representing only one surface type (Dennison and Roberts, 2003). This analysis is based on a comparison between the reflectance curves of the selected endmembers to the reflectance curves associated with each pixel.

Typically a shade endmember is selected to account for illumination variability, and additional endmembers are used to represent different surface components. The number of end members used is limited by the number of bands within an image (i.e. $n-1$). Assuming a linear combination, SMA can be used to determine each endmember's contributing signal at the pixel level. The sum of all endmember contributing proportions, for a given pixel location, should be equal to approximately 1.

The spectral signatures of each endmember can be determined in the field or laboratory using a spectrometer, selected from image pixels, or derived through automated methods. Pasher et al. (2007) compared SMA results using manually selected endmembers from within the imagery, endmembers selected from graphical display of n -dimensional spectral space, as well as from an automated method. They found that the results from each method were quite similar; preference was given to the automated method given its simplicity.

It should be noted, however, that SMA results are largely dependent on the purity of endmember spectra (Dennison and Roberts, 2003). In a forested environment, non-

linear mixing can occur as a result of multiple scattering caused by canopy architecture, for example, and violates the assumption that the signal received by a sensor is a linear combination of different endmembers. This is the most significant limitation to SMA, but despite this, sub-pixel information has provided invaluable information for many remote sensing applications, and has helped to reduce modelling errors and infer spatial variability (Simic et al., 2004).

2.2.3 Texture based vegetation indices

Spatial heterogeneity across a landscape can also be inferred through measures of image texture. These are unique indices that are based on the signal variations across an image and consider the statistical relationships between neighbouring pixels (Wulder et al., 1998). First-order texture variables include statistics such as the local standard deviation or variance, which can be calculated within a moving window or specified size passed through the image. Second order textures can be derived frequency distributions of pixel values, such as the grey level cooccurrence matrix (GLCM), which is constructed from values of pairs of pixels separated by a user defined angle and distance. These data transforms help to highlight homogenous regions across space, and indicate dissimilarities.

In combination with a SVI, texture measures can significantly improve regression-based empirical models. Using 1 m Compact Airborne Spectrographic Imager (CASI) data, Wulder et al. (1998) showed that texture variables can explain an additional 20% of the variance in LAI models. Texture indices applied to relatively coarse

resolution sensors such as Landsat, for example, may not be good indicators of local variability.

With respect to mapping vegetation quantity, canopy gaps or variable tree heights are often associated with maturing forests where LAI is typically high. These forest structures may cast shadows that reduce the vegetation signal (Wulder et al., 1998). Image textures can be used to describe residual behaviour associated with shadowing, highlight homogenous regions in terms of structure, and help to describe the variability of a canopy's surface architecture across space to help potentially reduce modelling errors. A spectral or spatial movement between image dates can be used to infer ecosystem changes and is the focus of the following section.

2.3 Detecting change in vegetation quantity using remotely sensed data

The detail with which change can be detected is highly influenced by the spatial resolution and acquisition frequency of a remote sensor (Coppin et al., 2004). Daily acquisitions made by satellites such as the Advanced Very High Resolution Radiometer (AVHRR) make intra-annual changes associated with seasonality and weather variability possible to detect. Unfortunately, the generalizations of a 1 km pixel make it difficult for these data to describe change that is useful for management purposes (Lu et al., 2004).

Conversely, the Landsat satellite provides imagery with 30m pixels, a resolution that closely matches the scale at which land management often operates (Powell et al., 2010). It is difficult, however, to obtain suitable intra-annual frequencies as a result of clouds and the 16 day image acquisition interval. Therefore, near-anniversary image

dates are generally used to detect inter-annual changes. Near-anniversary images help to reduce error by controlling for seasonal differences in phenology and sun angle geometry (Lu et al., 2004). For forest remote sensing and monitoring, imagery acquired during the stable part of the growth season is preferred.

In the past, data availability and cost usually limited detection of inter-annual change to two image dates. These bi-temporal change detection techniques are well documented, and are discussed as being suitable for identifying abrupt land cover conversions, severe damage and assessing the overall change of a landscape over a given period in time. Vogelmann et al. (2009) and Powell et al. (2010) modelled the dynamics of a forested landscape over about a 20 year period using 10 and 14 near-anniversary Landsat images, respectively. These studies effectively captured gradual, cumulative, and persistent changes, and demonstrated that multiple images can be used to improve the precision with which change can be detected. There is no set methodology for this type of application, but with the opening of the Landsat image archive, increasingly reliable techniques will inevitably emerge.

Using Landsat imagery, Lunetta et al. (2004) modelled ecosystem regeneration rates in North Carolina using a 3-, 7- and 10-year interval analysis. They concluded that the 3-year analysis produced the most acceptable results, but excessive omission errors were still identified. Such errors refer to actual changes that were not detected. The opposite scenario is referred to as an error of commission; i.e. change detected that did not actually occur. Many authors refer to these map attributes as producer's and user's accuracy, respectively.

The types of change that can be detected using remote sensing techniques are generally limited by either space or time. An additional concern is image alignment (Singh, 1989). In order to detect accurate change, the pixels representing the Earth's surface at a particular moment in time must be precisely located. Offsets more than half a pixel can significantly distort change detection results, especially near land cover boundaries (Hall et al., 1991). Without near-perfect alignment, image comparisons would be erroneous, regardless of data quality and the remote sensing techniques used.

2.3.1 Change detection using two image dates

An intuitive method to detect bi-temporal change has been referred to as a post-classification comparison. This technique compares two classified image dates of the same region using cross tabulation to produce a matrix of change summarizing the types of land cover conversions that have occurred (i.e. vegetated surface to a bare surface). Rates of change are difficult to estimate using this technique, but, since each image is independently classified, atmospheric conditions have less of an effect on the results. However, in order to classify each image reliably, field or other reference data are generally required to select training samples for the classifier and they are often not available for historical scenes (Lu et al., 2004). Finally, the accuracy of a post-classification comparison, as a worst case scenario, can be equal to the product of the accuracies of the initial input maps (e.g. $0.80 \times 0.80 = 0.64$), and therefore error propagation can become an issue (Coppin et al., 2004).

Hall et al. (1991) used a post-classification comparison to monitor forest succession over a 10-year period. They used supervised classification on a 1973 and 1983

Landsat image to map five forest classes: conifer, mixed, broadleaf, regenerating, and cleared forests. The results provided evidence of a dynamic landscape as more than half the pixels changed state. Minor classification errors were identified, and were often associated with mixed, regenerating and cleared forests.

Other change detection techniques represent change mathematically through techniques such as image differencing, principal component analysis (PCA), or change vector analysis (CVA). Data inputs can be raw or calibrated image bands, as well as transformed data. Using two image dates, image differencing can be used to highlight positive and negative change at the pixel level. Assuming a normal distribution, changes further than 2 standard deviations from the mean are commonly mapped as significant (Coppin et al., 2004). Other multiples of the standard deviation have been used that are often determined by testing a series of discrete thresholds and assessing their accuracy in relation to change (Im et al., 2007).

In PCA, multispectral images from two dates are combined and reduced to a few uncorrelated components that effectively describe the majority of the variance in the two dates, with one or more components representing reflectance change (Singh, 1989). PCA assumes that input data are normally distributed, and relies on linear relationships within a multivariate dataset (Ceballos and Bottino, 1997). This is because a PCA uses a linear transformation with a rotating axis along lines of maximum variance in n -dimensional space.

CVA uses a spectral or spatial vector that describes the magnitude and direction of change. Two inversely related surface gradients are used to define this vector, and

empirical relationships are used to identify the minimum magnitude representative of change (Sohl, 1999). If change is modelled as a linear vector in spectral space, the minimum change that can be detected is equal to the standard error of the slope, which can be viewed as noise (He et al., 2011).

The methods used to determine a minimum change threshold have a significant effect on the results and the reliability of most change detection applications (Im and Hodgson, 2009). The more traditional approach is to find the threshold that yields the highest detection accuracy based on tests of a few discrete values (i.e. 5 - 10 thresholds), and accuracy assessments are usually based on comparisons with ground data (Im et al., 2008). Although most authors generally use common thresholds, the methods used to determine them can be time consuming, and are susceptible to biased results.

Im et al. (2007) developed an automated method that tests a continuum of thresholds using an “exhaustive generate-and-test search strategy”, which eliminates the heuristic search for a “good enough” threshold, but requires advanced modeling techniques. It determines the threshold that reduces user and producer errors. Others have used a simulated annealing approach (Kirkpatrick et al., 1983), which examines the behaviour of a continuous variable across a range of discrete thresholds. The threshold where asymptotic or stable behaviour begins is selected.

Francesco and Denoel (2009) state that ecological thresholds are usually defined as “points, or zones of abrupt change in ecological relationships”, but it is difficult to objectively define meaningful thresholds because they are often site- and species-specific, and require a holistic understanding of the ecosystems of interest. Additionally,

their reliability has direct implications for ecosystem management. They claim that linear models provide a means to objectively identify “break point positions” in gradual patterns, or sharp transitions.

While Francesco and Denoel (2009) focus on species-habitat relationships, their perspectives can be applied to linear models of vegetation dynamics. Figure 4 shows two hypothetical trends, one that represents an abrupt forest disturbance, and one that is comparatively subtle and gradual over time. If two observations before and after an abrupt event are available, and the spectral change is greater than noise, abrupt change can be reliably detected. Depending on the monitoring interval, however, spectral changes for areas that are gradually growing or deteriorating may not be considered significant (i.e. the magnitude of change is less than data noise). If the monitoring interval is too wide, some abrupt events may remain undetected as a result of fast recovery, and subtle trends within the landscape may be misinterpreted as an abrupt land cover conversion.

Figure 4: Hypothetical abrupt (a) and subtle (b) trends (Figure redrawn from Francesco and Denoel (2009)).

2.3.2 Change detection using multiple image dates

The ability to reliably and remotely model the spatial and temporal variability of change within a landscape generally requires more than two observations in time (Lunetta et al., 2004). By using narrow and frequent monitoring intervals, additional abrupt changes can be detected. Pixel locations associated with an increasing or decreasing trend, within a variable ordered in time, can be flagged as a gradual change trajectory. The slopes (or vectors) of these trends can be used to infer the magnitude and direction of change (Gomez et al., 2011). Current research has mostly modeled landscape trajectories as linear spectral changes (Sonnenschein et al., 2011; Powell et al., 2010; Vogelmann et al., 2009), in most cases using a linear regression analysis (de Jong et al., 2011). Francesco and Denoel (2009) claim that the best way to objectively represent ecological change, is by modelling it as a linear process.

Model extension, in space or time, has been performed by many authors, and it is also commonly executed as a linear representation of reality. Cohen et al. (2001) developed a method to map forest attributes as continuous variables using multiple scenes across space. Their approach used a centrally located 'source' scene for model development, which was extended to 7 neighbouring 'destination' scenes. These 7 scenes were relatively calibrated and merged into a Landsat mosaic representing the growth season of 1988 in western Oregon (7 275 713 ha). While Cohen et al. (2001) extend their model parameters to multiple images in space, a similar approach should theoretically work for image data ordered in time.

The Theil-Sen (TS) slope estimator, which was proposed by Theil (1950), and modified by Sen (1968)), is commonly used in remote sensing to calculate pixel-level median slope within an image time-series (Neeti and Eastman, 2011). TS slope calculations are based on all pair-wise combinations for the available observations in the forward direction ($= n(n - 1)/2$). According to Neeti and Eastman (2011), the number of outliers within a time-series can be as great as 29 % of the sample size without having an effect on the estimated slope.

An additional non-parametric technique called the Mann-Kendall test (Mann, 1945; Kendall, 1975) can be used to analyze the significance of a Theil-Sen slope (Neeti and Eastman, 2001). Pair-wise iterations ordered in time are ranked with time as a reference, and are used to compute an S-stat; which can be used to reject the null hypothesis (H_0) of no trend (H_0 is accepted if $S\text{-stat}=0$). A spectral trajectory is considered the most significant if all possible iterations in the forward direction show a positive (or negative) change vector. Based on the vectors of all iterations, the probability of a monotonic trend can be computed at the pixel-level (Schlagel and Newton, 1996). Mann-Kendall test is commonly used to assess the significance of a trajectory and is suitable for time series with missing observations (Yue et al., 2002), which are inevitable in remote sensing. While the Mann-Kendall significance test indicates the presence of a monotonic trend and the Theil-Sen slope estimate describes its direction and magnitude.

Neeti and Eastman (2011) describe a more novel approach for calculating the significance of a trend which they refer to as the Contextual Mann-Kendall (CMK) test. This test incorporates spatial autocorrelation and assumes that trends in neighbouring pixels should be similar. For an individual pixel, the significance is determined using data

from neighbouring pixels (e.g. 3 x 3 pixel window). They recommend this test for remotely sensed time series data, as it makes intuitive sense from a geographical perspective.

Powell et al. (2010) discuss that modelling errors can occur when mapping biomass in space and time; however, they showed that the consistency of a calibrated Landsat image time series can be used to identify very real trends in vegetation dynamics. By comparing several empirical modelling methods, they also showed that no one method that provides the best results, concluding that relative changes are potentially accurate, and corroborating evidence helps to at least partially confirm them.

A diversity of decisions exists at all stages of any change detection application. Depending on the remotely sensed imagery, the pre-processing methods and the change detection techniques used, the results for a given study area may be very different. Field data help to aid interpretations of spectral trends, and are widely agreed as being necessary for reliable detection of change (Coppin et al., 2004; Lu et al., 2004; Singh, 1989). Beyond image alignment errors, radiometric errors caused by the atmosphere provide an additional challenge. Image calibration is often necessary to ensure that the remotely sensed data are radiometrically comparable and to reduce noise between images from different dates.

2.3.3 Establishing a temporally stable interannual image time series

Ideally the signal (L_S) received by a remote sensor representing a source target indicates its true surface radiance (L_T), however atmospheric effects make this difficult to

achieve without some degree of image processing. Atmospheric effects can be broadly referred to as path radiance (L_p), representing the proportion of the spectral radiance that has been scattered, reflected or absorbed by different atmospheric constituents. Adjacent non-source targets may also contribute to L_p (Jensen, 2000). In most cases, $L_s = L_T + L_p$, but their contributing proportions vary over space and time. Given the day-to-day variability within the atmosphere, removing L_p from an image is critical prior to detecting change.

Scattered energy as a result of the atmosphere or a non-source target is one form of path radiance, and is considered as a multiplicative radiometric error. Additive effects, caused by the albedo of the atmosphere for example, are much more straightforward to correct for since this type of error can be modelled as a linear effect. Gas molecules (oxygen and nitrogen) cause what is referred to as Rayleigh scattering, which affects smaller wavelengths. Since blue light is the shortest visible wavelength, the sky appears blue on a clear day as a result of Rayleigh scattering. Dust particles (0.1 to 10 μm) are much larger than gas molecules and affect longer wavelengths. This type of scatter is referred to as Mie scattering, and causes the unique colours observed during a sunset (Jensen, 2000).

It is expected that some degree of radiometric distortion will exist in a remotely sensed dataset; however, image calibration helps to reduce these errors, and provide a more reliable spectral representation of a landscape. It should be noted that calibration to true surface radiance (L_T) or reflectance is not necessary to detect change with remotely sensed data; rather, radiometric consistency between image dates is most important (Paolini et al., 2006; Schroeder et al., 2006; Vicenteserrano et al., 2008); i.e., images can

be relatively calibrated to each other. Extensive efforts have been made to develop effective and operational solutions to remove the effects of the atmosphere, but it is clear that a universal method does not exist. This is because depending on the application, study area, remotely sensed data and research question, certain techniques may be more suitable than others.

Applications that use daily acquisitions of a forested landscape have shown that the relationship between a SVI and LAI varies across a single growth season, and follows three distinct phenological stages: leaf production, leaf-constant, and leaf senescence (Wang et al., 2005). For interannual forest monitoring, capturing scenes during the stable leaf-constant stage is critical to control for phenological variability. The use of near-anniversary images helps to control for sun angle geometry and surface illumination, however, they are not able to control for the effects of the atmosphere (Coppin et al., 2004). The techniques currently used to reduce radiometric errors can be broadly classified as being either absolute or relative.

2.3.3.1 Absolute correction of atmospheric effects

Based on radiative transfer theories, several absolute atmospheric corrections to convert L_S measurements to L_T have been developed. These transformations range in complexity, and make different assumptions about the atmosphere during image acquisition. In general, they make use of two wavelength-specific equations which in combination, convert raw image brightness in digital number (DN) values to at-satellite spectral radiance (L_S , in units of $W/m^2 \cdot sr \cdot \mu m$). The first equation is applied to the raw

DNs measured by a remote sensor, and the goal is to remove sensor- and band-specific gains and offsets introduced by the imaging system (Chavez, 1996):

$$L_S = \text{DN} \times \text{Gain} + \text{Offset} \quad (10)$$

Once an image has been converted to L_S , it is absolutely corrected to obtain true surface reflectance values for each band using:

$$P = \frac{(\pi \times (L_S - L_{Haze}))}{(T\theta_v \times (E_o \times \cos(TZ) \times T\theta_z + E_d))} \quad (11)$$

where P = surface reflectance, L_S = irradiance on the sensor, L_{Haze} = upwelling radiation that has been scattered or emitted by the atmosphere in the direction of the sensor, $T\theta_v$ = atmospheric transmittance along the ground-to-sensor path, E_o = the spectral irradiance at the top of the atmosphere (function of time of year), TZ = the solar zenith angle (angle of incidence), $T\theta_z$ = atmospheric transmittance along the sun-to-ground path, and finally E_d = spectral irradiance at the target surface due to scattering (Chavez, 1996; Pax-Lenny et al., 2001; Jensen 2000).

Unfortunately, the data required to absolutely correct an image using Equation 11 are often unavailable. If data are available, they are likely represented by a few sparsely located weather stations, making it difficult to accurately portray a three dimensional atmosphere (Butson and Fernandes, 2004). As a result, image-based absolute methods are becoming a preferred strategy (Chavez, 1996), which can be used to estimate values for many parameters defined in Equation 11 from the image itself (Zhang et al., 2010). Many authors state that image-based corrections retrieve similar, if not more reliable results

than some of the more complex radiative transfer models (Pax-Lenney et al., 2001; Song et al., 2001).

Dark object subtraction (DOS) is a common simplified image-based absolute method. It assumes a homogenous atmosphere, and relies on the presence of dark targets. These image elements theoretically have zero, or very low surface reflectance (Song et al., 2001). Therefore, in DOS, the minimum DN value of the darkest target within a scene can be used to estimate L_{haze} in Equation 11 (Chavez, 1996). There are several image-based absolute methods that can be used, but if the development of a reliable time series is the goal, Schroeder et al. (2006) showed that the exclusive use of an absolute calibration may retrieve erroneous results, and concluded that relative techniques are generally more effective.

2.3.3.2 Relative correction of atmospheric effects

Since data representing the atmospheric conditions during image acquisition are often difficult to obtain, relative methods have been developed, which make use of within scene elements or ground-based measurements of spectral reflectance to develop scene- and band-specific calibration equations (Schott et al., 1988). Ground-based measurements, however, are not suitable for operational or broad scale applications.

A technique known as the PIF method relies on pseudo-invariant features (PIFs) common to multiple image dates of the same scene. Bright PIFs are typically human-made, and show consistent reflectivity over time regardless of seasonal variations. Quarries and lakes are commonly used as examples of bright and dark features, respectively (Janzen et al., 2006). If such features can be identified in the imagery, their

reflectance distributions can be used to normalize one image date to another, using (Schott et al., 1988):

$$DN_{1i} = m_i DN_{2i} + b_i \quad (12)$$

where m_i and b_i are constants used to transform the at-sensor reflectance DN distribution for the i^{th} band of date 2 to an equivalent distribution represented by date 1.

For the development of an image time series, one image date is used as the master image and all other images are calibrated to it. The goal is to match band-specific histograms over time so that each image looks as though it was “acquired using the same camera settings” (Coppin et al., 2004). The master image should be of the highest quality and acquired close to the near-anniversary date (median day of the year) of the time series (Song et al., 2001). The PIF data extracted from the master image for each spectral band are considered the dependent variables, and by regressing them against the data from the corresponding spectral band being calibrated (independent data), model parameters provide m_i and b_i (slope and intercept, respectively).

A disadvantage of the PIF method is that it is time consuming and difficult to implement operationally. In addition to this, some scenes may not include adequate PIFs. A simple regression (SR) technique can be used to develop the same relative calibration equation described by Equation 12. A density plot (see Figure 1 in the Appendix for an example) comparing the same band, but of different dates, can be used to define both m_i and b_i (Song et al., 2001). Due to its simplicity, this technique is becoming a popular calibration strategy (Chen et al., 2006a).

An alternative relative calibration technique, referred to as an “absolute-normalization”, can be used if physically meaningful estimates of surface reflectance are required (Schroeder et al., 2006). This technique applies a full absolute correction to one image within a time series, and the corrected image is subsequently used as the master image to relatively calibrate the other images. This technique is especially useful if data about the atmosphere are only available for one image date, and has been found to provide the best normalization when compared to many absolute or relative methods (Schroeder et al., 2006).

3.0 Study area and research context

This research focuses on the temporal dynamics of the forests of Gatineau Park, which are located in southern Québec, just north of Ottawa, Ontario (Figure 5). The 36 131 ha area is within the Great Lakes St. Lawrence Forest Region of the Canadian Shield (Pisaric et al., 2008), and is thought to have previously been a peninsula in the Champlain Sea. As a result of glacial morphology, remnants of the Laurentian Mountains are evident as rolling hills; distinct 300m cliffs of the Eardley Escarpment mark the southern limits of the park.

Close to 80% of Gatineau Park is currently forested and managed by the National Capital Commission (NCC). A spatially variable landscape creates a diverse range of microclimatic, topographic, and geologic conditions, and as a result, the park’s species richness is uniquely high (NCC, 2005a). Gatineau Park hosts 27% of the plant and

vertebrae species found within Canada, with 118 species listed as endangered or rare (CPAWS, 2008).

Up until at least the 1950s the area was used for mining and forestry, which have at least partially influenced the current state of Gatineau Park (NCC, 2005b). Plans to give the park national status were initiated in 1912, but the First World War, followed by the great depression, interfered with the process. Gatineau Park continues to be the only federal park not protected by the National Parks Act, a situation that has direct consequences on its ecosystems.

To some degree, as a result of historical logging of white pine (*Pinus strobus*) and other coniferous species, about 55% of the park is now dominated by hardwood stands (Pasher and King, 2009). Especially in the southern portion of Gatineau Park, Sugar maples (*Acer saccharum*) is now the dominate species, however, pockets of American beech (*Fagus grandifolia*), trembling aspen (*Populus tremuloides*), and red oak (*Quercus rubra*) can be found. Other less dominant deciduous species include, but are not limited to, red maple (*Acer rubrum*), American basswood (*Tilia americana*), ironwood (*Ostrya virginiana*), white ash (*Fraxinus americana*), black ash (*Fraxinus nigra*), white birch (*Betula papyrifera*), and black cherry (*Prunus serotina*). In the northern parts of the park, mixed and coniferous forests are more abundant, and include species such as the Eastern white pine, Eastern white cedar (*Thuja occidentalis*), Eastern hemlock (*Tsuga canadensis*), white spruce (*Picea glauca*), and black spruce (*Picea mariana*). Red pine (*Pinus resinosa*) and scots pine (*Pinus sylvestris*) are found too, but mostly occur in plantations.

As seen in Figure 5 (below), Gatineau Park covers a large portion (about 7%) of the National Capital Region of Canada. Its proximity to Canada's fourth largest urban centre (Ottawa) has resulted in frequent visitation and recreation. The park receives about 2.5 million visitors a year, which is one of the highest visitation rates of the federal parks in Canada. Camping, hiking, rock climbing, cross country skiing, and downhill biking/skiing are common forms of recreation. Other unregulated activity also occurs in the more remote regions of the park, and often involves motorized vehicles. Suburban development surrounding the study area and regional pollution pose additional threats.

Figure 5: Shows Gatineau Park (in green), situated within the National Capital region of Canada (NCC, 2002).

Beyond these human induced forms of disturbances, Gatineau Park is also exposed to natural agents of change such as insects or storm damage. The ice storm of 1998 is a recent example: this natural disturbance significantly altered the canopy structure of portions of the southern region of the park; damage and recovery was observed as being site- and species-specific (King et al., 2005; Pisaric et al., 2008). In 2010, the southern portion of the park was exposed to a severe insect defoliation event as a result of an unusually high forest tent caterpillar (*Malacosoma disstria*) population. Another major agent of forest change is the beaver (CPAWS, 2008), which is known to cause major changes to surface water hydrology. At the outset of this research, these natural agents were expected to have likely caused abrupt or gradual changes in the forests of Gatineau Park that should be detectable using remotely sensed data.

These known stresses have also partially been catalysts for revisions of the Gatineau Park Master plan (NCC, 2005b), which focuses on establishing a balance between recreation and conservation. These revisions will be based on research carried out during the period between 2005 and 2015; this thesis research was intended to provide spatio-temporal information on forest dynamics in Gatineau Park over the last 23 years. The methods investigated and evaluated will provide insight towards an effective, affordable and spatially extensive monitoring system for the management of Gatineau Park and other similar landscapes.

Current monitoring within the park is generally focused on single species, primarily using field-based methods. Legal obligations have made species at risk a top priority (NCC, 2005b). Recent research with high resolution airborne and satellite

imagery has used portions of southern Gatineau Park as a study area in forest structure and health monitoring (King et al., 2005; Pasher and King, 2009; Pasher and King, 2010). This research project is the first to assess and map the spatial distribution and temporal dynamics of the forests of Gatineau Park as a whole, using remotely sensed data.

4.0 Methodology

4.1 Satellite imagery acquisition and processing

Thirteen Landsat TM5 scenes (path 16, row 28) were used in this research. They were acquired from the United States Geological Survey (USGS) EROS (Earth Resources Observations and Science) archive (using <http://glovis.usgs.gov/>) with Level 1T pre-processing. This is the highest level of image processing provided; it incorporates ground control points and a digital elevation model (DEM) to improve radiometric, geometric, and topographic accuracy (USGS, 2010).

Landsat TM5 was launched March 1, 1984, and moved along a polar and sun-synchronous orbit at an altitude of about 705 km for over 27 years (image operation suspended November 11, 2011). A single scene represents a 185 x 185 km area of ground, repeat coverage occurs every 16 days, and the Thematic Mapper (TM) sensor simultaneously records incident radiance for 7 different bands. TM bands 1 to 5 and 7 correspond to blue (0.45 - 0.52 μm), green (0.52 - 0.60 μm) red (0.63 - 0.69 μm), near infrared (0.76 - 0.90 μm), and shortwave infrared (1.55 - 1.75 and 2.08 -2.35 μm) bandwidths, respectively. The nominal ground pixel size is 30m. TM band 6, with 60m pixels, represents thermally emitted radiation (10.4 - 12.5 μm) and was not used in this research.

For the purpose of detection of abrupt and gradual change over a period of more than two decades, Landsat 5 data were the most appropriate because its archived data represents the longest record from a single sensor, thus being appropriate for monitoring vegetation at scales relevant to park management. Finer resolution imagery was not considered since such a long temporal record did not exist, the cost of a single scene is high, and several scenes would be required to cover the park.

4.1.1 Landsat TM5 data – assessment and scene selection

Table 1 lists the 13 near-anniversary Landsat scenes selected for this research. The image representing the earliest part of the growth season was acquired on July 3, 2002 and the latest was captured on September 11, 2010. This 71-day temporal range, centred on August 7 (median date), falls within the stable part of the growth season for the study area. The image retrieved on September 11, 2010, is the most recent, and was acquired in the same year as the field data for this research. The oldest image was acquired on August 11, 1987, resulting in a time span of 23 years for the study period.

These image dates were primarily selected to minimize variability in sun angle geometry, local acquisition time, and atmospheric effects. Atmospheric effects were identified through visual assessments, and helped to identify scenes with abundant clouds and haze. Clouds within some available scenes either covered most of the park, or eliminated important stable targets required for calibration. These scenes could not be used for the development of a relatively calibrated image time series since this technique requires imagery clear of significant atmospheric distortions and stable targets common to all image dates. A few spare clouds were present within some of the selected scenes

(Table 1). These regions were removed from the imagery using manually digitized bitmap masks, i.e. their respective pixels were treated as missing observations.

Table 1: Acquisition details of the selected Landsat TM 5 imagery (1987 to 2010). Summary statistics do not include winter imager.

Year of growth season	Day of year	Local Acquisition Time	Sun Azimuth (degrees)	Sun Elevation (degrees)
1987	Aug.11	10:16:35	133.33	51.33
1989	Jul.31	10:17:42	130.60	53.63
1989**	Jan.04	15:20:57	153.90	17.01
1990	Aug.19	10:10:35	133.85	48.49
1994	Jul.29	10:08:23	127.05	52.81
1995	Sept.2	09:53:12	133.17	42.62
1999	Aug.28	10:27:57	142.36	48.09
2001	Aug.1	10:30:58	135.48	55.09
2002	Jul.3	10:26:26	129.47	58.99
2003	Aug.23	10:27:46	140.79	49.52
2003**	Jan.27	15:23:16	151.22	20.60
2004*	Aug.9	10:33:29	138.78	53.61
2006	Jul.30	10:43:53	139.85	57.12
2007	Jul.17	10:44:18	137.56	59.59
2010	Sept.11	10:40:52	151.21	44.90
2010**	Jan.30	15:40:30	155.14	22.80
Max	Sept.11	10:44:18	151.21	59.59
Min	Jul.3	09:53:12	127.05	42.62
Range	71	00:51:06	24.16	16.97
Ave	Aug.7	10:24:47	136.42	51.98

* Used as master image, ** Winter imagery used in section 5.4

4.1.2 Development of a relatively calibrated image time series

Experimentation with absolute, absolute-normalization, and relative techniques to calibrate two images of the same growth season (August 3rd and 19th, 1990) showed that relative calibration produced the most radiometrically comparable image data. Assuming that negligible vegetation change occurred between the two image dates, comparisons between calibration techniques were made based on the radiometric consistency of scene- and plot-level spectral reflectance, and spatial variability. These comparisons showed that the differences of the means and standard deviations of the absolutely corrected image pairs were more than 5 times greater than all relatively corrected pairs. Also, for temporal analysis, since true surface reflectance was not required, relative methods were deemed to be suitable for the development of a calibrated image time series. This finding is consistent with other studies such as Schroeder et al. (2006).

Each Landsat scene was re-projected to a Universal Transverse Mercator (UTM) geographic co-ordinate system (Zone 18T) using a NAD83 datum to match the coordinate system used by vector data provided by the NCC representing the roads and water boundaries within the area. Alignment errors between the image and vector data showed an average root mean square error (RMSE) less than 0.25m, so no further geometric processing was required. It was clear, however, that radiometric calibration was required before using the imagery in temporal analysis. This was based on a comparison between each scene's band-specific histogram statistics (Figure 9). Imagery was not calibrated to radiance, rather in one step digital numbers (DNs) were relatively calibrated using the PIF method. Testing showed this approach provided radiometrically comparable imagery for Gatineau Park.

4.1.2.1 Selecting pseudo invariant targets (PIFs)

Prior to image calibration, potential PIF locations were identified to sample the range of brightness values for each band and image date. This required isolating dark and bright targets that could be considered relatively stable over time. If present in all image dates, these targets were considered for the calibration process. Large bodies of water are often used to represent dark PIFs. Lakes were preferred over rivers since their surface reflectance can be assumed more stable over time. Gatineau Park is surrounded by several quarries, which can serve as effective bright PIFs (Schroeder et al., 2006). Airport runways and large parking lots were also considered as potential bright PIFs but were found to be quite variable compared to quarries. Figure 6 shows a quarry near Gatineau Park represented by a Landsat image in relation to a Google Earth image.

Figure 6: Example image of a quarry located near Gatineau Park, represented by Landsat (left) and finer imagery available in Google Earth (right).

For each potential PIF, a training polygon was delineated based on a visual assessment of the portion that was common to all image dates. Some quarries either expanded or contracted during the time period of this study so training polygons required strategic delineation. Linear regression analysis of brightness against time was used to identify PIFs that statistically represented the most stable surfaces (i.e. no slope). Twenty dark and 20 bright targets were considered and nine of each type were retained that had the most stable NDVI trajectories (Range of $R^2 = 0.00022$ to 0.06532 ; Range of slope = 0.00003 to 0.00101).

Depending on the PIF shape and size, each polygon represented between four and nine pixels. In addition, PIFs in close proximity to Gatineau Park were given preference since relative methods assume a homogenous atmosphere (Coppin et al., 2004). Atmospheric variability potentially increases as the area of interest increases, so reducing the coverage of each image was deemed necessary. Figure 7 shows the 2004 master image of the park and the locations representing the bright and dark PIF locations selected to calibrate the image time series.

Figure 7: PIF locations used for calibration (overlying the master image acquired in 2004).

4.1.2.2 Normalizing the image time series

The data distributions representing the combined bright and combined dark PIFs were used to develop band-specific linear calibration equations using the August 9, 2004 image as the master. This scene visually appeared the least affected by the atmosphere and was also acquired closest to the centre of the temporal window for this study (Table 1). The PIF data extracted from the master image were used as the dependant variable; all other image dates were normalized to this image using their respective PIF data as the independent variable. The resulting linear calibration equation was used to determine m_i and b_i in Equation 12.

Table 2 summarizes the band-specific calibration regressions for all dates. It can be seen that the PIF data for each calibration equation were well correlated; however their data distributions were individually investigated to identify significant outliers. This served as an additional means to highlight areas within certain PIFs that were not statistically stable. Modifying the sampling footprint of these PIFs helped to improve the calibration results.

Table 2: Summary of the band-specific calibration equations (m_i and b_i are from Equation 12).

TM BAND	R^2			Regression Slope (m_i)			Y-intercept (b_i)		
	Average	Min	Max	Average	Min	Max	Average	Min	Max
1	0.986	0.958	0.998	1.080	0.899	1.391	-5.819	-16.563	3.547
2	0.987	0.964	0.997	1.069	0.937	1.333	-2.382	-5.346	1.263
3	0.988	0.969	0.997	1.084	0.964	1.346	-1.722	-3.820	1.007
4	0.991	0.983	0.998	1.073	0.975	1.265	-2.477	-5.792	1.225
5	0.981	0.958	0.995	1.050	0.935	1.254	-0.903	-3.168	1.197
7	0.973	0.946	0.992	1.023	0.884	1.272	0.336	-0.850	2.339

Figure 8 shows a few example scatter plots representing the data for different combinations of image dates and bands. A total of 72 calibration equations were developed, and applied to the imagery. The nine dark PIF points are clustered and overlapping near the origin while the nine bright PIFs show a wider range.

Figure 8: Example scatter plots used to develop calibration equations using the image acquired in 2004 as the master image (dependent variable).

4.1.3 Assessing the precision of the image time series

A mask representing the forested area of Gatineau Park was created using the vector data provided by the Québec Ministry of Mines and Forest (QMMF). This mask was used to extract histogram statistics of the forest pixels in each band and image date, and provided a generalized time series of the park. A comparison of the same statistics prior to calibration helped to assess the effectiveness of the calibration. Although some variability is expected, the histogram statistics of the entire population of forest pixels should be relatively similar between growing seasons. This is based on the assumption of

a dynamic equilibrium, where some areas gain biomass and other areas experience a loss.

Figure 9 shows the average band-specific forest brightness (DN) of Gatineau Park before and after image calibration for TM bands 3, 4 and 5 across time.

Figure 9: Average forest spectral brightness before and after image calibration for TM Bands 3 (red), 4 (black) and 5 (grey).

Average spectral brightness for each band was more variable prior to calibration compared to post-calibration. This is especially true for the visible bands (TM1, 2, and 3). The infrared bands also show improvements, however there are a few anomalous years. Given the ecological relevance of infrared surface reflectance with respect to vegetation quantity and health, these image dates were assumed to be related to forest change events, seasonal variations, and moisture differences.

PIFs that were not used to develop the final calibration equations were used to assess the post calibration residual variance not related to change. Five terrestrial PIFs

were selected and their spectral time series for each band and other data transforms were analyzed. As expected, R^2 values for brightness versus time were low, indicating that temporal trends were insignificant. Although these PIFs were considered to be spectrally stable over time, there was a level of residual error within the time series, which will hereafter be referred to as the noise floor. It was considered to be a combination of the remaining non-linear atmospheric effects following image calibration and errors associated with the imaging system.

Model parameters of these independent PIFs were used to infer the precision and reliability of each spectral domain (i.e. individual image band or data transform). As a preliminary test, an NDVI time series was generated for each independent PIF. Addition of the absolute average slope and standard error of the slope was used as a method to estimate the NDVI noise floor ($0.000451 + 0.000432 = \pm 0.0009$), which indicates the minimum value of an NDVI trajectory (slope) that can be considered ecologically relevant, and not an artefact of the sensor or residual atmospheric effects.

Independent PIF locations were also compared to locations in the park known to have experienced change during the time series. Figure 10 shows NDVI time series of two field plots (see section 4.3 for field plot descriptions) that were assessed in the field as changing; one represents deteriorating conditions and the other one represents growing conditions. These plots show significant negative and positive NDVI trends, respectively (R^2 of 0.64 and 0.74), and their slopes are 4 to 5 times that of the NDVI noise platform. This indicates a significant and ecologically relevant spectral trajectory.

Figure 10: Independent PIF NDVI time series compared to plot-level NDVI time series representing deteriorating as well as growing conditions in the park. Plot-level trajectories are well above the NDVI noise platform.

Figure 10 illustrates quite clearly that plot-level spectral trajectories exist within the calibrated image time series, and suggests that the image pre-processing for this research was successful in producing radiometrically comparable imagery. This image time series was then used to model the forests of Gatineau Park over a 23 year period. The ground-based data collected during the growth season of 2010 were integrated with the image data of the same year to gain an understanding of the spatial and temporal dynamics of Gatineau Park. The following two sections discuss the geospatial data as well as the ground-based data used in this research.

4.2 Geospatial variables

A range of geospatial data sources were considered for this research. In brief, several spectral and spatial variables, known to be correlated with vegetation quantity,

health and structure, were derived from the Landsat imagery. A 30m digital elevation model (DEM) was used to extract plot-level topographic variables. Vector data sources, aerial sketch maps, and aerial photography were used for the purpose of mapping and stratifying Gatineau Park's forests, and also helped to corroborate change results. Additional details on these datasets are provided below.

4.2.1 Spectral variables

Each Landsat image was used to derive several spectral vegetation indices (SVIs) related to vegetation quantity and health. The SVIs used were selected based on results and recommendations made in the literature. Empirical modelling techniques, using the image and ground-based data acquired in 2010, helped to determine the suitability of each image variable for subsequent spatial and temporal analyses.

NDVI was selected since it is widely used in forest remote sensing and is often well correlated with field measured vegetation quantity metrics (Coppin et al., 2004). Other reflectance theory-based SVIs such as EVI, EVI2, TCB, TCG and TCW, described in Chapter 2, were also derived. EVI2 was considered because the blue band data were found to be artificially elevated due to a high gain factor in the sensor and they were also expected to provide the least reliable spectral information as a result of Rayleigh scattering. This caused spectral signatures that included TM band 1 to deviate from what would be expected for forest pixels (Figure 2).

To compensate for this, the minimum brightness value observed by the blue band across all image dates was used as a broad estimate of L_{haze} in Equation 11, which essentially represents the albedo of the atmosphere, and can be modelled as a linear

transformation using the principles of DOS. Subtracting the same value from all blue band images maintained the results of the image calibration, and helped to improve the spectral signatures of vegetated regions. The DOS-modified blue bands were used as inputs to derive EVI imagery, tasselled cap features, and fractional images.

Fractional images were produced using SMA to investigate sub-pixel information, which was considered to be potentially useful given the resolution of a Landsat image. It was found, however, that the visible bands (TM 1, 2 and 3) were highly correlated, and therefore including all of them would likely provide redundant information to the analysis. Since red reflectance is known to be highly correlated with presence and abundance of vegetation, and is least affected by Rayleigh Scattering, this band (TM3) was selected to represent the visible wavelengths in SMA, in addition to the infra-red bands (TM 4, 5 and 7). Three endmembers were extracted from the master image (acquired in 2004), using the automated Iterative Error Analysis (IEA) method described in Staenz et al. (2000). The spectral signatures of the resulting endmembers closely resembled the theoretical patterns for shadow (or water), vegetation and bare surfaces (Figure 2) and were used to produce fractional images for the other image dates.

4.2.2 Spatial variables

Section 4.3.1 discusses the field plot design. The standard deviation of image brightness in each field plot ($n = 9$) represented by each TM band and SVI were extracted as first order texture variables, as well as the five GLCM texture measures (Contrast, Entropy, ASM, Correlation and Homogeneity) used by Pasher and King (2010). That

paper referenced several other studies that demonstrated the utility of these second order texture measures for the purpose of modelling forest structural attributes.

The GLCM textures were derived from a 3 x 3 moving window, since this extent matches that of the field plots (described in section 4.3). The texture value of the centre pixel of each plot was used to represent the local brightness variability.

4.2.3 Topographic variables and other ancillary data

Leaf-off LiDAR data (NCC, 2008) were used to derive a 30m resolution DEM using bare earth ground returns and an inverse distance weighted interpolator (Richardson, 2011, pers. comm). Aspect, slope, and hillshade maps were derived from this DEM to provide topographic variables for each plot and interpret change results. Although the topography of an area is relatively static, change may be associated with topographic conditions since they partially control microclimate. Observations during the field season showed that south and west facing slopes were targeted by the forest tent caterpillar, which require that spring temperatures remain above 15° C. Since these slopes are exposed to more direct daily incident radiation, they are generally warmer than slopes facing other directions.

Vector data (NCC, 2002) were used to map recreational trails, roads, water, and the boundaries of Gatineau Park as well as its management sectors. Additional vector data produced by the previous Québec Ministry of Mines and Forests (QMMF) in collaboration with the NCC outlined homogenous forest patches within the park (NCC, 1991). Each patch was labelled as deciduous, mixed or coniferous dominated forest, referred to hereafter as the three functional groups of Gatineau Park. In addition, the

dominant overstory and sub-canopy species and their estimated ages were given for each patch.

The QMMF also delineated non-forest classes of water, agriculture, and bare or non-vegetated. These data were used to create bitmap masks for each functional group and to delineate specific regions of interest within the park, such as the distribution of forest plantations or regions dominated by a particular species. This aided analysis for the third objective of this research, which was to assess how the vegetation communities have changed over the last 23 years.

Other data sources delineated the forest fire history (NCC, 2002) within Gatineau Park, as well as past insect defoliations (Louis, 2008; Louis, 2009). While the forest fire data were available in digital format, the delineated events were sparse; insect defoliations were only available in hardcopy but showed frequent occurrences, and for some growth seasons, large tracts of land were identified as showing significant seasonal damage. These maps were used to corroborate the changes detected using the Landsat imagery.

Other corroborating vector data (NCC, 2002) included controlled and uncontrolled beaver dam point locations, and outlines of spruce budworm defoliation events. While the spatial distribution and severities of these defoliation events are digitally described, the timing of each event is not. Regardless, these datasets were considered useful for interpreting historical changes since ground-based data were not specifically collected for this research during past growth seasons of interest. A 20 cm colour ortho-image (NCC, 2007) was acquired in 2007, and provided a high-resolution

perspective of leaf off conditions for Gatineau Park. This was useful for interpreting change results.

4.3 Field data

Field data were acquired during the growth season of 2010 to develop a physical understanding of the types of forest conditions, areas that appear to be changing, and relationships between field and image data that could aid interpretation of spatial and temporal gradients in the image time series. Sampling locations were chosen to capture the existing range of forest conditions. For the purpose of assessing plot-level spectral trajectories and rates of change, it was also necessary that a portion of the plots be located in areas that showed evidence of a previous, recent or cumulative disturbance.

Following King (2000), field data were collected from areas covered by 9 TM pixels (3 x 3 pixel window, 90 m x 90 m plots) to effectively capture image variability. A purposeful sampling strategy was selected to ensure that a range of forest conditions could be surveyed within a single growth season. Thirty-three plots were established in locations where the characteristic forest structure occupied a horizontal space larger than the plot size. While some redundancy between plots was desired, a gradient of conditions sampling a representative range was required to develop useful empirical models. Field data collection started at the beginning of the leaf-on season, and each plot met these additional criteria:

- 1) Near-homogenous conditions with respect to topography, forest structure, and health.
- 2) Located near recreational facilities, or relatively isolated locations within the park.
- 3) Represents stable forest conditions, or a previous, cumulative, or recent change.

Reconnaissance visits were made prior to field work to identify potential plot locations. As areas of growth and deteriorating forest conditions are relatively rare, cloud free near-anniversary NDVI images from 1987 to 2007 were used to assist locating such areas. An exploratory bi-temporal change map (ECM) was created through image differencing with a threshold of ± 0.5 standard deviations to highlight subtle and abrupt, positive and negative vegetation changes over the 20 year period.

It was found that many regions identified as having changed on the ECM closely matched existing wetlands. Based on the abundance of standing dead wood, some of these wetlands appeared to have previously been forested. Other changes were obviously abrupt, and were associated with the development of infrastructure such as roads. These areas were not used for plot locations, but they were geographically located as reference points. Remaining highlighted change areas that were field verified to have deteriorating or recovering/growing forest conditions, and that met the plot criteria, were used for plot locations.

Field verification for plot selection was visual, and based on the relative amount of dead wood and an assessment of the overall health of the area. Young and growing forests were confirmed by determining the age of a few dominant canopy trees with a tree core. Visual assessments also helped to confirm the presence of early successional forest structures and species. Figure 11 shows the ECM and a few plot locations to demonstrate the utility of this field method.

Figure 11: Exploratory change map (ECM) used for site selection, with example plot locations showing forest deterioration (a), growth (b) and stable conditions (c).

4.3.1 Field plot design and sampling method

Plot centres were located in the field using GPS receivers with integrated maps or imagery. When available, a Trimble Juno GPS unit helped to locate the centre of a plot based on the boundaries of a 3 x 3 pixel window. This was possible since this unit provides the ability to view a georeferenced Landsat image at an extremely large cartographic scale in the field. When that unit was not available, the change map discussed above was converted to vector format, which could be viewed on a Trimble GeoXT GPS unit. In all cases, for consistency and maximum accuracy, the centre coordinate of each plot was taken as the average location of 200 to 400 points collected by the Trimble GeoXT real-time differential (WAAS) GPS. After post-processing, using

the Gatineau SOPAC base station (IGS Code = CAGS (IGS, 2011)), horizontal accuracy of these plot centres was expected to be within about 1 m (c.f. Pasher and King, 2010).

Figure 2 in the appendix shows the locations and plot IDs for the thirty three plots used in this research, and Appendix Table 2 provides their UTM coordinates, as well as some of the field data associated with each plot.

A nested sampling design was used to obtain direct measurements of several structural attributes within each plot. Nine circular sub-plots (radius = 8 m) were evenly distributed about the plot centre (Figure 12). Each sub-plot was intended to correspond to one of the nine plot pixels. Determining the boundary of a circular plot is more time efficient and spatially precise compared to square plots. In addition, a circle has a smaller edge to area ratio, and therefore, less chance for edge trees (NFI, 2008). This helped to reduce sampling bias and time, and provided the means to assess the spectral variability of each plot in relation to the spatial variability observed on the ground.

Figure 12: Plot and sub-plot design in relation to a 3 x 3 pixel window. Shows the subplots that included tree core samples as well as the field variables of interest.

Since the pixels within a Landsat image are aligned to the local direction of true north, each plot was surveyed using bearings that compensated for magnetic declination ($\sim 13^\circ$). This helped to ensure that the sub-plots established on the ground correlated with their intended pixels. This nested sampling method is similar to Hall et al. (1991); however, they used 60 m plots and only five sub-plots, omitting the diagonal neighbours.

Given that a Landsat pixel represents the average surface reflectance over 900 m^2 , the detail with which a forest ecosystem can be mapped and monitored is limited. According to Xie et al. (2008), Landsat imagery is suitable for vegetation mapping at the community-level. Therefore, the field observations and measurements were used to directly infer species composition, tree size and age distributions, canopy layering, and understory conditions at the community level.

4.3.2 Direct measurements of forest structure attributes

Neumann and Starling (2001) claim that diameter at breast height (DBH) performs extremely well as a structural indicator. Given the simplicity of the methods used to measure DBH, it was used as the main indicator for estimating the tree size distribution of each sub-plot. Within each sub-plot, DBH was measured at about 1.3 m above the ground for all standing trees, dead or alive, with $\text{DBH} > 10 \text{ cm}$. The species of each tree was also identified. The number of tree stems per sub-plot was used as an additional indicator of live, dead and total stand density. Live, dead, and total basal areas were estimated using these DBH and stem density data in relation to the area of each sub-plot ($\sim 200 \text{ m}^2$). Using these data, the average and standard deviation of each variable over the whole plot ($n = 9$) was calculated.

In each sub-plot, a 16 m transect (plot diameter) running north-south and intersecting its centre point was used to evaluate the understory conditions. Sampling points were located at the start and endpoint, and every 1m between them ($n = 17$). For each point, the dominant surface condition was noted as being bare soil, rock, moss, CWD or litter, and the dominant vegetation was identified within five vertical sampling intervals based on height (0-0.1 m, 0.1-0.5 m, 0.5-1 m, 1-2 m, and >2 m). An individual species was only considered once, and was assigned to the interval closest to its peak height. The objective was to infer the presence and abundance (percent of all sampling locations within a particular plot) of tree saplings, grass, ferns, herbaceous plants, shrubs and junipers, make comparisons between plots, and infer the successional stage of a forest. The presence of junipers, for example, helped to identify early stages of growth, whereas an abundance of tree saplings below a mature and layered canopy indicated older stages of growth (as discussed in section 2.1).

Tree cores were extracted from the base of ten trees in each plot using a structured, purposeful sampling strategy. Only the centre sub-plot and the sub-plots in all four cardinal directions were used (Figure 12). A minimum of two trees were sampled in each of the five sub-plots ($n = 10$), and if a distinct sub-canopy layer was present, half the samples were representative of this cohort. The goal was to sample a representative range in tree size to develop site-specific regressions between DBH and age.

Since growth rates are site-specific and depend on the recent history of the system, calibrating a plot's DBH distribution through empirical methods helped to infer an age distribution, and provided ecologically relevant information in relation to change (He et al., 2011). Sub-canopy species under the average age of 30, for example, provided

corroborating evidence that a new canopy layer had emerged within the time period of this study. Direct estimates of the age distribution of a forest highlighted important differences between plots with similar DBH distributions.

4.3.3 Indirect estimates of forest structure attributes

Each tree with DBH > 10 cm was classified as being part of either the overstory or sub-canopy layer. If more than 50 % of a tree's crown appeared to be overshadowed by an overstory tree, it was considered part of the sub-canopy layer. This helped to infer canopy layering and the successional stage of each plot. If a tree showed evidence of insect damage, it was also assigned a defoliation score. This visual index ranged from 0 to 3, where 0 indicated minimal damage (0-10 % defoliation), and a value of 1, 2, or 3 was assigned to trees with 10-30, 30-50, and > 50 % defoliation, respectively. Trees with missing limbs or crowns as a result of storm damage, and/or trees with signs of disease were noted. The presence and abundance of defoliation, storm damage, or disease helped to highlight unique forest conditions whose structure and composition has likely changed within the time period of this study.

Canopy openness and LAI are commonly measured through indirect methods. In each plot, five digital hemispherical photographs were captured near the plot centre and approximately 23 m in all four cardinal directions using a Nikon Coolpix 8800 camera with an FC-E9 fisheye lens. This camera system was positioned on a tripod so that the imagery was acquired parallel to the surface, at a height of 1.5 m. Each image (8 megapixels) represents a 180° field of view looking up through the forest canopy of interest, and the top of each image was oriented to true north to maintain consistent sampling methods. If relatively young understory saplings were present, and covered the

camera lens, they were pulled back prior to image acquisition. This ensured that each image sampled the dominant canopy and sub-canopy trees.

Figure 13 shows the theoretical sampling footprint of the 5 image acquisitions, and is based on a 55° to 60° zenith angle range used for calculation of LAI (Jonckheere et al., 2004) and an average tree height of about 26 m (based on previous measurements in Pasher and King (2011)). This sampling footprint represents about 25 % of the entire plot, but is expected to vary depending on the average height of the canopy of interest.

Figure 13: Theoretical hemispherical photography sampling footprint for an individual plot (in relation to a 3 x 3 pixel window) based on an average tree height of 26 m. Each ring represents the footprint for one of 5 images acquired in the plot's centre, and 23.5 m from that location in all four cardinal directions.

Hemispherical photos were acquired during the stable period of the growth season, between July 8 and August 11, 2010, during diffuse sky conditions. Acquiring imagery under diffuse sky conditions helped to capture a near-binary image, where black

portions represented vegetation components and white represents sky. Camera settings (shutter speed and aperture) were determined based on *in-situ* conditions, and were adjusted following a visual assessments of each image acquisition. Figure 14 shows a range of example images prior to processing.

Figure 14: Raw hemispherical photographs from select plot locations. A – deciduous dominated (P28), B – red pine plantation (P14), C –growing forest (20 to 30 year old white pine overstory P25), D – coniferous dominated (P17), E – severely defoliated, F – deteriorating mixed forest (dominated by black spruce, Eastern white cedar and black ash, P23).

Hemispherical image processing followed similar methods to Pasher and King (2011). DHP (v. 4.5.2) and Tracwin (v. 4.1.1) software, developed by Leblanc (2002b), were used to determine canopy openness and LAI from each image. LAI_e was based on the gap size frequency distribution extracted from a 55° to 60° zenith angle range. Canopy openness was also determined, and was based on the gap fraction extracted from

a 0° to 60° zenith angle range for each image (Frazer et al., 2000). These data were separately refined using the CC, LX, and CLX clumping indices to adjust for non-random canopy components. Leblanc et al. (2005) recommends the CLX clumping index, however all three corrections were implemented.

A needle-to-shoot ratio was also used to refine the LAI data for conifer and mixed forest plots. Species-specific ratios, based on documented values in the literature (see Table 3) were used to develop a needle-to-shoot ratio for each plot. Similarly to the methods of Torontow (2010), a weighted average based on basal area, was used to derive a plot-specific needle-to-shoot ratio for conifer and mixed forest plots (Deciduous plots are assigned a value of 1). Table 3 describes the values used for each species, with the studies locations and citation.

Table 3: Describes the location for each species-specific needle-to-shoot ratio (y_e) found within the literature, and used in this research.

Tree Species	Needle-to-shoot ratio (y_e)	Location of Research	Source
White Pine	1.91	southern Ontario	Chen et al. (2006)
Hemlock	1.65	Chelsea, Québec	Torontow (2010)
Black Spruce	1.57	Québec,	Chen et al. (2006),
Red Pine	2.08	Boreal	Chen and Cihlar (1995)
Cedar	1	N/A	N/A – assumed to be flat
White Spruce	1.27	Kananaskis, Alberta	Hall et al. (2003)
Scots Pine	1.75	Finland	Gower et al. (1999)
Balsam Fir	1.71	New Brunswick	Chen et al. (2006)

4.4 Preliminary analysis

Preliminary tests were conducted on the field and image data to reduce these datasets to the most effective variables for subsequent spatial and temporal analyses.

Several field and image variables were considered, guided by the literature; however some of these variables were expected to be either redundant or ineffective for the objectives of this research. The data highlighted by this preliminary analysis as being the most suitable were then used to assess the spatial and temporal dynamics of Gatineau Park.

4.4.1 Data reduction through principal components analysis and empirical modelling

First, PCA was performed on the field data with the intent to reduce or eliminate statistical redundancy. The first principal component (PC) is, to some extent, analogous to the line of best fit of a linear regression, and therefore a large proportion of the input variables are expected to be in close proximity to this line. As a result, the first PC is also expected to explain the largest proportion of the variance (Kambhatla and Leen, 1997). Consecutive components are based on the clustered outliers, or variable vectors, that are orthogonal to the previous PC, and each subsequent PC explains an additional proportion of the variance within the dataset (Kambhatla and Leen, 1997).

Each PC is assigned an eigenvalue, which is a direct measure of the variance explained by an individual component. A value greater than 1 indicates a significant component (Kaiser, 1960). Each PC's eigenvalue is calculated by the sum of the squared factor loadings of each input variable in relation to each PC's axis, similar to the correlation co-efficient (r) of a linear bivariate regression. Input variables with the highest factor loading indicate the strongest association with a particular component. Similar to the methods of Ceballos and Bottino (1997), a varimax rotation was used to achieve the best representation of the entire dataset. High factor loadings following

rotation helped to verify which variables explained a significant proportion of the variance within the field dataset.

The field variables highlighted as being significantly related to the major PCs were used as dependent variables within a bivariate correlation matrix against the image variables. These bivariate models were also stratified to investigate three distinct functional groups: coniferous, mixed, and deciduous forests. The objective was to highlight the most effective image variables for this research by investigating statistical relationships between the field and image data.

Image variables that frequently showed the strongest correlations with a particular field variable were selected as being the most effective indicators of the vegetation gradients. Linear regression analysis was used to assess the magnitude, direction and significance of plot-level trajectories using each image variable as a temporal indicator of vegetation quantity. The image data that showed the strongest trajectories were considered to be the most effective. Several field plots used in this research showed considerable evidence of either a deteriorating or growing forest, and were expected to be associated with a significant spectral trend.

4.4.2 Interpreting the spatial distribution of vegetation quantity

The image variables representing Gatineau Park's forests were viewed as linear surrogates for vegetation quantity in both space and time. The 2010 field data were regressed against their corresponding image data to develop linear empirical models representing the park during this growth season. These models helped to confirm the utility of each image variable, and helped to identify intuitive and relevant relationships

within the dataset. Based on these relationships, the spatial distribution of vegetation quantity for the growth season of 2010 was mapped across the park.

4.4.3 Stratifying the park into functional units

As Gómez et al. (2011) point out, there is no single technique that can be used to partition a landscape into ecologically relevant hierarchical classes. They recommend, however, that at least three levels of organization should be considered. Generally lower level landscape units are compared to higher levels, or vice versa. The objective is often to confirm trends and gradients common to all levels of the analysis, and gain an improved understanding of the data. Following this logic, this research adopted a top-down approach to the analysis; the park as a whole, the functional units within the park, and plot-level data collected.

Bitmap masks were created for each functional group using the QMMF data previously described in section 4.2.3. Figure 15 shows the spatial distribution of each functional unit, as well as other non-forest land covers.

Figure 15: Spatial representation of the three functional forest groups in Gatineau Park, and other land cover classes (water, agriculture, and bare surfaces).

4.5 Mapping abrupt forest change and gradual trends at the pixel level

Statistically significant relationships between the image and field data, interpreted as being related to changes in vegetation quantity, were used to guide the temporal analysis. The approach taken was similar to that of Cohen et al. (2001) described in section 2.3, but extends model parameters in time to investigate the changes in Gatineau Park's forests.

For the park as a whole, a forest mask was applied to determine the average vegetation quantity metrics based on their relationships with each spectral indicator. Initial assessments compared these broad scale trends across the park to temperature and precipitation anomalies, which were calculated using monthly weather data representing

the growth season (May to September) for the study area. Anomalous growth seasons were identified by the percent difference in temperature and precipitation from averages calculated from 1980 to 2010. Daily weather data were used to calculate an average temperature and total precipitation 7 days prior to each image acquisition. The goal was to identify whether seasonal trends were correlated with spectral trends. A similar investigation was performed for each functional group.

4.5.1 Mapping abrupt forest change

Change was modelled at the pixel-level, using image differencing to detect abrupt changes between two image dates. The resulting bi-temporal change map represents variations in time as a positive or negative vector for each pixel location; and therefore considers change as a linear process, as recommended by Francesco and Denoel (2009).

To efficiently and objectively determine acceptable thresholds of change, this research uses the simulated annealing approach as described in section 2.3 (c.f. Kirkpatrick et al., 1983). A range of discrete standard deviation thresholds (increments of 0.25) were implemented, and the area of change for each threshold was calculated. For positive and negative change separately, the threshold value where the area of change begins to stabilize was used as the minimum threshold. All pixels with a change vector greater than this minimum were mapped as a continuous change class (positive or negative) to assess the spatial gradient of abrupt change for a particular growth season. This helped to identify the spatial variability of the severity (or magnitude) of the events. Field data and other corroborating sources of evidence were used as additional

verification of the changes detected, and helped to determine the vegetation communities being impacted.

4.5.2 Mapping gradual forest trends

Detecting abrupt changes using satellite imagery is an extremely useful tool for forest management and it is becoming a routine application. Contemporary research efforts (including this study) are now focusing on the development of more precise monitoring methods. This temporal analysis was divided into two separate parts: the primary focus was on investigation of the spectral trends within the calibrated Landsat image time series representing summer, leaf-on conditions in Gatineau Park, and to interpret these trends based on knowledge acquired on the ground; a secondary trend analysis was designed to understand how the spatial distribution of coniferous dominated forests (>60%, based on stem counts) had changed, using winter Landsat imagery.

4.5.2.1 Detecting and mapping subtle and gradual forest trends

The Theil-Sen slope estimate and the Contextual Mann-Kendall significance test (as described in section 2.3) were implemented for trend analysis using the calibrated summer image time series to identify the pixel locations associated with significant but subtle or gradual trends (positive or negative), assumed to be related to changes in vegetation quantity or health. For both non-parametric techniques, relatively small sample sizes can be used (Neeti and Eastman, 2001); given that the maximum number of observations for any pixel location representing Gatineau Park is 13, this was considered beneficial to the analysis.

Pixels with significant monotonic trends at the 95% confidence level ($p \leq 0.05$) and slopes greater than the noise floor of a particular SVI were mapped as positive or negative subtle and gradual change. As an initial investigation, the entire image time series, representing growth seasons from 1987 to 2010 was used as an input. Lakes and wetlands were removed using a bitmap mask created from NCC vector data so that trends were based only on forested land cover. Clouds were manually removed from each image date and were treated as a missing observation in time. The start and end period of this input image time series was also modified to investigate the effects of modifying the temporal range of the observations included in the analysis. Pixels highlighted under slightly different scenarios were considered the most reliable estimates of changing locations within the park.

The image time series was also modified to examine whether the results are influenced by the monitoring frequency of the input time series. The monitoring interval of the initial time series was between 1 and 3 years, with the exception of one 4 year gap. Observations from this time series were selected to form two alternative time series, the first one used a 4 to 5 year monitoring interval, and the second one used a 6 to 7 year interval.

The image time series was also divided into three separate 11 to 13 year intervals, representing the beginning, middle and end of the available range (1987 to 1999, 1994 to 2004, and 1999 to 2010). These intervals were selected so that each temporal window included a similar number of years and remotely sensed observations (13, 11 and 11 years; $n = 6, 7$, and 7 , respectively). The intention was to highlight the timing of an event,

and describe its dynamics in greater detail. Pixel locations associated with a significant trend for all three intervals helped to identify persistent and cumulative changes.

4.5.2.2 Conifer-specific analysis using winter imagery

A winter image acquired in January 2010 was used to estimate a more recent distribution of conifer-dominated regions within Gatineau Park. Two additional scenes from January 2003 and 1989 were used to infer this functional group's dynamics over a 21 year period (image details in Table 1). These images had the least atmospheric distortion and were evenly distributed throughout the temporal period of this study. Weather data also confirmed minimal snowfall prior to each image acquisition, which was considered important since snow-covered tree crowns are a potential source of error (Klein et al., 1998). Since the spectral reflectance of coniferous foliage in winter is distinct from deciduous vegetation (Royle and Lathrop, 1997), imagery during this time was deemed an effective means for interpreting conifer-specific distributions and gradients.

Based on stem counts, the proportion of coniferous species for each plot ($> 1\%$), which was assessed in the summer of 2010, was regressed against its respective mean NDVI data captured in the winter of 2010. This simple bivariate empirical model was applied to the NDVI image representing the winter of 2010, and the resulting pixels estimated to have more than 60 % coniferous species were mapped.

The results of this map were compared to QMMF vector data (collected in 1991) to ensure that the majority of the map coincided with mixed or coniferous forests. A visual assessment between the modelled results, and leaf-off orthoimagery served as an

additional assessment. It was expected that errors would exist; however, some of these errors may be a result of change, as the two data sets were acquired close to 21 years apart. A temporal analysis using winter imagery helped to confirm if disagreements between the two data sets represented a change in this functional group, or an error in the maps.

The empirical model developed for the 2010 winter image was extended to imagery acquired during January 1989 and 2003 to map coniferous dominated regions (> 60 %) for these years. To improve the reliability of this model extension, image calibration was considered necessary. Unfortunately, the PIF locations used to calibrate the summer imagery were not applicable due to snow and ice cover.

Instead, similar methods to Chen et al. (2006) were used, which normalize SVIs directly rather than using band-to-band calibrations. A bitmap mask delineating only forest pixels was used to compare each scene, and density plots were used to derive the calibration equation for 1989 and 2003 using the 2010 scene as the master image (2003 vs. 2010 $R^2 = 0.96$; 1989 vs. 2010 $R^2 = 0.90$). The respective calibration equations were derived from the density plots in Figure 16, and were applied to their corresponding images to normalize the historical imagery and estimate 1989 and 2003 coniferous dominated distributions.

Figure 16: NDVI density plots for winter calibration using the SR method (2010 image was used as the master image).

The reliability of this model extension was assessed by comparing the estimated 1989 distribution to the forest inventory provided by the QMMF, which was created in 1991. These vector data were the best ancillary data available to develop an accuracy statement. Since a threshold of 60 % coniferous species was used to remotely map coniferous dominated regions, some of the space delineated was expected to be associated with mixed forests. If a pixel classified as being coniferous dominated in 1989 closely matched QMMF delineated deciduous forest, this was considered an error in either the field or remote sensing methods. This error assessment used 30 random points to determine the quality of the model extension. Each point considered the remotely sensed prediction of conifer-dominated regions and the QMMF map, to determine a user's and producer's accuracy. Following this, coniferous distributions throughout the park were interpreted over time.

5.0 Results

5.1 Preliminary analysis

A total of 18 normally distributed field variables were used as inputs in a PCA. Initial results showed that the first six PCs cumulatively explained 88 % of the total variance within the original dataset (Table 4). These PCs all had eigenvalues greater than or approximately equal to 1, which according to Kaiser (1960), is an objective cut-off point for selecting significant components. The field variables with the highest factor loadings on each of these PCs were considered the most important.

Table 4: First 7 eigenvalues and their respective and cumulative explanation of the variance.

PC	Eigenvalue	% of Variance	Cumulative %
1	6.45	35.86	35.86
2	4.01	22.26	58.12
3	1.85	10.29	68.41
4	1.52	8.43	76.84
5	1.12	6.20	83.05
6	0.99	5.52	88.56
7	0.68	3.80	92.37

A varimax rotation revealed a similar set of variables, however, the first four PCs showed the strongest and most interpretable factor loadings. Given that the first four eigenvalues account for 76 % of the total variance (Table 5), this was considered an acceptable cut-off point. Table 5 shows the factor loadings associated with each field variable for the first four principal components.

Interpretations of each PC were based on the magnitude and direction of the loadings, but ecologically meaningful relationships with respect to forest dynamics and

change were given priority. PC1 represented a gradient of decreasing number of stems associated with larger DBH. PC2 represented increasing basal area, increasing number of stems, and decreasing undergrowth and DBH variability. PC3 represented a strong gradient of decreasing vegetation quantity (PAI or LAI_e(y_e-LX)) and canopy openness. Other vegetation quantity related estimates derived through hemispherical photography showed relatively weak correlations. PC4 increased with reduced mean dead DBH and decreasing age. All of these relationships follow typical gradients observed during the development of a forest (as discussed in section 2.1), and can be interpreted from the perspective of either subtle or abrupt forest change.

Table 5: Factor loadings for the first four principal components (PC).

Field variable	Factor Loadings			
	PC1	PC2	PC3	PC4
Mean # of stems (DBH>10cm)			-0.001	-0.001
# of tree species (DBH>10cm)	-0.429	-0.119	0.209	-0.007
Mean live DBH (cm)		-0.177	0.128	-0.336
Mean dead DBH (cm)	0.487	-0.271	-0.077	
Mean overstory DBH (cm)		-0.188	0.136	-0.456
Mean sub-canopy DBH (cm)		0.068	0.176	-0.408
Std. deviation DBH (cm)	0.484		0.142	-0.056
Total Basal Area (m ² /ha)	0.335		0.069	-0.394
Live Basal Area (m ² /ha)	0.422		0.151	-0.290
Mean Age (yrs.)	0.231	-0.208	0.132	
Mean Canopy Age (yrs)	0.228	-0.240	0.158	
Mean Sub-canopy Age (yrs.)	0.114	0.264	0.105	
Mode age (yrs.)	0.408	0.163	-0.017	
Total Sapling Index	-0.002		-0.089	-0.268
>2m Sapling Index	0.141		0.041	-0.294
Openness	0.051	0.117		0.577
PAI _e	0.009	-0.016		-0.342
LAI _e (y _e -LX)	0.148	0.347		0.397

Each of the 10 field variables discussed above were regressed against the image data. These bivariate models were stratified to investigate coniferous, mixed, and deciduous forests separately, which helped to identify the image variables that uniformly showed the strongest bivariate correlations. Table 6 shows the field variables selected from the PCA, and if applicable, the image variable that showed the strongest positive or negative correlation (Pearson $r > \pm 0.3$).

Table 6: Strongest functional group-specific bivariate regression of the PCA field variables and the selected image data (based on Pearson r values).

Dependent Field Variable	Strongest independent image variable for each forest group					
	Coniferous	r	Deciduous	r	Mixed	r
Mean # of stems (DBH>10cm)	EVI2*	-0.83	EVI2	0.32	EVI2**	-0.85
Mean live DBH (cm)	n/a	n/a	TCB	0.40	EVI2*	0.78
Mean dead DBH (cm)	TCW*	-0.84	n/a	n/a	n/a	n/a
Std. deviation DBH (cm)	TCB*	0.91	NDVI	-0.30	TCB*	0.76
Basal Area (m ² /ha)	EVI2	-0.61	TCW**	-0.33	TCW*	0.90
Mean Age (yrs.)	TCW**	-0.64	n/a	n/a	EVI2	0.44
>2m Sapling Index	EVI2*	0.68	n/a	n/a	EVI2	0.65
Openness	n/a		EVI2	0.50	TCW**	-0.80
PAIe	EVI2	0.54	EVI2**	0.56	TCW*	0.93
LAIe(ye-LX)	TCW**	0.94	EVI2**	0.58	EVI2	0.56

** p value ≤ 0.05 , * p value ≤ 0.01

It can be seen in Table 6 that EVI2 and TCW often showed the strongest correlations. These image variables were considered to be the most effective spectral indicators of vegetation quantity. Deciduous models were generally the weakest; initially this was thought to be a result of the severe insect defoliation that occurred in some of these plots during the growth season of 2010, but only slight improvements were observed when these plots were removed from the analysis. A wide range of spectral and

spatial image variables were considered, however for most dependent field variables, only a few image variables showed strong correlations. First and second order texture variables were rarely correlated, and in all cases, fractional image data showed the weakest relationships. Thus, texture and image fraction variables were not considered further in temporal analysis.

For each of the image variables highlighted in Table 6, the significance, magnitude and direction of their respective plot-level trajectories were investigated. The objective was to determine the suitability of each image variable as a temporal indicator of forest change. EVI2, NDVI and TCW plot-level trajectories detected the majority of the plot locations representing forest change. Other image variables showed fewer plots with significant trajectories or none at all. This investigation was based on correlation coefficients, as well as the slope of each trajectory in relation to the noise platform for each image variable. TCW stood out as the most suitable temporal indicator as all its trajectories had strong R^2 values (between 0.66 and 0.90) and each one was associated with plots known to be located within a growing or deteriorating forest.

Plot-level correlations between EVI2, NDVI, and TCW image variables confirmed, as expected, that EVI2 and NDVI are highly correlated ($r = 0.99$), and therefore, likely provide redundant information. However, they were far less correlated with TCW indicating that this image variable may provide additional change information ($r = 0.11$ and 0.10 for EVI2 and NDVI, respectively). When comparing the range of EVI2 and NDVI data for each plot and image date, it was found that EVI2 had a much broader range (averages across all image dates = 0.83 and 0.30 for EVI2 and NDVI, respectively). In relation to their respective noise platforms and data range, EVI2 was preferred since

the relative error associated with it was 50 % less than that of the NDVI (0.0014, and 0.0009, respectively).

This preliminary analysis confirmed that correlations existed between the field and image spectral data. It also helped to reduce the initial dataset to the most suitable image variables (EVI2 and TCW). These variables were viewed as linear vectors of vegetation quantity, and were used to assess the dynamics of Gatineau Park across space and time. The results of this investigation are presented below, and a variety of corroborating evidence is provided to support them.

5.2 Spatial analysis of forest structure in Gatineau Park

Understanding the relationships between the image and field data acquired during the growth season of 2010 aided interpretation of the spatio-temporal forest gradients for Gatineau Park. Since field data were only available for the growth season of 2010, and the image data were relatively calibrated, the relationships identified for this year were assumed to be applicable to the other image dates. Example 2010 bivariate regression analysis is provided below for the park as a whole, each functional group, and the plot data.

5.2.1 Empirical models representing the growth season of 2010

Using all 33 plots, the field variables in Table 6 were regressed against the respective plot means of EVI2 and TCW, which were derived from 9 pixels/plot. EVI2 was negatively correlated with two plot variables (Figure 17), the average number of stems ($r = -0.61$) and canopy openness ($r = -0.57$). TCW had one strong and positive

correlation (Figure 18) with LAI ($r = 0.81$). These three relationships were considered statistically significant (p value well below 0.001), however, as illustrated in Figure 17 and 18, some degree of noise is evident, especially for EVI2. The relationships identified for EVI2 were weak by comparison, but expected relationships were highlighted by both image variables.

Figure 17: Significant bivariate regressions for average number of stems and canopy openness (%) of all plots ($n = 33$), against their respective mean EVI2 values derived from 9 pixels in each plot.

Figure 18: Significant bivariate regressions between LAI of all plots ($n = 33$), and their respective mean TCW values derived from 9 pixels in each plot. A distinct gradient can be seen among the three functional groups.

Stratifying the plot data into the previously defined functional forest groups helped to reduce scatter, and identify additional relationships for both image variables. EVI2 showed the strongest deciduous-specific LAI model ($r = 0.57$, $p = 0.08$); however, it was quite weak compared to the coniferous (r value = 0.87 , $p = 0.01$) and mixed (r value = 0.9 , $p = 0.02$) models (Figure 19).

Figure 19: Strongest functional group-specific LAI (LX-ye) models for EVI2 and TCW.

Deciduous models likely performed poorly as a result of the insect damage incurred by this functional group. The resolution of the hemispherical photography may not have detected small partially consumed leaves or small leaves that appeared following defoliation, and therefore, gap-fraction based estimates of vegetation quantity may not have been representative. In addition, an enhanced background signal as a result of an increase in canopy openness may have altered the remotely sensed estimate of vegetation quantity for the defoliated plots. In combination, these potential errors may have increased the level of noise for deciduous models, and therefore, only a small proportion of the variance could be explained.

Field variables other than LAI also showed strong correlations with EVI2 and TCW, however, deciduous models continued to perform poorly. In contrast, coniferous and mixed forest plots showed several statistically significant correlations. Figure 20 shows the top two conifer-specific models for both image variables. The strongest TCW model formed a negative relationship with average dead DBH ($r = -0.84$, $p = 0.02$). For EVI2, the variability of DBH produced the strongest model ($r = -0.63$, $p = 0.12$), but it was statistically much weaker.

Figure 20: Conifer forest-specific models between field data and EVI2 (left), and TCW (right).

Mixed models for both TCW and EVI2 showed strong correlations with canopy openness, however, the TCW model was statistically stronger ($r = -0.80$ and -0.76 ; $p = 0.06$ and 0.08 , respectively). The strongest TCW model, however, was with live basal

area ($r = 0.90$, $p = 0.01$). As illustrated in Figure 21, EVI2 showed the strongest relationship with the average number of stems of each plot ($r = -0.84$, $p = 0.03$). Similar to the coniferous forest models, the mixed forest models show better fit with TCW as the independent variable.

Figure 21: Mixed forest-specific models between field data and EVI2 (left), and TCW (right).

The above analysis shows that ecologically meaningful relationships exist between the 2010 image spectral data and field data. In particular, TCW was strongly correlated with LAI, which was considered to be the main estimate of vegetation quantity for each plot. Stratifying the plot data into functional groups helped to identify additional empirically defined relationships, however the number of observations was considerably smaller, especially for coniferous and mixed forest plots. The combined set of models for

the whole park and by functional group revealed that certain image variables were strong indicators of horizontal and vertical vegetation structure, providing potential for their use in modeling and monitoring forest structure spatio-temporal dynamics across Gatineau Park.

5.2.2 Spatial distribution of vegetation in Gatineau Park in summer 2010

EVI2 and TCW images of the forested regions of Gatineau Park during the growth season of 2010 were classified using 20 geometrical intervals and a continuous colour gradient to visually interpret each image variable in terms of vegetation quantity. This classification scheme applies breaks that optimize the number of values represented by each class (ESRI, 2008).

Different vegetation indices sometimes had conflicting interpretations of forest conditions. As an example, Figure 22 shows a map of a red pine plantation within the park, represented by EVI2 and TCW, which highlight this conifer-dominated region as an area of low and high vegetation quantity, respectively. Seed and King (2003) discuss how the canopy architecture of a coniferous forest produces darker shadows than deciduous forests, and may affect the value of a SVI. With reduced NIR reflectance, EVI2 would theoretically become lower. Low and positive weighting is applied to the NIR band (TM4) and high and negative weighting is also applied to the mid-infrared bands (TM5 and TM7) when calculating TCW, so low near infrared reflectance would result in higher values for this SVI.

Figure 22: Spatial interpretation of vegetation quantity, for the growth season of 2010 using EVI2 and TCW. Maps focus on a red pine plantation, and an area dominated by coniferous species.

Interestingly, during the same growth season, the south-east portion of the park, which is dominated by deciduous forests and was severely defoliated in 2010, was highlighted as an area of low vegetation quantity by both image variables. Under normal conditions though, TCW consistently highlighted deciduous forests as being on the low end of the vegetation scale, which was corroborated by the field LAI data shown by the y-axis in Figure 19. When considering the strong relationship between TCW plot data and LAI (Figure 18), TCW appears to be the most reliable indicator of vegetation quantity. The remainder of this section summarizes the spatial analysis when viewing the image data for each functional group, and at the plot-level.

5.2.3 Local spatial gradient analysis

All pixel values representing the three functional forest units in Gatineau Park were extracted from both the EVI2 and TCW 2010 images using bitmap masks derived from the QMMF vector data. Table 7 lists the number of pixels representing each forest

type, their respective areal coverage, and the means and standard deviations for both image variables:

Table 7: Summary of TCW and EVI2 data for the growth season of 2010, for all three functional groups in Gatineau Park.

Functional Group	# of pixels	Areal coverage (ha)	Mean TCW	Standard Deviation TCW	Mean EVI2	Standard Deviation EVI2
Deciduous	218323	19649	-17.59	6.455	1.37	0.141
Mixed	96058	8645	-11.51	6.337	1.29	0.192
Coniferous	14415	1297	-9.16	7.092	1.18	0.196

Figure 23 compares the distribution of each index within each functional unit and across the entire forested area of Gatineau Park. In addition to the summary statistics provided in Table 7, it can be seen that these distributions show some degree of spectral separability, especially between deciduous and coniferous forests. TCW appears to differentiate best between these two forest types. For mixed forests, a natural gradient exists with respect to the proportion of deciduous or coniferous species, and therefore, overlap between these distributions was expected.

Figure 23: Functional group-specific forest histograms, for EVI2 (A), and TCW (B).

Using plot-level data, the average spectral signature of each functional group was graphed. Figure 24 shows that spectral differences between the functional groups of Gatineau Park are most evident within the near- and mid-infrared spectral regions, within which, as expected, reflectance from coniferous vegetation is much lower than deciduous. Although markedly smaller, even the visible Landsat bands show coniferous forests to be darker/less reflective than deciduous.

Figure 24: Spectral signatures for Deciduous, Conifer and Mixed forest plots (average values).

To further investigate the spectral data associated with deciduous forests during the growth season of 2010, the plots that showed signs of severe insect defoliation were compared to the plots where insect damage was not visually evident on the ground (Figure 25). The most noticeable difference in their spectral signatures is evident within the near-infrared (TM4) reflectance regions, but slight differences can be seen in the mid-infrared bands as well (TM5 and 7). The additional infrared bands used to compute TCW may help to improve estimates related to this type of disturbance.

Figure 25: Spectral signatures of defoliated and non-defoliated deciduous plots. At the time the 2010 image was acquired, most defoliated plots had a second set of small light green leaves.

Regardless of functional unit or insect defoliation, plots that were assessed as growing or deteriorating in the field were grouped into two separate classes. Figure 26 shows that the average spectral signatures for each group are quite different. The most distinct differences are seen in the infrared regions, and help to confirm that these plots are represented by very different spectral signatures that may have emerged during the time period of this study.

Figure 26: Average spectral signature of growing and deteriorating forests plots surveyed in 2010.

The strong relationship between TCW plot data and field measured LAI (Figure 18) was encouraging. Overall, TCW was seen to outperform EVI2 from a spatial perspective. Figure 27 shows a TCW map of the forests in Gatineau Park with colour gradients separately applied to each functional group in an effort to portray the spatial distribution of vegetation quantity (i.e. showing high and low regions for each functional group). Field plot locations are also shown, and are classified into 4 different groups representing low (2 – 4), medium (4 – 6), high (6 – 8), and very high (8 – 12) LAI values. These data points visually follow a very similar spatial trend as the TCW map.

Figure 27: TCW specific vegetation quantity gradients with plot-level LAI measurements representing 2010. A few closer views of this gradient are provided by the inset maps outlined in blue, purple and black.

The subset maps in Figure 27 show three different plot locations situated within distinct low or high LAI regions. As expected, plot values reveal a similar indication of vegetation quantity. Trees within the subset map outlined in blue appeared in the field to be deteriorating as a result of surface water hydrology; the soil remained saturated for the entire growth season, and trees were either falling over or declining as a result. The subset map outlined in purple shows a forest patch dominated by coniferous species, which was estimated by both TCW and hemispherical photography to be on the high end of the vegetation quantity scale. The location outlined in black is associated with the lowest LAI class since it was severely defoliated in 2010. Based on these subset maps,

and other similar visual assessments, the field and TCW image data seem to follow a similar gradient.

5.3 Temporal analysis of Gatineau Park and the corroborating evidence of change

The empirical models developed using the 2010 field and image data showed that TCW and EVI2 were the best indicators of vegetation quantity; TCW appears to be the most robust, however temporal analysis could demonstrate different behaviour. The temporal component of this research was intended to determine the precision with which Landsat data can detect forest change. The results are summarized below.

5.3.1 Trend analysis across the entire time series

SVI trends were analyzed for the park as a whole and separately for each functional group. It was found that trends were quite similar for both scales, so just the functional group forest trends are provided below (Figure 28). Although for each image variable a similar pattern can be seen for all three functional groups, there are differences for some growth seasons, especially for TCW trends, which suggests that it is either a more dynamic indicator of change, or more sensitive to noise.

The growth season of 2010 showed the most obvious change for deciduous forests, most likely because the forest tent caterpillar targets deciduous species. A similar deviation can be seen for 2006. For 1990 and 2003, deciduous forests show average TCW to be much lower (more negative) than the previous year while mixed and coniferous forests show an increase. Conversely, in 2004 deciduous reflectance increased compared to 2003 while mixed and coniferous forests show a decrease. The functional group-

specific changes described in Figure 28 may represent real change that can be potentially corroborated through ancillary data acquired in the field.

Figure 28: Mean functional time series for EVI2 and TCW (data points are connected with a line for illustrative purposes only, for intervals larger than 1 year the certainty of this line is unknown).

As a final comparison, plot-level spectral trends for two plots (Figure 29) surveyed in 2010 show that plot 31 (located in subset map outlined in blue in Figure 27) is situated in a deteriorating forest while plot 22 represents a very young and growing forest. Most trees in plot 22 were estimated to be less than 25 years old and had a relatively large DBH.

Figure 29: EVI2 and TCW plot-level trajectories of a growing (P22, in green) and deteriorating forest (P23, in red).

Although noise (year-to-year variations) is evident within the overall trends of each image variable in Figure 29, it is clear that the temporal signal for TCW is stronger than EVI2. For both plot locations, persistent and cumulative changes are known to be occurring but TCW shows a stronger (higher R^2 value) trajectory than EVI2, suggesting that it is less sensitive to noise. It should be noted, though, that a forest is not always in a state of growth or deterioration; in more stable forests vegetation quantity may vary year-to-year as a result of weather variability.

For each image date available, average TCW and EVI2 for the park as a whole and each functional group were regressed against the average monthly and daily temperature and total precipitation anomalies. Signal changes extracted from the Landsat imagery across the study period did not appear tightly correlated to weather, suggesting that seasonal trends had little influence on the SVI trends. Although weather variability between seasons is expected to have an influence on the productivity of a forest (Spies, 1998), inferring these dynamics likely requires more detailed data. Weather variability in

this case may be more realistically viewed as an indirect influence along with other environmental controls.

5.3.2 Analysis of short term change

Overall, TCW appears to be the preferred image variable for monitoring Gatineau Park's forests, and was used exclusively for the remainder of the temporal analysis as the main indicator of change across space and time. This section summarizes the abrupt changes detected using imagery from the relatively calibrated TCW image time series.

5.3.2.1 Forest tent caterpillar defoliation

Based on evidence presented in Figure 28 and observations in the field, abrupt change analysis was investigated to map damage induced by the tent caterpillar outbreak of 2010. The 2007 TCW image was subtracted from the 2010 version to map positive and negative forest change. Comparing the cumulative area of negative change to increments of 0.25 standard deviations from the mean showed that after about 1 standard deviation, asymptotic behaviour occurred (i.e. simulated annealing approach discussed in section 2.3.1). This suggested that beyond this threshold value, negative change was significant. Based on the same analysis, very little positive change was detected during this period.

Figure 30 shows the spatial distribution of negative change assumed to be associated with the 2010 insect defoliation. It highlights the pixels < -1 standard deviation from the mean, and focuses on the southern region of the park where the insect defoliation was concentrated. It also includes a zoomed in portion of the change results, showing that the majority of this change is associated with deciduous forests. Coniferous

and mixed forests are highlighted in this subset image, showing that they experienced very little change. This makes sense since the forest tent caterpillar targets deciduous species.

Figure 30: 2010 forest tent caterpillar outbreak mapped through image differencing (2010-2007). Comparisons with Gatineau Park's functional groups (left) showed that the majority of the changes detected (right) correspond to deciduous forests.

5.3.2.2 Gypsy moth defoliation

Another change event that appears to be related to insect defoliation was mapped for the 2003 growth season (Figure 31). While field data were not available for that year, the spatial pattern of the event closely resembles a map produced by the QMNR for 2008 (map 'B' in Figure 31), which outlines an area defoliated by gypsy moths. For the TCW change map, asymptotic behaviour was observed after about 2 standard deviations from the mean, and was used as the mapping threshold for this change detection scenario.

Figure 31: Results of a 2004 – 2003 TCW image difference (A), and a map produced by the Quebec Ministry of Natural Resources and Fauna(QMNR) in 2008 mapping a gypsy moth defoliation event (Louis, 2008). Both maps show a similar region of change.

TCW differencing for 1990 and 1989 showed a similar pattern to map ‘A’ in Figure 31, which suggests that this area may be prone to periodic gypsy moth defoliation. According to Liebhold et al. (2000), gypsy moths can persist with extremely low population densities, however, if environmental controls are optimal, they can increase to severe defoliating levels within a few years (> 5000 egg masses/ha). Liebhold et al. (2000) provide temporal records for 5 different regions in North America showing that outbreaks are irregular and difficult to predict. While some statistical evidence suggests a 10- to 11-year interval, there is high variability. Based on evidence derived from the relatively calibrated Landsat time series and map produced by the Quebec Ministry of Natural Resources and Fauna (QMNR), the southern regions of Gatineau Park seems to have been exposed to at least three gypsy moth defoliation events during the time period of this study.

5.3.2.3 Road construction

A major road connecting Aylmer and Hull, Boulevard des Allumettières, was completed in 2007. This road cuts through the southern tip of Gatineau Park, and was expected to be easily detected through image differencing. The TCW 2007-2004 difference image, with a negative threshold of 3 standard deviations, highlighted the spatial extent of this road development. The pixels identified as significant negative change can be seen in relation to an ortho image captured in 2007 during the final stages of development in Figure 32. There are a few areas, however, that appear to have been misclassified (i.e. change that occurred that was not detected). These areas may have already changed prior to the dates used, or the pixel size of the Landsat image may not be suitable for accurate delineation of change areas that are as small or narrow in extent such as this.

Figure 32: Results of a 2007 – 2004 TCW image difference. A change threshold of < -3 standard deviations highlighted Boulevard des Allumettières, a road developed in 2007.

5.3.2.4 Ice storm of 1998

Unfortunately changes induced by the ice storm of 1998 were not detected using the imagery available for this research. Imagery representing the growth season of 1995 and 1999 were the closest dates available to the timing of this event, but did not show statistically significant spectral differences. King et al. (2005) showed that the storm increased canopy openness significantly, exposing persistent understory species to increased levels of light. This was seen to significantly promote the growth of these species and by the following year, produced a strong background signal for most of the damaged forests, confusing the results of the change analysis. If an image was available of the 1998 growing season, this change event may have been mapped with greater success.

The events mapped above are just a few examples that could be corroborated with existing information. An exhaustive investigation of bi-temporal change was not implemented for this research because at this point this is not a novel application (deBeurs and Townsend, 2008). Nonetheless, it was important to show that the imagery selected for this research could be used to detect abrupt changes. Detecting subtle and gradual change is the focus of the subsequent section.

5.3.3 Mapping long term spectral trends

As seen in section 5.3.2, two calibrated images can be used to detect the overall change between two image dates, however, change results are limiting since it is difficult to differentiate between the abrupt and subtle changes for a given time period. For management purposes, and to understand ecosystem dynamics in greater detail, it is

important to determine whether a detected change occurred at one particular moment in time, or as a gradual and persistent change. This section shows that more than two images can be used to further analyze these types of change characteristics; the methods examined and evaluated are considered to be a practical management approach.

5.3.3.1 Mapping the location, direction, timing and magnitude of change

To detect trends within all forest types of Gatineau Park related to vegetation quantity, at a scale relevant to its management, trend analysis was applied at the pixel level (30 m resolution) to the image time series representing summer leaf-on conditions. Outputs from the Theil-Sen (TS) and the Contextual Mann-Kendall (CMK) techniques provided an indication of the statistical significance of each pixel's spectral trajectory, and each trajectory's slope.

Using the CMK methods described in Neeti and Eastman (2011), a pixel's trajectory was considered significant at the 95 % confidence level ($p \leq 0.05$). If its respective TS slope estimate was greater than the TCW noise floor (± 0.36) it was mapped as an area of persistent and cumulative change. Based on the models developed against specific forest parameters (Section 5.2.1), these trajectories were presumed to be associated with a change in vegetation quantity, with the direction of each slope indicating potential forest growth or deterioration. Several analyses were implemented, each one using different combinations of calibrated TCW image dates. The intention was to examine the utility of the combined Theil-Sen and Mann-Kendall approach for mapping the location, direction, timing and magnitude of long term forest change.

The first analysis used all TCW images, however, the growth season of 2010 was removed from the analysis because the severe insect defoliation resulted in many pixels being extreme outliers; when included in the analysis the space delineated as changing was clearly unrealistic. The significance of a trend, calculated by the Mann-Kendall test, is based on the number of iterations in the forward direction that demonstrate a particular direction of change (positive or negative) compared to the total number of possible iterations in the time series. If the final observation in the time series is extremely negative compared to the observations made previous to it, then the true direction of change may be misinterpreted, and the S-stat may make it difficult to reject H_0 . The entire image time series included 13 images, and therefore, if the final observation is an extreme outlier, this would potentially introduce about a 15 % (12/87) uncertainty to the significance calculation. Removing the 2010 image significantly improved the results of the Mann-Kendall analysis, and therefore, the observations between 1987 and 2007 were used ($n = 12$), referred to hereafter as the 20 year time series. Figure 33 shows the results for this time series, highlighting about 995 ha and 549 ha as significantly decreasing and increasing in vegetation quantity, respectively.

Figure 33: Shows the results of the gradual trend analysis using all images available (1987 to 2007). Areas highlighted in red and green represent significant negative and positive spectral trajectories, respectively (slope > noise, $p \leq 0.05$).

To examine the sensitivity of these results, the beginning and end dates of the 20 year time series were slightly modified. One analysis used data from 1987 to 2004; and another used data from 1990 to 2007, hereafter referred to as the early- and late-17 year time series, respectively, each comprised of 10 images. Table 8 provides a broad summary of the analyses, used to compare the changes detected in each of these periods.

Table 8: Area (ha) of positive and negative change for three different time series analyses.

Time Period	Observations (n)	Significant positive change		Significant negative change	
		Area (ha)	% of park	Area (ha)	% of park
1987 to 2007	12	549	1.5	995	2.65
1987 to 2004	10	1021	2.8	394	1.1
1990 to 2007	10	352	1.0	679	1.9
Average	11	641	1.8	689	1.9

The spatial coverage of positive and negative change modelled by each analysis is quite different, but for all analyses change is relatively low for the park as a whole. The park's forest cover is not deteriorating overall, but there are local areas where change is significant. It can be seen that the two largest estimates of positive change included the earliest available observations in the analysis (1987 and 1989); conversely, the two largest estimates of negative change included the most recent observations (2006 and 2007). Interestingly, the majority of the predicted gradual changes for each time series are in similar locations, and the mean of all three estimates for each direction of change shows equilibrium conditions for the park as a whole.

Two prominent forest areas where vegetation quantity appeared to be decreasing in vegetation quantity were identified during 2010, the year when field work was conducted. Losses appeared to be for the same reasons discussed for the subset map outlines in blue in Figure 27. These two locations were also highlighted using the 20-year and both 17-year time series, which provided spectral and statistical evidence of persistent and gradual change. The spatial distribution of predicted change is notably different, but the same general area is being targeted as deteriorating for all three time series (Figure 34). The early 17-year time series appears to show the least amount of change, and as later observations are included in the analysis, the area of change increases.

Figure 34: Example regions associated with significant negative TCW trajectories for the 20- and 17-year time series.

Figure 35 shows a location in the park that was cleared by the Bannister family and used as pasture until around 1940. This area is located just west of a popular hiking trail known as “Hickory Trail”, and educational signage along this trail, provided by the NCC, describes the history of the area. Following its use as pasture it was later converted to a gravel pit operation, which was abandoned a few years later. Now this area is used by the NCC as an educational example of an early successional forest; the mature and relatively stable surrounding forests are used for comparative purposes. It can be seen in Figure 35, that the results of the early-17 year time series analysis shows the largest area of overall growth for this region, especially when compared to the late-17 year time series. The 20 year time series shows a similar area of change as the early-17 year time series, however, the periphery pixels are considered more stable. Although all three analyses highlight this area as positive growth, the size of the estimated area seems to be dependent on whether or not earlier observations are included in the analysis.

Figure 35: Example site associated with significant positive TCW trajectories for the 20- and 17-year time series.

After modifying the monitoring interval of the input image time series, it was found that the results of the 4 to 5 year monitoring interval were similar to the change results of the initial 20-year time series. The results of the 6 to 7 year monitoring interval were comparatively conservative, and suggested that very little change occurred (Figure 36).

Figure 36: Gradual trend analysis results for time series using a 1 to 3, 4 to 5, and a 6 to 7 year monitoring interval.

Figure 36 shows a zoomed in portion of Gatineau Park, illustrating areas of both negative and positive change, for all three monitoring interval scenarios. Although visually similar, the results of the 4 to 5 year analysis appear to show more positive change than the initial 20 year time series, which seems to show more negative change comparatively. These visual interpretations are corroborated in Table 9 below:

Table 9: Area of positive and negative change for three different time series scenarios, one using all available observations, one with a 4 to 5 year frequency interval, and another one with a 6 to 7.

Monitoring Interval	Number of observations (n)	Significant positive Change (ha)	Significant negative Change (ha)
1 to 3	12	549	995
4 to 5	6	743	569
6 to 7	4	218	113

Though the estimated areas of change are slightly different when using a 1 to 3 or 4 to 5 year monitoring interval, the locations of the changes being detected are quite similar. It should be noted, however, that as the monitoring interval becomes wider, the number of observations that can be included decreases. While both Theil-Sen and Mann-Kendall techniques are considered robust even for small sample sizes, larger samples are generally considered more statistically reliable (Yue et al., 2002). Therefore, it is difficult to truly compare the results of the 6 to 7 year monitoring interval since the number of observations for this time series is very low ($n = 4$). Despite this, it is clear that the results are influenced not only by changes to the start and end date of the input time series, but also the monitoring interval. While the results of the 1 to 3 year interval are likely the most reliable, comparable results can be achieved using a 4 to 5 year monitoring interval, a notion that is useful from a management perspective.

To map change with greater confidence for the period of 1987 to 2007, the 20 year time series and the early- and late-17 year time series were used to create a 'combined change map'. This map shows the pixels that were highlighted, for all three scenarios, as being part of a negative or positive spectral trajectory. These pixels were considered to be representative of the most confident spatial distribution of gradual change; mapping them provided the location and direction of the overall change for Gatineau Park. However, describing the magnitude and timing of these changes, as well as the vegetation communities being impacted were also important objectives of this research.

The magnitude of an event was interpreted by thresholding the slopes of each trajectory identified by the Theil-Sen analysis. Pixels with a spectral trajectory greater

than 2 times the noise floor (NF) were assigned to one of three slope classes: gentle (slope = 2 to 4 x NF), moderate (slope = 4 to 6 x NF) and severe (slope > 6 x NF). This mapping criteria was used to threshold the results to allow comparisons by separating the most extreme trajectories (severe slope) from the less drastic. From a management perspective for example, this stratification could be used to identify priority regions.

Figure 34 (above) illustrates two locations in the park that were considered to be associated with a significant negative change trajectory using the 20-year time series. Figure 37 shows the same regions (outlined in black), but includes a map describing the slope class of each pixel's trajectory. It can be seen that region 'B' has pixels associated with all three slope classes, whereas region 'A' is associated with only the gentle slope class. Region 'B' appears to have changed more drastically during the given time period, and the most severe change seems to have occurred in the centre of the delineated area. The magnitude of change becomes less severe towards the periphery of the outline for region 'B'. The results in Figure 37 are not surprising. In the field, region 'B' was observed to be in a state of severe deterioration since it was largely composed of standing dead trees. Region 'A' was obviously in a state of decline, but had a much larger proportion of standing live trees. Both sites were modelled modeled to be decreasing in vegetation quantity.

Figure 37: Maps of two known locations of deteriorating forests in Gatineau Park, showing the magnitude of the changes between 1987 to 2007. The magnitude (or slope) of a significant trajectory was assigned to one of three classes based on the TCW noise floor (NF): gentle (slope = 2 to 4 x NF), moderate (slope = 4 to 6 x NF) and severe (slope > 6 x NF). Area A showed a gentle change while Area B showed mostly severe change over the twenty year period. Both sites are in proximity to uncontrolled beaver monitoring sites.

In an effort to understand the timing of a particular change event, observations extracted from the original 20 year time series were used to compile three new image time series. The intention was to interpret change for the early, middle, and late portion of the available time series (1987 to 1999, 1994 to 2004, and 1999 to 2007, respectively). Although these time series represent slightly different durations in time (9 to 12 years), they include a similar number of remotely sensed observations ($n = 6$ or 7).

The beginning and end date of each 10-year time series was modified, and the combined mapping methods described above were used to highlight the most confident regions of change for each period. The results were intended to help determine the timing and duration of different change events identified by the initial 20 year time series, and to identify additional and intermittent changes that occurred between 1987 and 2007. Table 10 shows the area of change for each 10-year time series and compares these results to the combined mapping method of the initial 20 year time series.

Table 10: Summary of gradual trend analysis results for each 10-year time series, as well as the results of the combined change map for the 20-year time series analyses.

Time Period	Number of Observations (n)	Significant positive Change (ha)	Significant negative Change (ha)
Early (1987 to 1999)	6	143	63
Mid (1994 to 2004)	7	69	90
Late (1999 to 2007)	7	14	439
All observations (1987 to 2007)	12	249	202

It can be seen that the early 10 year time series showed the most positive change compared to the mid and late 10-year time series. Interestingly, about 25% of the space estimated to be associated with a positive trajectory overlaid the plantations mapped by the QMMF in 1991, which were expected to be associated with a positive spectral trajectory. Figure 38 shows a section of northern Gatineau Park where many of these plantations can be found. The analysis for the early 10-year time series highlighted portions of these plantations as growing regions, but it can also be seen that the majority are considered stable (i.e. no significant trajectory). Regardless, the space delineated does seem to correspond to regions within the park that are more than likely in a state of progressive growth. This suggests that the results of the early time series has a high user's

accuracy, but potentially a lower producer's accuracy with respect to detecting and mapping growing forest conditions (Figure 38).

Figure 38: Significant positive gradual change for the 1987 to 1999 image time series. Plantations in the area are also indicated, which were mostly about 10 years old in 1990. Many of them are highlighted by the results of the gradual trend analysis.

The negative change detected using the early time series was comparatively sparse, however as an example, one of the larger patches corresponded to region 'A' in Figure 37, which suggests that a decreasing trend for this region began as early as 1987. Region 'B' was not highlighted by the results of the early 10-year time series, however, evidence of decreasing vegetation quantity was identified by the results of the mid 10-year time series, suggesting that this area did not begin decreasing in vegetation quantity until the early 90s. Both locations are near major bodies of water, associated with a known uncontrolled beaver monitoring sites. Unfortunately, data describing the timing of

the development of each dam was not available. Given the proximity (within a 500m radius) of these dams to each negative change site (region 'A' and 'B' in Figure 37), as well as visual evidence in the field, change is likely at least partially a result of beaver activity.

As detailed by Table 10, the mid-10 year time series showed a moderate amount of both positive and negative change compared to the early- and late- 10 year time series. This is consistent with the results presented in Figure 28 (in section 5.3.1), which presents the average reflectance for each functional group for each image date available. The period of time that corresponds with the mid 10-year time series on this graph also appears to be relatively stable, especially compared to the observations before and after this period.

Finally, Table 10 shows that the late 10-year time series experienced very little positive change, but, compared to all other periods, it showed the most negative change. While some regions of negative change for the late-10-year time series correspond to regions detected using the whole 20-year time series, close to 60 % of the detected area of decreasing vegetation quantity represents additional regions of spectral change from 1999-2007. Unfortunately, it was difficult to validate these results. A few patches were visited during the field validation of 2011; most did not appear to be deteriorating, rather these forests appeared to be undergoing a compositional change as deciduous species appeared to be emerging as the dominant canopy species.

Figure 18 shows that conifer-dominated regions are associated with a brighter TCW signal compared to areas dominated by deciduous species. If deciduous species

eventually establish within the canopy of what used to be a coniferous or mixed forest, the TCW signal will likely decrease over time. These types of forest dynamics are likely to occur in many of the older plantations in Gatineau Park, where shade tolerant deciduous species may develop when not managed. Based on Figure 18, this change in species composition could be highlighted as deteriorating conditions.

A total of 440 ha were highlighted by the late 10 year time series as a negative TCW spectral trajectory. About 10% of this change (~44 ha) was associated with the space delineated as being a coniferous forest by the QMMF in 1991, and approximately 30 % (~127ha) was associated with mixed forests. When considering the area of change estimated by both the late 10-year time series and the initial 20-year time series, almost 100 % of the change associated with mixed and conifer forests for both simulations overlap. Therefore, it is difficult to explain the additional area detected as deteriorating as being related to a forest converting from coniferous to deciduous. It was noticed, however, that the magnitude of these new negative trajectory regions are for the most part of a gentle slope class, suggesting that change is very subtle and gradual.

Since consistent corroborating evidence was not available to validate the results of each 10-year time series, it was difficult to assess their reliability. A few methods of assessment, however, suggested that errors may be present (e.g. Figure 38). In general, the results of the 10-year time series seemed to be less reliable than the results of the 20-year time series, which may be primarily related to the number of observations included in each time series. In some cases, the results of all 10-year simulations helped to infer the timing, and duration of a particular change event modelled by the 20-year time series, but this was not always the case.

Since the results of the 20-year time series are likely the most reliable, they were used to assess the vegetation communities being impacted for this period. An assessment of the reliability of the 20-year time series is presented in the next section. Table 11 shows that deciduous forests experienced the most negative changes and mixed forests show the most positive change when considering the overall area detected. When considering the proportion (α) of these changes for each functional group, positive and negative change for coniferous forests is the most significant. Over 10 % of the total area of coniferous forests was highlighted as deteriorating, and over 4 % was identified as growing. Mixed forests show higher proportions than deciduous forests, for both directions of change. When viewing the change results this way, deciduous forests appear relatively stable.

Table 11: Summary of functional group-specific gradual change for the period between 1987 to 2007. The total area of change, as well as the proportion of change for each functional group is detailed.

Direction of Change	Total Change Area	Functional specific change (area and proportion of each class)					
		Conifer		Mixed		Deciduous	
		Area (ha)	% of Class	Area (ha)	% of Class	Area (ha)	% of Class
Positive	434	61	4.4	216	2.5	157	0.8
Negative	987	149	10.9	360	4.1	478	2.5

Stratifying the results of the early and late-17 year time series, as well as the combined mapping method for the 20-year time series, coniferous forests are consistently represented as the functional group with the highest proportion of change. Figure 39 shows a bar graph that describes the proportion of change for each functional group in

relation to all 20-year time series. While the proportion of change differs, the relative difference between functional groups, for each time series, remains quite consistent. Coniferous forests show an extremely high proportion of change when simulated using the 20-year and late-17 year time series, but for every simulation, this functional group was always identified as having the highest proportion of positive and negative change.

Figure 39: Proportion of change (positive and negative) for each functional group (conifer, mixed, deciduous) detected by each input time series considered in the analysis.

5.3.3.3 Plot-level analysis and field validation

As expected, the results of the 20-year time series highlighted most of the field plots that were considered representative of either positive or negative change. Only one plot, assessed as being young and growing, was not considered temporally dynamic. An independent validation was used to provide an unbiased assessment.

Thirty separate sites for both the positive and negative changes highlighted by the 20-year time series were randomly selected and visited during the stable part of the growth season of 2011 (Show in the Appendix a map or the UTM coordinates of these sites). Of the 30 positive sites, 28 (93 %) of them were clearly growing forests. Eight (27 %) of these sites were plantations, and the remaining 20 (66 %) were in very early stages of forest succession. Although growth occurs during more mature stages of succession, the related signal changes may be difficult to detect compared to the changes during early successional stages. While plantations are obviously growing forests, as seen by the early 10-year time series, there seems to be a low producer's accuracy when modelling this type of forest. This may be a result of the structure of a plantation, and how it changes over time.

Of the 30 negative sites visited, 23 (77 %) of them were clearly deteriorating forests. For 14 sites (46 %), change was likely a result of surface water hydrology since their soils were heavily saturated while another 5 sites (17%) were associated with portions of a plantation that were clearly growing very poorly. The remaining sites were difficult to categorize, but generally showed evidence of deterioration in the dominant overstory species. While 7 of the sites could not be considered deteriorating forests, 4 of those (13 %) seemed to be more closely related to a forest undergoing a compositional change. In general, these sites had younger deciduous trees beginning to reach the canopy heights of more mature coniferous species. As mentioned earlier, these types of forest dynamics would also be associated with a negative TCW trajectory.

Overall the field validation showed that the results of the 20-year time series analysis were very reliable, especially from a user's perspective. To investigate the

results further, the TCW spectral trajectories of these validation sites were extracted, as represented by the average of all pixels of each site for each growth season available. Figures 40 to 47 show example trajectories, along with a representative image of each site.

Figure 40 and 41 show the trajectories of two validation sites that appeared to be deteriorating as a result of surface water hydrology. In the site of Figure 41, beaver engineering was evident as there was an uncontrolled dam in close proximity and the area was completely inundated.

Figure 40: Negative validation site. Deterioration appears to be a result of local changes to surface water hydrology.

Based on the relationship of TCW with LAI (Figure 18), both sites in Figures 40 and 41 appear to have decreased by an LAI of about 3 (change in average TCW by about 15). These trajectories seem realistic when viewed as a relative change, however, for Figures 40 and 41, average TCW in 2007 is about -10 and -20, respectively, or an LAI between 3 and 6 (Figure 18). This appears to be high, as seen by the pictures acquired in

the field in 2010 for each site, and may show some bias; which could be introduced by ground and water vegetation in these areas.

Figure 41: Negative validation site in close proximity to an uncontrolled beaver dam. Dense standing dead trees are completely inundated as a result.

Other sites associated with a negative trajectory appeared to be related to changing canopy structures. These sites often included a relatively high proportion of standing dead trees, and large canopy gaps (Figure 42). Interestingly, TCW values are higher for these sites compared to the inundated sites discussed above, where most trees were dead.

Figure 42: Negative validation site with crown species clearly deteriorating, and forming large canopy gaps.

Figure 43 was a unique trajectory within the 2011 validation set, as it appeared to be partially a result of the ice storm of 1998. In the field, dead and live trees were bent in the shape of an arc, a signature left behind by the storm. The area also seemed to be affected by surface water hydrology. Based on the spectral trajectory for this location, deterioration occurred before the storm, which potentially made this area susceptible to storm damage. As seen in Figure 43, one of the lowest average TCW values for this site occurs just after the ice storm, during the growth season of 1999. For the remainder of the trajectory, average TCW for this site is variable, but does show a further decrease in vegetation quantity. Change in for this area may be a result of both abrupt and gradual changes.

Figure 43: Negative trajectory that seems to be associated with surface water hydrology, but also the ice storm damage of 1998 (Mean TCW for this site drops significantly by 1999).

Other decreasing trajectories appeared to be associated with poorly growing plantations (Figure 44). Although the cause of vegetation loss was difficult to determine, the spectral trajectory for these types of sites could be used to interpret the timing and magnitude of the changes being detected. The site representing the spectral trajectory in Figure 44 seems to show the majority of change between the period of 1995 to 1999, other than a few spurious points, this area is associated with a persistent negative spectral trajectory; potentially a result of poor soil, or perhaps the plantation was not thinned properly.

Figure 44: Poorly growing plantation, associated with a significant negative spectral trajectory.

As previously mentioned, some negative validation sites could not be considered as deteriorating forest, or as an area decreasing in vegetation quantity. Instead, some sites appeared to be related to a compositional change. Figure 45 shows a site that was associated with a gentle negative spectral trajectory compared to Figures 40 to 44. Observations in the field suggest a mature and healthy forest. Intermediate deciduous trees do appear to be encroaching on the older coniferous upper canopy species. A few sparsely located upper canopy species also appeared to have recently fallen, and therefore, overtime the signal received by the sensor may be influenced by an increase in deciduous reflectance, but also the mortality of a few large conifer species.

Figure 45: Negative validation site that appears to be related to a compositional change rather than a change in vegetation quantity. Relatively young deciduous trees are reaching similar heights as the older coniferous canopy species.

Sites highlighted as being associated with a positive spectral trajectory were in most cases associated with either a plantation, or a very young early successional forest. In general these sites were clearly associated with growing forests, and showed a higher user's accuracy. Based on the empirical relationship in Figure 18, the plantation highlighted in Figure 46 shows a LAI increase of about 2, and the early successional forest in Figure 47 represents an increase of about 4 LAI.

Figure 46: Positive validation site associated with a healthy and young red pine plantation.

Figure 47: Positive validation site associated with an early successional forest.

Unfortunately, it was difficult or impossible to validate the other trends as a result of time constraints and lack of validation data prior to 2010. Negative and positive sites highlighted by the early and late 10-year time series, as well as sites that were considered stable were sampled to extract representative spectral trajectories. The intention was to

assess the spectral trajectories associated with these regions to help further understand the results of the gradual trend analysis. These sites were sampled at the plot-level, using a 3 x 3 pixel window, but were not visited in the field. The mean TCW range of the stable sites was quite low (6.63), especially compared to sites that were highlighted as changing (13.68). Figure 48 shows three trajectories: one representing an area modeled as being stable, a positive trajectory site that that was only highlighted by the early 10-year time series, and a negative trajectory site that was only highlighted by the late 10-year time series. Based on the spectral trajectories of these locations, it is quite clear why each site was modeled as described above.

Figure 48: Plot-size trajectories extracted from an area simulated by all analyses as stable, and an early positive trajectory as well as a late negative trajectory.

Overall, the gradual trend analysis highlighted regions in the park that are indeed associated with changing forest dynamics. The information extracted from this analysis provided additional information about Gatineau Park's forest dynamics over the last 23 years. While two image dates were successfully used to map abrupt changes, the Theil-Sen and Mann-Kendall analysis, applied to a longer time series, helped to detect gradual and persistent trends associated with vegetation quantity. Although ground-based data is necessary to interpret and evaluate the results, the required efforts are minimized when integrated with remotely sensed data. The methods used provide a cost effective and time efficient means for determining priority regions in the park, and for gaining a better understanding of the dynamics of a landscape.

5.4 Mapping and monitoring coniferous forests using winter imagery (a case study)

Data provided by the QMMF described the spatial distributions of each functional group in 1991. This was the most recent forest inventory available, but changes to the distributions of each group over a 20 year period were expected. Based on knowledge acquired during the field season, many coniferous dominated plantations have been established in the last 30 years. In addition, it is known that successional processes often involve changes in species composition. For example, shade-tolerant deciduous species often occupy the understory of coniferous dominated forests, however, as they mature their growth rates accelerate allowing them to become the dominant overstory species. Summer imagery showed that there were distinct differences in the signals representing each functional group. Winter imagery was viewed as a tool to specifically isolate coniferous forests, and interpret changes to their distribution across space and time.

January 2010 NDVI data showed a strong relationship with the plot data describing the percent of coniferous species stems in each plot (Figure 49). Only a small proportion (20 %) of the variance is not explained, which may be related to species- or structural-specific spectral properties of the sampled forests. LAI data or canopy openness, measured during leaf-off season, may have showed a stronger relationship, but this data was not available.

Figure 49: Linear regression between average January, 2010 NDVI of each plot and the proportion (%) coniferous species based on stem counts.

This model was applied to the winter 2010 NDVI image to map the distribution of forests dominated by coniferous species (> 60 %). Figure 50 shows this map, in comparison to the coniferous, mixed and plantation forests delineated in 1991 by the QMMF. The area shown is the north-west part of the park, where the majority of coniferous dominated forests are located. The goal was to estimate a more recent

distribution of coniferous dominated regions of the park that could be compared to estimates made using historical Landsat winter imagery.

Figure 50: Comparison between QMMF delineated conifer species, with a remotely sensed empirical estimate using a 2010 Winter NDVI image, and ground-based estimates of % coniferous species to map regions with proportions > 60 %

It can be seen in Figure 50 that there is a very good spatial agreement between the Landsat NDVI based estimates of coniferous species > 60 % (light green and yellow), and the forests delineated by the QMMF as being either mixed, coniferous or plantation forests (dark green). The areas that do not coincide with Landsat winter estimates are likely associated with mixed forests where the proportion of conifer species is relatively low (< 60 %). In addition, a few areas can be seen (yellow) where Landsat detected

coniferous vegetation does not match a coniferous area mapped by the QMMF in 1991. These areas may be a result of errors made by either mapping method, or may indicate the space within the park where coniferous species have become the dominant species since 1991.

Figure 50 also provides an inset map, showing a zoomed in view of the same red pine plantation (outlined in red) delineated in Figure 22. While the majority of the area detected by the Landsat winter NDVI analysis matches the boundaries of this plantation, it can be seen that to the north-east, forests with more than 60 % coniferous species are estimated for 2010 that were not identified in 1991 by the QMMF. A field plot (indicated by black square in the inset), was established outside of this plantation because the coniferous species that dominated the area were estimated to be on average about 20 to 25 years old and likely represented a growing forest. The remotely sensed data, in comparison to the QMMF forest inventory, reveal a similar story.

The winter 2010 Landsat based coniferous map was also compared the 2007 leaf off colour orthoimagery of Gatineau Park. Figure 51 shows the two datasets for a small subset of the park. It can be seen that the Landsat-based estimates of the coniferous boundaries closely align with the dark green regions representing coniferous vegetation. Smaller areas that are clearly coniferous dominated in the ortho-image that were not identified by the remote sensing method may be a result of snow cover, or represent areas where the proportion of coniferous species is less than 60 %.

Figure 51: Comparison of winter 2010 Landsat based estimate of coniferous dominated forests (> 60 %) in orange to 2007 leaf-off ortho-image. The darker green tones of the ortho-image represent coniferous forest.

Both the ground-based and remotely sensed observations confirm that there are areas of emergent or growing coniferous dominated forest, winter imagery appears to be effective for updating the coniferous-specific spatial distribution of the park. The ability to separate coniferous areas based on winter spectral reflectance characteristics is important as it allows analysis of forest dynamics stratified by functional group.

5.4.1 Conifer-specific trend analysis

The 1989 and 2003 winter NDVI images were calibrated to the 2010 NDVI winter image. This allowed the 2010 bivariate model predicting areas with more than 60

% coniferous species (Figure 49) to be applied to the data for these years, followed by an assessment of conifer specific changes over a 21 year period.

In 1989, 1577 ha of the park (4.75 %) were estimated to be dominated by conifer species. In 2003, this coverage increased to 1808 ha (5.45 %) and in 2010 to 2166 ha (6.52 %). This represents a 37 % increase for this functional group, and about a 2 % increase for the park as a whole.

To assess the reliability of the model extension, the results of the map representing remotely sensed conifer-dominated regions in 1989 were compared to the coniferous and mixed forest map produced by the QMMF in 1991. This was the best ancillary data available for the analysis, and was used to assess the user's accuracy of the model extension. Of the 30 randomly selected polygons representing conifer-dominated regions in 1989, 25 corresponded to either mixed or coniferous forests. This shows that the model extension was about 80% accurate from a user's perspective, and helps to confirm the validity of these results.

Figure 52 shows the distribution of coniferous-dominated regions for the same red pine plantation mentioned in Figure 50. In 1989, this plantation has the least number of highlighted pixels of the three years. Data provided by the QMMF suggests that in 1989 this plantation was less than 10 years of age. From 1989 through 2003 to 2010, the plantation delineated by the QMMF fills in and areas outside the plantation also become highlighted as having over 60 % coniferous species. These results were validated by field observations within and outside the plots shown in Figure 52.

Figure 52: Example change for conifer-dominated regions, estimated using winter Landsat imagery for 1989, 2003 and 2010.

Results suggest that beyond this plantation, several forest patches in the northern part of the park are becoming dominated by coniferous species. Figure 53 illustrates the estimated coniferous-dominated distributions for the 1989, 2003, and 2010 winter image analysis. It can be seen that this forest group appears to be expanding in many regions in the northern part of the park. A few areas in Figure 53 were validated during the field season of this research as being either a plantation, or a forest in a state of early successional growth (plot 14 and 25, respectively), and appeared to closely relate to the remotely sensed estimates.

Figure 53: Change in distributions of remotely sensed estimates of conifer-dominated regions (> 60 %) using winter NDVI images representing 1989, 2003, and 2010. Plot 25 was observed in the field to be associated with a young and growing conifer species. It was also associated with a significant and positive TCW spectral trajectory.

Using a simple three image date time series, it can be seen that winter images of the park can be used to infer conifer-specific changes. Comparisons to leaf-off winter imagery show that the changes detected appear to be realistic. Additional imagery and historical ground-based data would have helped to confirm changing distributions. Regardless, relatively simple ground-based data and image processing can be used to create an up-to-date and reliable view of the spatial and temporal dynamics of coniferous forests in Gatineau Park, a task that would be quite tedious using ground based data exclusively.

6.0 Discussion

While the detailed results of this research are specifically applicable to Gatineau Park, the empirical modelling and remote sensing methods used and evaluated herein provide insights towards remote monitoring systems and ecosystem management for temperate humid environments. The sections that follow present a discussion about the methods and results, their applicability to forest ecosystem monitoring, as well as the limitations of the analyses. Suggestions for further research are also provided.

6.1 Significant findings

Prior to the development of this research project, several published works demonstrated the utility of a Landsat image time series for change detection (Coppin et al., 1994; Coppin et al., 1995; Song et al., 2003). Of the relevant studies reviewed, many of them focused on semi-arid coniferous forest environments, and/or in regions where forest change was quite drastic over the time period (Royle and Lathrop, 1997; Vogelmann et al., 2009; Sonnenschein et al., 2011). Spectral reflectance in those environments is potentially very different than Gatineau Park, since the park is situated within a temperate humid environment dominated by deciduous species. Therefore, the research findings reported here are potentially very useful for applications in such temperate forests and possibly in the boreal which is dominated by coniferous species with patches of mixed and deciduous. The closest known studies of a similar nature and scale focused on conifer and mixed forests in Minnesota, USA (Coppin et al., 1994; Coppin et al., 1995; Song et al., 2003), about 2000 km away from Gatineau Park.

This research successfully showed that integrating ground-based data with a relatively calibrated image time series is a practical means to infer the spatial and temporal dynamics of a large forested landscape such as Gatineau Park. It also provides the capability to estimate change in physical parameters such as LAI from associated changes in imagery. The use of multiple image dates provided unique information about change, which would have not otherwise been detected using two image dates. From a management perspective, one of the more significant findings of this research is that the integration of field and image data can significantly reduce the efforts required in the field. Mapping forest change over a 23 year period would be an extremely difficult task without remotely sensed data.

6.1.1 Modelling vegetation quantity in forested environments

The advantages of empirical modelling are clearly stated in the literature, and have been thoroughly demonstrated by this research. One of the most obvious advantages over mathematical models (based on image data and spectral theory alone) is that the results can be validated with much greater certainty. Liu and Zhou (2004) proposed a method to evaluate change detection results when simultaneous reference data are not an available option for validation; they admit, though, that physical observations are the ideal data source.

This study found that TCW was the most suitable image variable for mapping and monitoring vegetation quantity in Gatineau Park. Without ground-based data, image variable selection is generally based on recommendations in the literature. While this avoids the need for time consuming data collection in the field, model results may not be

as robust. Song et al. (2003) also found TCW to be a strong indicator of coniferous forest succession in Western Oregon, however, that area is quite different from Gatineau Park, so their findings may not have been considered relevant during a literature review.

Although empirical methods are inherently time consuming, a noteworthy advantage is that they often lead to scientific discovery. As an example, the conifer-specific relationship between TCW and average DBH of standing dead trees (Figure 20) was surprisingly strong ($r = 0.84$). Although further work would be required, this relationship could be potentially useful for mapping changing dead wood distributions. The ability to detail this landscape characteristic has direct applications in carbon budget estimation, biodiversity and habitat management and forest inventory (Pasher and King, 2009).

Another example can be seen by the strong and positive relationship between LAI and TCW (Figure 18). A distinct gradient was observed between the functional forest groups of Gatineau Park, where deciduous forests generally had the lowest TCW and LAI, and coniferous forests had the highest. Knowledge of this relationship may be of use for interpreting compositional changes over time. To corroborate this notion, several negative validation sites appeared to be transforming from coniferous or mixed forest to deciduous dominant. Based on Figure 18, it makes sense that these sites would be associated with a negative TCW trajectory. These examples help to illustrate the notion that empirical modelling often reveals unexpected information that can be potentially useful for future applications. Empirical models are inherently site-specific (Lahde, 1999), and as a result, the models developed in this research may be limited in

application to environments similar to Gatineau Park. However, the methods used are universally applicable in forested environments.

6.1.2 Mapping abrupt forest change

Damage caused by insect defoliation and the development of a new road are both examples of abrupt change events that could be mapped for Gatineau Park through image differencing (presented in section 5.3.2). These disturbances were mapped using an image acquired during the same year of the event, and an image acquired 1 to 3 years before or after that date. While the development of a road is essentially permanent change, insect damage is often temporary. In Gatineau Park, recovery from this type of forest damage generally occurs by the following year. Therefore, the success of these maps (Figures 30 and 31) can be largely attributed to the availability of an image representing the growth season of the event.

For permanent change events, such as the newly developed road (Figure 32), change signals are quite distinct (< -3 standard deviations) from those of a vegetated surface. Therefore, as long as imagery acquired before and after the disturbance is available, change detection results will likely be acceptable. The road development detected in Gatineau Park was easily corroborated using the ortho-image acquired in 2007 during the final stages of its development (Note: change regions can be imported into Google Earth to corroborate similar types of change, which is a free and accessible option to most analysts, although the user does not have control over the quality nor timing of available images). Unfortunately, validation for other events was not always

this straight-forward, especially for disturbances occurring further back in time, lacking ancillary field data or expensive aerial imagery.

For example, Figure 31 shows a map of an assumed gypsy moth defoliation event for 2003. This assumption was based on a visual comparison with a paper sketch map delineating a gypsy moth event in 2008 (Louis, 2008); both maps delineate a very similar disturbance area. Greater certainty in validating the remotely sensed change map would have been achieved if ground-based observations or other ancillary information were available.

Signal changes associated with the 2010 tent caterpillar defoliation event (Figure 30) were assessed using ground-based data collected during the same growth season, which helped to determine an appropriate change threshold. The resulting area of change was also seen to coincide primarily with deciduous forests (target species), and this helped to validate the resulting map. Unfortunately this level of corroborating evidence is not always available, but as seen in this research, and many other studies, by integrating field data with Landsat imagery, the efforts required in the field can be greatly reduced in mapping the spatial extent of an abrupt short term forest change. Since Landsat data are now free, the only cost of a similar type of analysis would be for the time spent in the field and on analysis. For managed landscapes similar to Gatineau Park, this is a realistic task. The field data for this research were for the most part collected by one individual over a 12 week period (for about 4 weeks of that time, field assistance was available); and with a predefined methodology, the analysis could be achieved in a few months. It should be noted though, that comparatively less time would be required to survey the data necessary to corroborate an abrupt short term (or permanent) forest change event.

Unfortunately the canopy damage induced by the ice storm of 1998 could not be mapped using the available data for the study area. As mentioned previously, if imagery closer to the timing of the event were available, mapping this event may have been more successful. Fast growth rates within the understory of the damaged forests, observed by King et al. (2005), likely masked the signal related to forest change. Environments with slower successional rates produce the most durable disturbance signals (Healey et al., 2005), so for these types of environments, wider monitoring intervals may be applicable for bi-temporal change detection methods. The results presented above suggest that for Gatineau Park, narrow time intervals may be necessary for successful image differencing, but this depends on the nature and severity of the change event.

6.1.3 Mapping gradual forest change

Similar to Neeti and Eastman (2011), the combined Theil-Sen slope estimate and Mann-Kendall significance test was used in this research to detect gradual trends. Not only does this method estimate the magnitude and direction of a spectral trajectory, it also provides an indication of its significance. These are essential components of any trend analyses (Neeti and Eastman, 2011), however many of the studies reviewed did not report on the significance of change results. The spectral trajectories mapped in this research were considered to be statistically significant at the 95% confidence level, providing a distinct level of certainty to the analysis.

Modifying the start and end date of the input time series, as well as its monitoring interval, revealed important information about the utility of the gradual trend analysis for monitoring forest change. Minor alterations to the input image time series (i.e. early- and

late-20 year time series) had some effects on the final change results, but overall, the same locations were targeted as changing. More drastic modifications (i.e. early-, mid- and late-10 year time series) were seen to highlight very different regions as changing, and showed the potential for identifying less persistent trends, or the timing of an event. Unfortunately, narrowing of the temporal period decreased the number of observations in the time series, which may reduce the reliability of the trends being detected. In addition, trends representing less recent time periods are difficult to corroborate.

Modifying the monitoring interval of the image time series showed that change results may be acceptable using a 3 to 5 year monitoring interval. This finding is similar to Lunetta et al. (2004)'s, that a minimum monitoring frequency of 3 to 4 years was required when using a Landsat TM 5 image time series for ecosystem monitoring. They also stated a reduction in modelling errors could likely be achieved if the temporal frequency of the image time series was increased to a 1 to 2 year interval. While tighter monitoring intervals are ideal, knowledge of a minimum monitoring frequency is extremely important for forest and data management purposes.

Field validation was used to assess the results of the gradual trend analysis for the initial 20-year time series (1987 to 2007, $n = 12$). Results showed that detected positive trends were more reliable (93%) than negative trends (77%); this was purely based on an assessment of user's accuracy (i.e. detected changes that actually occurred). As previously discussed, compositional changes also resulted in decreased vegetation estimates for a few randomly selected negative validation sites.

It was much more difficult to objectively assess producer's accuracy (i.e. changes that occurred that were not detected), since additional reference data not used in the trend analysis that described the locations of known changes were not available. Due to feasibility constraints, a customized data set could not be acquired. Further research would be required to estimate the reliability of the methods and analysis used in this research from a producer's accuracy perspective. Regardless, the approach used in this research appears to be suitable for mapping forest dynamics. For ecosystem managers to determine whether or not mitigation is necessary, field verification of detected change areas can be conducted along with assessment of potential mitigation strategies.

6.1.4 Applicability to Gatineau Park

The methods and results of this research are directly applicable to ecosystem monitoring of forested environments. The maps produced could be especially useful to the NCC, since revisions of the park's current *Master Plan* will be based on research carried out during the period of 2005 to 2015 (NCC, 2005b). The first phase of priority actions, as stated by the park's *Conservation Plan*, will be prepared and implemented by 2015 (NCC, 2010). The results of this research may help to locate priority regions and describe the last 23 years of forest dynamics within these sites. The methods could be utilized for continual monitoring, which would help to assess the implemented management strategies.

The development of a monitoring system is clearly stated as being a primary concern for the park (NCC, 2005b). While the results in this study provide an initial assessment of change, continual ground-based data collection would benefit future

monitoring, and would help to improve the existing models. A sampling strategy could include permanent sample plots that are routinely surveyed as well as a temporary sample plot design for training and validation.

6.2 Limitations and recommendations for future research

Like most optical remote sensing applications, this research was limited by the quality, and availability of the image data. Many image acquisitions for Gatineau Park were highly distorted by atmospheric conditions, which forced many growth seasons within the time period of this study to be omitted from the analysis. Fortunately, this research showed that gaps within an image time series can be as large as 5 years before the reliability of the results diminish considerably. Missing data, however, was seen to affect image differencing for detecting some short term forest changes (i.e. canopy damage caused by the ice storm of 1998).

Image distortions outside of the study area also represented a significant limitation to the methods used in this research. This is because many of the stable targets (i.e. bright and dark PIFs) required for the calibration process were found 10 to 20 km outside the park. An image representing Gatineau Park under relatively clear skies could be considered unsuitable if atmospheric distortions in proximity to the park masked out these necessary targets for calibration.

The field data collected in this research were also limited. First, most physical estimates of vegetation quantity could only be made during the relatively stable part of the growth season (mid-June to late-August). This was especially true for LAI estimates, and ultimately constrained the number of field plots that could be sampled. Gatineau

Park's bounding coordinates cover 50 km (east-west) by 10 km (north-south) of rugged terrain, so navigation to more remote regions was time consuming. Lastly, since an individual plot covered close to 1 ha, each plot required between 6 and 10 hours of reconnaissance, installation and measurement time.

Overall, the field methods worked well, however refinements could be made to reduce sampling time. The sub-plot design (9 circular sub-plots of 8m radius) was intended to potentially correlate the variability of the field and image data. In the end, average estimates of forest parameters correlated the highest. Similar field data probably would have been acquired from one representative circular plot with a 20 to 30 m radius, for example. If this plot structure was used, data collection would have been faster and more plots could have been surveyed. Future research should evaluate the use of different field methods and their effects on the results of empirically-based remote sensing change detection models. Finding a balance between the time required to capture a particular field variable, and the level of detail provided are important considerations.

Modelling errors may have also been a result of the image and field data, rather than sample size. While extra care was taken during the calibration process for this research, remaining noise was still evident. This research only considered the results of one calibration method (the PIF method). Studies such as Song et al. (2003) state that a calibrated image time series produced through any method is generally more reliable than no correction at all, but it would be valuable to understand which technique is the most appropriate for a particular study area.

With Landsat trend analysis becoming common (Coppin et al., 2004), progressive research will help to refine image pre-processing methods. The challenges for forest trend analysis in remote sensing include reducing the effects of the atmosphere, topography, phenology, and view angle (Song et al., 2002). Some of these uncertainties are much more difficult to control for and the ways they affect the signals received by a sensor are not spatially homogenous. This research, along with other published examples (Powell et al., 2010), show that relative spectral changes are often very real and can be potentially corroborated.

Landsat's minimum mapping unit of about 1 ha may limit the ability to capture small areas where forest conditions are changing. The field data in this research were collected with Landsat's 30 m resolution in mind, so generalizations were made for both the image and field data with respect to vegetation quantity. This may be why sub-pixel information extracted from the image data did not show strong correlations with the field data. Future research could collect finer detail field data (in space and time) to determine whether or not fractional imagery correlates with relatively small scale disturbances in forest environments such as Gatineau Park (e.g. deterioration, or damage to an individual, or group of trees). As expected, texture measures applied to 30 m imagery were not good indicators of local variability, as they rarely correlated with the field data.

Landsat-based empirical models would greatly benefit from knowledge at the sub-pixel scale, but in opposition to this notion, some authors such as He et al. (2011) have scaled Landsat imagery to coarser resolutions, such as 500 m. They assert that even though small change events may be missed, if the goal is to detect large disturbance events, detection is more successful using such coarse resolution. Although this would

not improve detection of changes associated with a road, for example, insect defoliation maps may improve using coarser resolution imagery. Gradual trend analysis using the Theil-Sen and Mann-Kendall techniques may benefit too, however, changes highlighted may not be as applicable to forest management. These scale dependent questions would require additional research.

Overall, this research showed that a relatively calibrated Landsat image time series can be used to detect real changes associated with forest vegetation quantity. The most significant limitations were the availability of a continuous inter-annual image time series and the reduction of noise in that time series. As in Vogelmann et al. (2009), other Landsat-based sensors such as the multispectral scanner (MSS) or Enhanced Thematic Mapper Plus (ETM+) could have been used to reduce data gaps in the image time series. This research opted to use data from only one sensor to control the data consistency and avoid the need for sensor to sensor calibrations.

In the near future, the use of multiple sensors will likely become an important research topic of interest. This is largely because of the recent suspensions of Landsat TM 5 imaging operations, which first occurred November, 2011 when data transmissions made possible by an important electronic component showed signs of failure. On February 16, 2012 another 90 day suspension was announced, and is understood to be a potentially permanent condition (Campbell, 2012).

Without the availability of Landsat TM 5 data, continuity has become a significant concern since this imagery is frequently used for agriculture, geology, forestry, regional planning, education, mapping, and global change research (Irons,

2012). In response, the USGS and NASA are collaborating on the newest development of the Landsat program which they refer to as the Landsat Data Continuity Mission (LDCM). Landsat 8 is planned to be launched into orbit in January, 2013, and is intended to continue to provide data consistent with the previous Landsat satellites. The value of continuing Landsat image data collection is well understood, and has been demonstrated by this research, and many other studies. While other sensors can be used for trend analysis, no other sensor has imagery relevant to management over such a long time period (Irons, 2012).

The future of Landsat trend analysis and continual ecosystem monitoring using the methods evaluated in this research relies on the ability to continue the image time series acquired by the predecessors of Landsat 8. This will require extensive research on new sensor to sensor calibration methods. If this can be successfully achieved, it will without a doubt benefit remote sensing and ecosystem management.

7.0 Conclusions

Using an empirical framework, objective detection and mapping of forest change in Gatineau Park, Québec was implemented using a Landsat image time series. The methods used in this research provide a means to feasibly and efficiently monitor a large forested landscape. The data obtained through a field survey can be extremely useful when integrated with remotely sensed data such as Landsat. This paper shows that such data can be used to determine objective thresholds to map abrupt forest change events such as insect defoliation. The necessary data for this type of mapping can be acquired as

needed by forest managers in a relatively short period of time. Through empirical modelling, field data can also provide understanding of how satellite derived SVIs represent a landscape and can be used in modelling of forest structural parameters. These relationships can then be applied in mapping and analysis of forest dynamics in space and time. The derived change results from this research would have been impossible to acquire exclusively through ground-based methods.

From a remote sensing perspective, it was determined that reflectance theory-based SVIs are the most suitable indicators of vegetation quantity for Gatineau Park when using Landsat imagery. Tasseled-cap wetness was the most robust. Used in statistically rigorous temporal trend analysis, it highlighted many real changes related to an increase or decrease in vegetation quantity, and also showed a distinct gradient between deciduous and coniferous species that strongly correlated with ground-based measurements. This gradient is potentially strong enough to map and monitor changes in species composition over the study area in addition to changes in vegetation quantity.

The methods evaluated in this thesis are applicable to land use management in Gatineau Park and other similar landscapes. With continued Landsat-type sensor development the ability to analyze and understand forest ecosystem dynamics will improve, providing potential for development of permanent forest monitoring programs.

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Appendix:

Table 1: Band-specific weights for each Tasseled Cap feature (Gomex et al., 2011)

Tasseled cap feature	Weighting for tasseled cap transformation using Landsat TM data					
	TM1	TM2	TM3	TM4	TM5	TM7
Brightness	0.3037	0.2793	0.4343	0.5585	0.5082	0.1863
Greenness	-0.2848	-0.2435	-0.5436	0.7243	0.0840	-0.1800
Wetness	0.1509	0.1793	0.3299	0.3406	-0.7112	-0.4572

Figure 1: Example density plot comparing TM band 1 for 1988 and 1989 (Song et al., 2001). The black coloured 'ridge' represents the most frequent pixel values common to both dates and are used to develop a linear regression (Equation 12).

Table 2: Field plot Eastings and Northings (UTM zone 18T, NAD 83), and a few relevant field variables.

Plot ID	Easting	Northing	LAI (LX-Ye)	Mean Live DBH (cm)	Mean Dead DBH (cm)	Mean # of Stems	Mean Age (yr)	Canopy Openness (%)	% Conifer in Plot
P1	436214	5035899	3.8	28.2	24.7	9.2	69	11	0
P2	436805	5034952	4.6	21.8	27.8	10.9	62	4	1
P3	432322	5038258	4.1	23.5	25.0	10.6	85	11	0
P4	428881	5040475	4.0	21.0	20.7	15.0	65	7	0
P5	429543	5046395	4.5	31.7	23.0	8.4	58	8	0
P6	428375	5041083	3.8	21.3	15.2	16.6	53	10	0
P7	438564	5033562	3.9	16.1	12.4	12.2	35	24	3
P8	438844	5033451	4.7	25.7	22.7	12.2	96	5	1
P9	431497	5039583	2.5	24.8	23.7	13.8	55	22	5
P10	428867	5043479	5.1	22.3	23.8	14.9	56	5	0
P11	433998	5039649	3.4	21.9	25.5	13.0	60	11	5
P12	428675	5039522	3.1	19.1	15.7	20.4	66	15	0
P13	426267	5052947	8.4	25.0	21.7	17.7	68	4	79
P14	406813	5055311	11.5	20.7	12.2	26.8	35	6	98
P15	431040	5045528	4.1	15.8	16.1	14.0	41	5	0
P16	428412	5046607	6.0	22.1	20.7	9.8	55	5	20
P17	420774	5049960	8.2	21.5	20.3	17.0	50	11	74
P18	417976	5050460	5.7	22.3	28.8	11.6	66	2	0
P19	421861	5050096	7.0	26.7	20.9	7.1	106	8	22
P20	421532	5053012	4.0	18.7	15.3	20.2	55	7	1
P21	413152	5052692	6.6	23.5	15.0	14.2	41	19	93
P22	413585	5052515	7.2	20.5	20.4	12.0	30	31	84
P23	405748	5057703	3.7	16.5	15.7	18.4	50	25	57
P24	411004	5053321	5.6	22.8	17.4	9.8	59	7	0
P25	407176	5055589	7.6	22.2	14.4	14.1	33	22	98
P26	407937	5056039	6.4	18.9	15.0	16.8	49	4	21
P27	404749	5054232	7.4	22.1	17.6	20.6	68	5	30
P28	424619	5048382	6.3	30.9	30.2	7.2	68	2	0
P29	427753	5041443	3.2	29.7	27.4	8.6	61	13	0
P30	434187	5038235	5.7	20.6	18.7	8.4	47	20	45
P31	408714	5053424	3.4	21.4	24.2	26.0	64	18	78
P32	428796	5040677	4.3	20.5	23.0	15.2	50	6	0
P33	428885	5041531	4.4	28.2	29.5	10.0	73	8	0

Figure 2: Field plot locations used in this research (sampled during the growth season of 2010).