Quantifying Change in the Spatial Pattern of Forests: Assessing Impacts of Mountain Pine Beetle Infestation and Harvest

By

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ABSTRACT

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British Columbia's current mountain pine beetle epidemic has led to salvage and mitigation harvesting strategies intended to slow the dispersal of beetles, and recover economic value from infested timber stands. These resulting harvesting strategies will alter the spatial pattern of forest landscapes in impacted regions, often resulting in forest fragmentation. As a result, wildlife habitat, hydrologic regimes, local carbon budgets, and soil dynamics, amoung other ecological properties, are expected to be negatively impacted.

Monitoring of forest fragmentation in Canada is now required for the Montreal Process, an international forest monitoring policy. Effective methods that quantify changes in forest fragmentation, the breaking up of forest land cover into smaller, and more numerous parts, are required to meet forest monitoring objectives. This research provides two new methods that build upon existing approaches widely used for quantifying the spatial patterns of landscape features (i.e., landscape pattern indices).

The first approach I demonstrate aids the quantification of forest pattern change over two time periods, by accounting for the impact of composition on spatial configuration. The value of this method is demonstrated using a case study that highlights

the impacts of forest harvesting, associated with insect salvage and mitigation activities. This method allows landscapes that have changed primarily in composition to be distinguished from those that have experienced large configurational change.

In the second approach I use multivariate cluster analysis for regionalization (the grouping of objects in space), and identify regions within a study area where increased fragmentation is observed. Regions delineated based on forest spatial pattern can be linked to underlying processes. Ancillary information (e.g., elevation) can be used to identify areas where observed forest pattern is due to underlying physiological features. Pattern indices (e.g., patch perimeter-area ratio) can be used to distinguish between patterns arising from forest disturbance that is likely natural (e.g., fire) or anthropogenic (e.g., harvest activity) in origin. The methods presented in this thesis may be most appropriate when observed changes in landscape pattern can be attributed to substantial changes in landscape composition.

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1.0 INTRODUCTION

1.1 Research Context

The spatial pattern of forests governs many ecological processes (e.g., sediment loadings, Jones et al. (2001); the spread of wildfire, Turner et al. (1989); and dispersal by forest insects, Barclay et al. (2005)). Given the important linkages between forest pattern and ecological process, international forest monitoring initiatives are now required to track changes in forest pattern (Montreal Process Liaison Office 2000). Methods for quantifying change in forest pattern, which are effective across temporal and spatial scales, are required for addressing forest pattern monitoring objectives.

When quantifying forest pattern for a single time period it is useful to compare observed patterns from one region to another, and to differentiate between ecological processes that occur in each location (e.g., Wulder et al. 2008b). Similarly, researchers are often tasked with examining changes in forest pattern through time, and relating change to natural or anthropogenic processes (e.g., Hudak et al. 2007). The spatial pattern of forests can be considered in as two components: *composition*, which relates to the amount of forest cover and *configuration*, which refers to how the forest is spatially arranged (Gustafson 1998, Boots 2006). Methods for quantifying the spatial patterns of land cover features (e.g., forest) have rapidly developed (Cardille et al. 2005) and are supported by advances in geographic information systems (GIS), and land cover datasets derived from satellite and air-borne sensors. Measures of landscape pattern, termed landscape pattern indices (or landscape metrics), quantify a single aspect of composition or configuration. Only a single metric is necessary to quantify composition when the number of land cover types is small (i.e., forest versus non-forest) (Boots 2006). Due to its complexity several indices are often used in combination to characterize configuration (Boots 2006). Previous work using correlation analysis has suggested that there are four to five unique aspects of configuration to consider (Riitters et al. 1995, Hargis et al. 1997, Boots 2006). A large number of metrics exist, with many capturing similar pattern components (Riitters et al. 1995). Thus, it is necessary to avoid redundant metrics, and to select metrics relevant for a particular research question (Li and Wu 2004, Gergel 2007). This can be done by selecting metrics that measure the landscape pattern properties that reflect the process in question.

A large number of studies have utilized landscape pattern indices for quantifying landscape patterns. The proliferation of landscape pattern indices is due to their computational simplicity (McGarigal and Marks 1995), ease of calculation (McGarigal and Marks 1995, Mladenoff and DeZonia 2004), and broad applicability (Cardille and Turner 2002). However, landscape pattern indices have a number of limitations associated with their use including; redundancy and inter-correlation amoung metrics (Riitters et al. 1995), scaling effects (Wu 2004), interpretability (Li and Wu 2004) and lack of statistical inference (Remmel and Csillag 2003). Moreover, the dependency of landscape configuration on landscape composition presents difficulties when comparing values across temporal and spatial scales (Remmel and Csillag 2003). For example, as many indices vary non-linearly with composition, identical metric values for a variety of landscape states can occur. Thus, novel approaches that address the limitations associated with landscape pattern indices are warranted.

Researchers tasked with monitoring the spatial pattern of forests commonly relate observed forest patterns to forest fragmentation (e.g., Riitters et al. 2002, Wulder et al.

2008b). Fragmentation can be broadly defined as the breaking up of a habitat or land cover type into smaller, more numerous and isolated parcels (Forman 1995). Fahrig (2003) outlines two concepts of fragmentation: fragmentation as process, and fragmentation as pattern. Fragmentation as process can be understood using Forman's (1995) five spatial processes (*perforation, dissection, fragmentation, shrinkage, attrition*) that transform a landscape. Fragmentation as pattern is measured using the effects of the process of fragmentation on observed patterns: loss of habitat, increase in number of patches, decrease in patch size, and increase in isolation of patches (Fahrig 2003). Thus, forest fragmentation is commonly measured by quantifying the number, size, and spatial arrangement of forest patches (Haines-Young and Chopping 1996). In this research, I examine both process and pattern based concepts of forest fragmentation.

1.2 Research Focus

Currently, the largest known mountain pine beetle (*Dendroctonus ponderosae*) infestation is occurring in British Columbia, Canada. The areal extent of infestation in British Columbia is estimated to have increased from an estimated 166 000 ha in 1999 to 10.1 million ha in 2007 (Westfall and Ebata 2008). Short-term increases to the provincial allowable annual cut have been prescribed in the Prince George and Quesnel forest districts (selected as the study area), in order to recover economic value from infested timber resources (British Columbia Ministry of Forests and Range 2007). Mountain pine beetle salvage and mitigation activities will impact forest spatial pattern. Quantifying resultant changes to forest pattern is important for monitoring the impacts of increased harvest activities on ecological processes. It is expected that hydrologic regimes (Helie et al. 2005), local fauna (Bunnell et al. 2004), and the future distribution forest species and age classes (British Columbia Ministry of Forests and Range 2007) will be impacted. As well, consideration of resulting forest pattern may reduce the susceptibility of future landscapes to mountain pine beetle infestation (Barclay et al. 2005).

1.3 Research Goal and Objectives

The goal of my research is to quantify the effects of mountain pine beetle salvage and mitigation activities on forest pattern. To meet the goal I address two unique objectives and develop approaches that overcome methodological issues associated with landscape pattern indices.

The first objective is the creation of a new approach for examining temporal changes to forest pattern. Using two new measures, 2-D Displacement and Proportion of 2-D Displacement from Configuration, I highlight how mountain pine beetle salvage and mitigation activities are transforming the landscape. These measures allow forest configuration to be measured in the context of forest composition, addressing a key limitation associated with landscape pattern indices. I show that forest fragmentation is the most prevalent spatial process of landscape transformation occurring across the study area. I also demonstrate that the Proportion of 2-D Displacement from Configuration is an effective measure for differentiating landscapes where change is predominantly due to variation in composition from landscapes experiencing configurational change as well. Observed changes to forest pattern are linked to the mountain pine beetle salvage and mitigation activities occurring in a study area.

Secondly, I aim to develop an approach for examining the spatial distribution of forest fragmentation across a broad extent. To address the second objective I use regionalization (the grouping of objects in space) as a framework for organizing detailed multivariate spatial pattern data. Landscape pattern indices are used to measure forest pattern in a set of 1 km landscapes within the Prince George and Quesnel forest districts. Multivariate cluster analysis of several landscape pattern indices is employed to define spatial pattern regions (SPR), which represent landscapes containing similar forest pattern attributes. SPR are labelled to represent a forest fragmentation gradient, based on their forest pattern attributes. Observed forest patterns are linked to the topographical influence on land cover features. Anthropogenic factors affecting forest pattern are identified in the central and western portions of the study area. Here, the influences of mountain pine beetle salvage and mitigation activities are largest.

2.0 QUANTIFYING FOREST COMPOSITION AND CONFIGURATION FOLLOWING INSECT INFESTATION AND MITIGATION

2.1 Abstract

Despite a number of caveats associated with the use of landscape pattern indices, their prevalence in the peer-reviewed literature remains extensive. In this chapter I identify issues commonly raised and present an approach for considering changes in pattern over time. This often indicated limitation in the temporal use of landscape pattern indices is addressed through a new approach to quantify change in landscape configuration in the context of change in landscape composition. To do so, I propose two new measures; 2-D Displacement, which measures the magnitude of overall landscape change in two time periods, and the proportion of 2-D displacement from configuration, which identifies the relative amount of landscape 2-D displacement that can be attributed to changes in a configuration index. In a case study, I apply the 2-D displacement and proportion of 2-D displacement from configuration measures to a study area in British Columbia, Canada, which has undergone substantial forest disturbance, primarily as a result of large-area harvest activities in response to mountain pine beetle (*Dendroctonus ponderosae*) infestation. Using five spatial processes of landscape change (*perforation, dissection, fragmentation, shrinkage, attrition*) as a guideline, I identify the usefulness of the two new measures in distinguishing between differing landscape transforming processes. Similarly, I am able to detect the regions that have the largest overall magnitude of landscape change (2-D displacement) and those where changes are

primarily occurring in the configuration of landscape components (proportion of 2-D displacement from configuration).

2.2 Introduction

Landscape pattern indices have become a routine method for quantifying the spatial pattern of landscapes (Cardille et al. 2005). The spatial pattern of landscape elements has a quantifiable link with ecological process and the study of this phenomenon has developed as the field of landscape ecology (Turner 1989). Landscape pattern indices have a number of positive features, including ease of calculation (McGarigal and Marks 1995, Mladenoff and DeZonia 2004), broad applicability (Cardille and Turner 2002), and computational simplicity (McGarigal and Marks 1995). However, several limitations in the use of landscape pattern indices have been documented including; correlation amoung metrics (Riitters et al. 1995), scaling effects (Wu 2004), map misclassification (Langford et al. 2006), interpretability (Li and Wu 2004), lack of statistical testing (Turner et al. 2001, Remmel and Csillag 2003) and failure to link quantified patterns with processes (Li and Wu 2004).

The spatial pattern of a landscape can be broken down into the components of *composition* and *configuration* (Li and Reynolds 1993, 1994, 1995, Gustafson 1998). Composition represents the amount of a landscape component, whereas configuration represents the way it is spatially arranged. In binary class representations of a landscape (such as ‘forest’, ‘non-forest’) composition is easily quantified using a single metric, the proportion of forest or non-forest (Boots 2006). In contrast, there is no complete measure of configuration and previous work has identified 4-5 unique components of configuration (e.g., Li and Reynolds 1994, Riitters et al. 1995, Hargis et al. 1997, Boots 2006). It has been shown that many of the most commonly used measures of configuration have known systematic relationships with composition in random landscapes that become less systematic in real landscapes (see Gustafson and Parker 1992, Hargis et al. 1998, Remmel and Csillag 2003). These relationships are generally non-linear, and within them exists a considerable amount of dependency on other factors including spatial autocorrelation and anisotropic trends (Remmel et al. 2002). This relationship between landscape composition and configuration is problematic because similar configuration values can be achieved at different levels of landscape composition.

Past studies aimed at quantifying changing spatial patterns through time have focused on computing landscape pattern indices at multiple time periods and comparing results (e.g., Imbernon and Branthomme 2001, Lofman and Kouki 2001, Frohn and Hao 2006). Comparing landscapes through time enables researchers to hypothesize to the ecological consequences of changing spatial pattern. However, when comparing landscapes over time it is important to consider changes to configuration indices in the context of compositional change (Remmel and Csillag 2003) and the comparison of raw landscape pattern index values requires caution (Gergel 2007).

Recently, Cushman and McGarigal (2007) proposed a new method for tracking the trajectory of a landscape's spatial pattern through time. They compute four measures to describe how a landscape has changed based on a principle components analysis of several landscape pattern indices. I draw on one of their measures (displacement), focusing on the known relationship between composition and configuration when tracking landscape change between two time periods. Analysis of fine temporal resolution data can be conducted by considering the data as a series of two time comparisons. In this paper, I consider landscapes that have experienced substantive changes through time, and where changes in configuration may be largely attributed to compositional change. Change in landscape composition is particularly important given that ecological processes may be more responsive to changes in landscape composition than to changes in landscape configuration (e.g., McGarigal and McComb 1995, Fahrig 1997).

To illustrate the reason for considering composition and configuration together when characterizing change in landscape spatial pattern consider the following example. Edge density (ED) is a commonly used metric for quantifying the effects of forest disturbance. In binary simulated landscapes ED has been shown to have the hypothetical trajectory shown in Figure 2.1, with ED peaking when the proportion of each land cover category is 50% (see Remmel and Csillag 2003). If a predominantly forested landscape (T1 in Figure 2.1) were to undergo small (T2a in Figure 2.1), or large (T2b in Figure 2.1), amounts of forest disturbance, two markedly different landscapes would result. However, similar values for the configuration metric ED, and similar changes in ED would be expected for both scenarios. Ecological response to this phenomenon is likely to be different, and would not be captured in the ED metric. While each metric has different hypothetical trajectories, similar phenomena exist. The proposed method will enable change in configuration metrics associated with large or small amounts of composition change to be distinguished. With this it can be quantified whether the change is primarily related to composition or configuration.

The goal of this chapter is to strengthen the use of landscape pattern indices by quantifying temporal changes in landscape configuration while simultaneously considering changes in landscape composition. Thus landscapes can be differentiated based on relative components of compositional and configurational change. This can be important, for example, in forested landscapes where small changes in configuration may not reflect large changes in composition (e.g., through harvesting).

2.2 Methods

2.2.1 Derivation

I have developed two new measures for quantifying landscape change that enable configuration to be assessed in the context of composition. Prior to implementing the method, it is necessary to scale the values of each landscape pattern index used. The composition measure, class proportion, is scaled to a 0 – 1 range with similar scaling intentions for each configuration index. Configuration indices are scaled to a 0 – 1 range using observed maximum and minimum values for each index.

2-D Displacement

I wish to compute the displacement of the landscape similar to Cushman and McGarigal (2007) however I constrain it to a two-dimensional space where the x-axis is composition, and the y-axis is a configuration index. Using the Pythagorean Theorem I can calculate the distance between two landscapes (T1 and T2) on this plane.

$$D_i = \sqrt{d_x^2 + d_y^2} \qquad [1]$$

Where D_i is the 2-D displacement of the landscape for configuration index i, and d_x is the change in composition between the two time periods, and d_y is the change in configuration index i for the two time periods.

Proportion of 2-D Displacement from Configuration

The relative amount of the configuration change in relation to the change in composition is of interest when a given change in composition results in multiple configuration outcomes for a chosen index. The proportion of 2-D displacement measures how much of the change can be related to configuration. From [1] the following relationship exists:

$$D_i^2 = d_x^2 + d_y^2 \qquad [2]$$

Based upon this understanding, I propose the following derivation of the proportion of the 2-D displacement from configuration (P_y):

$$P_y = \frac{d_y^2}{D_i^2} \qquad [3]$$

Which has the following property if P_x is defined as the proportion of the 2-D displacement from composition:

$$P_x = 1 - P_y \qquad [4]$$

Increasing or decreasing configuration values

Whether configuration indices are increasing or decreasing is important to consider when interpreting results. Characterizing whether configuration indices are increasing or decreasing has important ecological consequences. I propose that direction of change for configuration index *i*, be defined in the following manner:

$$A_i = \begin{cases} 1 \rightarrow M_2 > M_1 \\ 0 \rightarrow M_2 = M_1 \\ -1 \rightarrow M_2 < M_1 \end{cases} \qquad [5]$$

Where A_i represents the direction of change for configuration metric *i*, and M_1 and M_2 represent the metric value at T1 and T2 respectively. It may also be helpful to reconsider the magnitude of changes in configuration, as it may lead to insight on the impact of such change. This can be done using the scaled configuration metric values, or reverting back to the original values.

2.3 Application

2.3.1 Background

To apply measures of evaluating landscape change, I examine the case of the mountain pine beetle and resulting salvage harvest activities in British Columbia. In British Columbia a large portion of the provincial interior is composed of managed forest lands; the recovery of timber from stands infested by the mountain pine beetle is important for the economy (Wagner et al. 2006) and has been used to manage the infestation (Nelson et al. 2006). This has resulted in large areas subject to salvage harvesting of lodgepole pine (*Pinus contorta*), the primary target of the mountain pine beetle (Taylor and Carroll 2004). Salvage harvesting activities are known to influence a number of ecological processes occurring on the landscape (Lindenmayer et al. 2004). These harvesting activities will alter forest composition and configuration, impacting hydrologic regimes (Helie et al. 2005), soil quality and nutrient retention (Dahlgren and

Driscoll 1994), regional carbon budget (Kurz et al 2008), and wildlife habitat (Bunnell et al. 2004). While some processes are primarily dependant on forest composition (e.g., carbon budget), others, such as wildlife habitat use, are dependant on a combination of composition and configuration. It is thus important to be able to quantify the effects of this forest disturbance on both forest composition and configuration. To do this I evaluate the changes in forest composition and configuration between the years 2000 and 2006, which represent roughly the onset of the infestation to near current conditions of mountain pine beetle infestation in British Columbia (British Columbia Ministry of Forests and Range 2007).

In general, there are four types of changes to composition and configuration to be distinguished when analyzing the spatial pattern of forest disturbance (see Figure 2.2). First, large changes in both forest composition and configuration measures may indicate natural disturbance or that forest management practices aimed at emulating natural disturbance have been implemented. In contrast large changes in forest composition and small changes in forest configuration may indicate harvesting activities that are generating large openings and simple shapes, and are not emulating natural disturbance. Third, regions where changes in composition are small but changes to configuration are relatively large may indicate small forest changes, such as new roads, or natural openings, that are primarily altering the configuration of the forested landscape. Lastly, regions where change in both composition and configuration is small can be identified. These regions are likely those that have been unaffected by large natural or anthropogenic disturbances. The context in which forest disturbance alters both composition and configuration will be considered separately for each configuration index used in analysis.

2.3.2 Study Area

Located within the interior plateau of British Columbia, the Prince George forest district (Figure 2.3) is situated primarily in the Sub-Boreal Spruce biogeoclimatic zone (Meidinger and Pojar 1991). The Sub-Boreal Spruce biogeoclimatic zone is characterized by extreme climatic fluctuations across seasons, with hot, moist summer months, followed by long, dry and cold winters. White spruce (*Picea glauca*), subalpine fir (*Abies lasiocarpa*), and lodgepole pine are the dominant forest species within this region. The Prince George forest district has experienced severe timber losses from mountain pine beetle infestation, and has been designated as a region where an increased allowable annual cut will be prescribed for the near-term future as a salvage and spread mitigation strategy (British Columbia Ministry of Forests and Range 2007). The study area is a 40 km x 40 km (see Figure 2.3) region that has been heavily impacted by the mountain pine beetle and related management activities. Using satellite imagery, forest loss can be observed in locations infested by the mountain pine beetle. The conditions present over this study area provide a suitable case for investigating the spatial pattern impacts of mountain pine beetle mitigation and salvage harvesting activities.

2.3.3 Data

A land cover dataset representing year 2000 conditions was obtained from the Earth Observation for Sustainable Development of forests (EOSD) program (see Wulder et al. 2003, 2008a). These data, derived from Landsat 7 ETM+ imagery with land cover products resampled to a spatial resolution of 25 m, represent an applicable spatial resolution for monitoring forest disturbance (Healey et al. 2007). The EOSD data consists of 23 land cover classes that can be aggregated into three base land cover classes: 'forest', 'non-forest' and 'other' (see Wulder and Nelson 2003). To detect change through time, I generated an analogous year 2006 'forest', 'non-forest', 'other' classification from Landsat imagery. Corresponding Landsat 5 TM imagery for the 2006 summer season was obtained (Path 48, Row 23). The enhanced wetness difference index (EWDI) change detection method (Franklin et al. 2001, 2002, Han et al. 2007) was employed to derive a binary forest change map for 2006. The 2000 EOSD data were updated to 2006 conditions, converting the 'forest' class to 'non-forest' where forest loss had occurred based on the EWDI method. This resulted in two land cover datasets representing land cover ('forest', 'non-forest', 'other') for the years 2000 and 2006.

The validity of the 2000 land cover dataset created under the EOSD program has been assessed in three separate studies (Remmel et al. 2005, Wulder et al. 2006, Wulder et al. 2007). Over all applicable EOSD classes (e.g., 13 class generalization to cover types) a target accuracy of over 80% was obtained using the mode class of a 3x3 spatial neighbourhood of the EOSD data (Wulder et al. 2007), which contains more detail than was used in this study, with accuracy found to increase as class generalization is undertaken (Remmel et al. 2005). I performed an accuracy assessment for the year 2006 'forest', 'non-forest', 'other' dataset. Systematic interpretation of 0.5 m digital imagery was used as independent validation data based upon an existing framework for interpretation of airborne video tiles used in the EOSD program (Wulder et al. 2004, 2007). An overall accuracy of 91.3% was obtained, with high user (100%) and producer (87.5%) accuracies for the 'forest' class.

2.4 Methods

2.4.1 Landscape Pattern Indices

Prior to change detection, I identified four landscape pattern indices that are suitable for assessing forest disturbance (Haines-Young and Chopping 1996, Trani and Giles Jr. 1999, De Clercq et al. 2006, Frohn and Hao 2006). These include: percent forest cover, edge density, number of forest (and non-forest) patches, and the largest patch. Percent forest cover (%FC) was chosen to characterize how the amount or composition of forest cover has changed over time. The remaining three measures characterize configuration. Edge density (ED), in m/ha, enables quantification of edge properties, which have been identified as a key component in promoting wildlife and plant diversity in forested landscapes (Ranney et al. 1981). Edge density has been shown to be an effective tool in evaluating the effects of patch shape and area, and the abundance of edge habitat (Hargis et al. 1998). Edge density values were scaled to 0 – 1 by dividing by the largest observed value. The number of forest and non-forest patches (NP-F, NP-NF) was also computed. Number of patches has been identified as useful in monitoring deforestation (De Clercq et al. 2006) and is a common metric used in quantifying habitat fragmentation (Fahrig 2003, Gergel 2007). The number of patches metrics are also scaled to 0 - 1, by dividing by the largest observed value. The largest patch index (McGarigal and Marks 1995) was calculated for the 'forest' class. The size of contiguous portions of forest habitat is important for species occupancy (Harris 1984). Largest patch index of forest (LP-F) has been identified as sensitive to changes in forest harvesting practices and has been demonstrated in forest disturbance applications (Lofman and Kouki 2001). While the choice of indices is far from exhaustive, I attempt to identify relevant measures for describing the spatial processes of interest in forest landscapes.

2.4.2 Spatial Processes of Landscape Change

From Forman (1995) five spatial processes associated with landscape change (*perforation, dissection, fragmentation, shrinkage, attrition*) are identified and related to forest disturbance. *Perforation* of forests results when holes are created in forest patches. *Dissection* occurs in forest landscapes when linear features, such as roads, subdivide the landscape. *Fragmentation* breaks apart the forest into smaller parcels with increased isolation. When forest patches decrease in area, this can be referred to as *shrinkage*. *Attrition* represents when forest patches are completely removed from a landscape. I categorized each landscape as having undergone one of these five spatial processes using the chosen landscape pattern indices and a logical rule-set (see Figure 2.4 and Table 2.1, but also see Forman 1995, p. 407). Any unaccounted for change cases are examined individually and used to refine the rule-set and process classes.

To evaluate the spatial distribution of the processes of landscape change, I segregate the study area into 1600, 1 km^2 (100 ha) landscapes (hereafter referred to as regions). Using the rule-set outlined in Figure 2.4 and Table 2.1, I derive the spatial process of landscape change that has occurred in each of these 1 km^2 regions. Landscape pattern index values and the new measures identified in this chapter can be compared between these processes to better understand the nature of forest disturbance under each spatial process. Knowing the spatial processes of landscape change prior to interpreting landscape pattern index results provides added context. Furthermore, it is expected that differing spatial process will impact landscape pattern index values, and that the new measures will portray this. As it is the purpose of this application, I will relate results back to altered harvesting activities resulting from mountain pine beetle infestation.

2.5 Results

The change in the forest composition of the landscape from the year 2000 to the year 2006 is shown in Figure 2.5. As evident, the 160 000 ha study area has undergone a substantial amount of forest disturbance, with forest cover decreasing by 28 700 ha, representing an 18% decrease in area (from 71% to 53%), largely due to intensified harvesting activities in response to mountain pine beetle infestation. However, the level of change in forest composition is varied across the study area, with some areas experiencing little to no change, while others incurred extensive forest loss.

2.5.1 Spatial Processes of Landscape Change

Based on the rule-set developed I have identified the distribution of the five spatial processes of landscape change across the study area (Figure 2.6). Regions of 'no-change' represent 23.1% (369/1600) of the study area. The process of *fragmentation* dominates the study area, and accounts for 48.8% (781/1600) of regions. *Perforation* and *dissection* are less prevalent and represent 14.2% (227/1600) and 5.6% (90/1600) of regions respectively. *Attrition* and *shrinkage* are present in fewer regions, 0.5% (8/1600) and 6.6% (106/1600) respectively. This resulted in 19 regions (1.2%) where based on the rule-set no spatial process was defined. I further examined these 19 undefined cases and determined they possessed the properties of *attrition* in that the NP-F was decreasing, but other forest loss was also occurring. I chose to include these cases in the *attrition* class as it was the most representative spatial process occurring in these landscapes. This raises the amount of *attrition* to 1.7% (27/1600) of the entire study area.

2.5.2 2-D Displacement

The spatial processes of landscape change are then used to stratify the study area to assess the level of 2-D displacement occurring under each spatial process (Table 2.2). On average the largest 2-D displacement is observed when a landscape has undergone the process of *fragmentation*. The least 2-D displacement is seen in landscapes having undergone *dissection*. On average the 2-D displacement value for each measure of configuration remained consistent for each spatial process of landscape change (e.g., the variation is small horizontally in 2-D displacement values in Table 2.2). This suggests that on average each spatial process of landscape change may provide a particular level of 2-D displacement regardless of which measure of configuration is used.

2.5.3 Proportion of 2-D Displacement from Configuration

The proportion of 2-D displacement from configuration values were likewise stratified using the spatial processes of landscape change (Table 2.3). ED is most affected by *attrition*, and least affected by *fragmentation*. NP-F is most impacted by *attrition*, but also by *dissection*. Surprisingly, landscapes undergoing *fragmentation* have a low influence on the NP-F measure, however this is likely due to the magnitude of the changes in composition occurring in these regions having a much larger impact on the 2-D displacement of the landscape and thus lowering the impact of the change in NP-F. NP-NF was most impacted by *perforation*, but in general did not experience a high degree of configurational change. In general the changes in proportion of 2-D displacement from configuration for LP-F were close to 0.5, except for *attrition*, which is a result of how *attrition* is defined. On average, the process of *dissection* contains the largest proportion 2-D displacement related to configurational change, while *shrinkage* has the lowest proportion of 2-D displacement related to configuration.

2.5.4 Spatial Distribution of Results

Here I identify the nature of the spatial heterogeneity that exists within the magnitude of 2-D displacement and proportion of 2-D displacement from configuration results. The magnitude of 2-D displacement can be used to provide extra context for interpreting the proportion of 2-D displacement from configuration results. Using 2-D displacement for each of the four configuration metrics used I am able to distinguish the regions that have experienced the largest or smallest overall change. The general trends in the spatial distribution of 2-D displacement are relatively consistent for all 4 measures of configuration (Figure 2.7). This follows from the 2-D displacement findings where little variation in the results between configuration measures for each spatial process of landscape change is identified.

Figure 2.8 portrays the spatial distribution of the proportion of 2-D displacement from configuration measure. Above I identified that each spatial process of landscape change has variable responses to proportion of 2-D displacement from configuration depending on the landscape pattern index chosen. As such, the spatial trends seen in Figure 2.7 are not duplicated in Figure 2.8. The proportion of 2-D displacement from configuration measure contains unique spatial trends for each measure of configuration employed.

2.6 Discussion

The mountain pine beetle epidemic is causing extensive mortality over British Columbia's lodgepole pine forests and forest management plans and practices are adapting in response. It has resulted in salvage harvesting and mitigation activities that are removing large portions of forest not seen in previous management scenarios (Eng 2004). I applied a new method for evaluating landscape change to a forested environment in British Columbia that has undergone a substantial (18%) decrease in forest cover over a relatively short period of time (6 years). I employed four landscape pattern indices (%FC, ED, NP-(F, NF), LP-F) having been identified in the literature as relevant when describing forest disturbance. With the creation of a rule-set that uses the direction and magnitude of change in landscape pattern indices, I link temporal changes in spatial pattern occurring over 1 km^2 regions with differing spatial processes. The first of the new measures for assessing change in landscape patterns, 2-D displacement, can be used to identify the magnitude of overall landscape change as related to forest disturbance. The second measure, proportion of 2-D displacement from configuration, can be used to evaluate the relative importance of change in forest configuration. By measuring configuration in the context of composition, I can detect regions where landscape pattern change is primarily related to forest composition or configuration. This has implications for forest management, as the composition and configuration in forested landscape are known to affect a number of ecological processes. Kurz et al. (2008) conducted an investigation of the carbon budget of British Columbia's forests. They demonstrate that the mountain pine beetle and its related salvage harvesting activities are altering forest composition to the point that it is reducing British Columbia's carbon sequestration levels. In a government report summarizing the potential effects of mountain pine beetle harvesting activities on terrestrial aquatic vertebrates, Bunnell et al. (2004) propose a number of strategies for maintaining landscape ecological function. Identified is the maintenance of remnant forest patches, both infested and non-infested, as well as large portions of un-salvaged landscape. Implementation of these strategies will translate into distinct spatial patterns emerging in regions undergoing salvage harvest and those being left for natural regeneration.

Fragmentation is the most prevalent spatial process of landscape change occurring in the study area. The spatial processes of *dissection* and *attrition* while small in magnitude were shown to have the largest proportion of change occurring from configuration. In regions heavily impacted by the mountain pine beetle and its related harvesting activities the landscape will be most affected by the spatial process of *fragmentation*.

In Figure 2.2, I provide four possible scenarios where landscape change can be related to forest disturbance, which in the study area is primarily due to forest harvesting activities. Using the 2-D displacement results (Figure 2.7), forest managers can identify regions where landscapes have undergone varying magnitudes of landscape change.

Proportion of 2-D displacement from configuration (Figure 2.8) can then be used to identify what proportion of change is occurring as a result of compositional change and what change is a result of configurational change. These results can then be linked to ecological questions. For example, consider a landscape where 2-D displacement is relatively low, but the proportion of 2-D displacement from configuration is high. Ecological responses to spatial pattern measured in these landscapes can be linked to changes in configuration with greater confidence. This type of analysis enables decision-makers to design management strategies with increased specificity to the current and previous landscape conditions in a spatial and quantitative manner.

This application focused on evaluating forest disturbance in the context of the current mountain pine beetle epidemic in British Columbia and the increased harvesting and mitigation activities that have been implemented. Quantifying forest disturbance is necessary for managing forest sustainability, and managing spatial pattern in forested landscapes has been included as a component in international forest management policy (Montreal Process Liaison Office 2000). The results I have generated provide managers with tools for identifying regions where forest composition or configuration have been most heavily impacted by some form of forest disturbance (natural or anthropogenic induced).

2.7 Conclusions

With the need for monitoring forest disturbance at the regional, national and global levels, relevant and feasible methods that accomplish this are required. This procedure for quantitatively identifying the spatial processes of landscape change is both straightforward and transparent. Although in the case study the driver of forest change is known, the methods implemented will have additional utility when it is necessary to determine the dominant spatial processes of landscape change. I have also identified a method for measuring the change in landscape configuration in the context of composition. I applied this method to a locally relevant set of landscape pattern indices to better understand forest disturbance, and acknowledge that other metrics may have utility in this or other contexts. The spatial process of *fragmentation* was most prevalent in the study area, while *attrition* was rarely observed. In the absence of these spatial processes of landscape transformation, 2-D displacement and proportion of 2-D displacement improve landscape pattern indices by considering change to configuration in the context of change to composition.

Previous works assessing the spatial distribution of the types forest disturbance at the regional (Riitters and Coulston 2005), national (Riitters et al. 2002), and global (Riitters et al. 2000, Wulder et al. 2008b) levels have used a similar land cover classification scheme but focused on singular time periods. The data processing requirements for this two time approach are most appropriate for regional level assessments and further work should be conducted to develop similar methods for application at national and global levels.

Table 2.1: Rule-set definition used to identify Forman's (1995) five processes of landscape transformation.

Rule-set Definition				Spatial Process
1.	If (A) and (B)	;		Attrition
2.	If (C) and (D)	;	check (H)	Perforation
3.	If (C) and (D)	;	check (I)	Shrinkage
4.	If (F) and (G)	>	crit. value	Fragmentation
5.	If (F) and (G)	<	crit. value	Dissection
6.	If (J) = NC			No Change

Table 2.2: 2-D displacement, results stratified using the spatial processes of landscape change.

Process	% of Study Region	2-D Displacement				
		ED	NPF	NPNF	LP-F	Average
Perforation	14.2	0.09	0.07	0.09	0.09	0.08
Dissection	5.6	0.04	0.05	0.04	0.05	0.04
Fragmentation	48.8	0.36	0.36	0.35	0.50	0.39
Shrinkage	6.6	0.06	0.06	0.06	0.08	0.07
Attrition	1.7	0.11	0.11	0.12	0.12	0.11

Table 2.3: Proportion of 2-D displacement from configuration, results stratified using the spatial processes of landscape change.

Process	% of Study Region	Proportion of 2-D Displacement from Configuration				
		ED	NPF	NPNF	LP-F	Average
Perforation	14.2	0.55	0.00	0.57	0.44	0.39
Dissection	5.6	0.36	0.63	0.33	0.42	0.43
Fragmentation	48.8	0.13	0.14	0.08	0.52	0.22
Shrinkage	6.6	0.39	0.00	0.04	0.34	0.19
Attrition	1.7	0.39	0.42	0.17	0.21	0.30

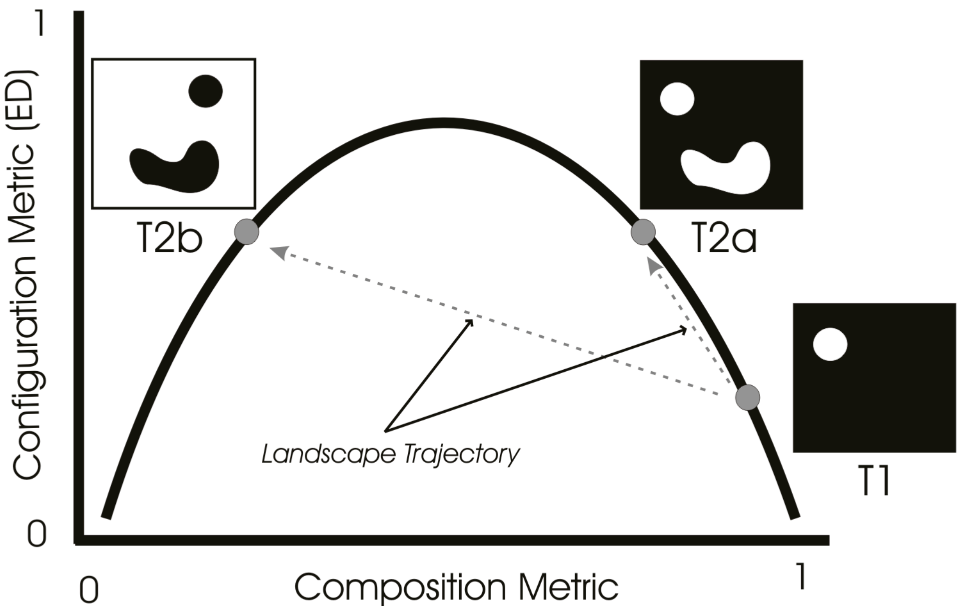


Figure 2.1: Hypothetical trajectory of a landscape that has experienced small or large changes in land cover proportion. Illustrating how similar metric results are obtained from two different scenarios.

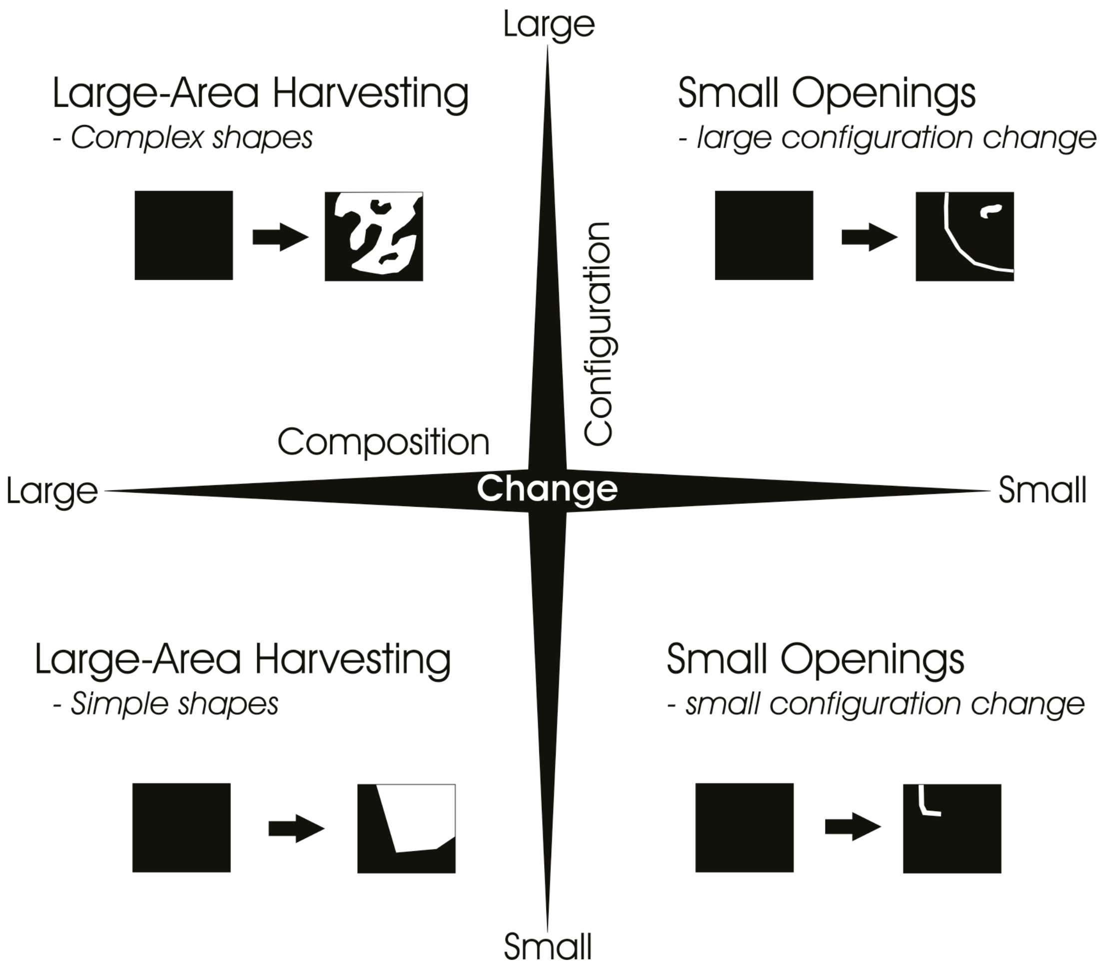


Figure 2.2: Relationship between changes to forest composition and configuration and expected link to forest disturbance processes.

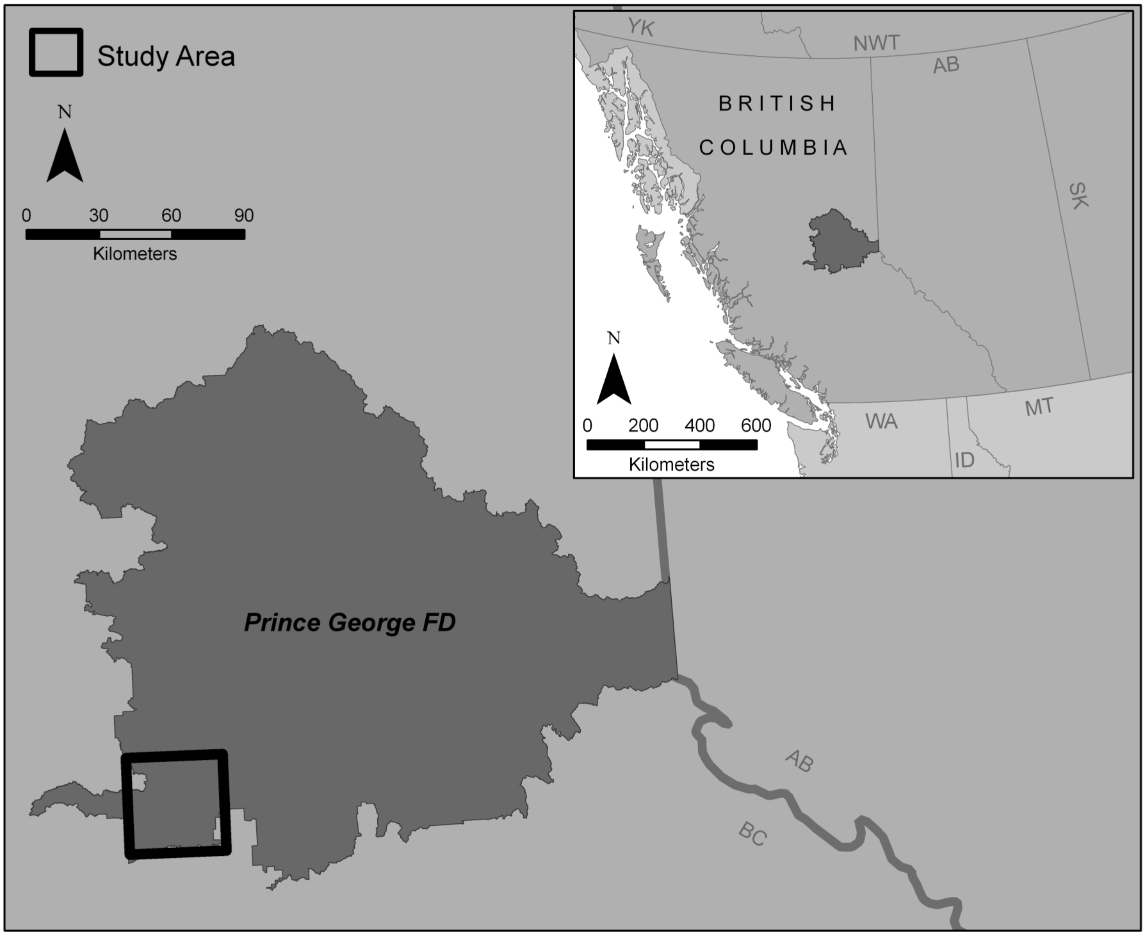


Figure 2.3: Map delineating 40 km x 40 km study area within the Prince George Forest District that has been heavily impacted by the mountain pine beetle and subsequent salvage harvesting activities.

Spatial Process		%FC	ED	NP-F	NP-NF	LP-F
No Change		NC (J)				
Perforation		↓ *Small*	↑ (H)	NC (C)	↑ (D)	↓
Dissection		↓ *Small* (G)	↑	↑ *Small* (F)	↕	↓
Fragmentation		↓ *Large* (G)	↑	↑ (F)	↕	↓ *Large*
Shrinkage		↓	↓ (I)	NC (C)	NC (E)	↓
Attrition		↓	↓	↓ (B)	NC	NC (A)

Figure 2.4: The five spatial processes of landscape change, and the expected direction of metric change for each process. Adapted from Forman (1995, p. 407, Fig. 12.1). NC = no change in metric value, ↑ = increase in metric value, ↓ = decrease in metric value. ***Small*** *or* ***Large*** *represent expected magnitude of change. Properties used in the rule-set definition (below) are identified by* (A).

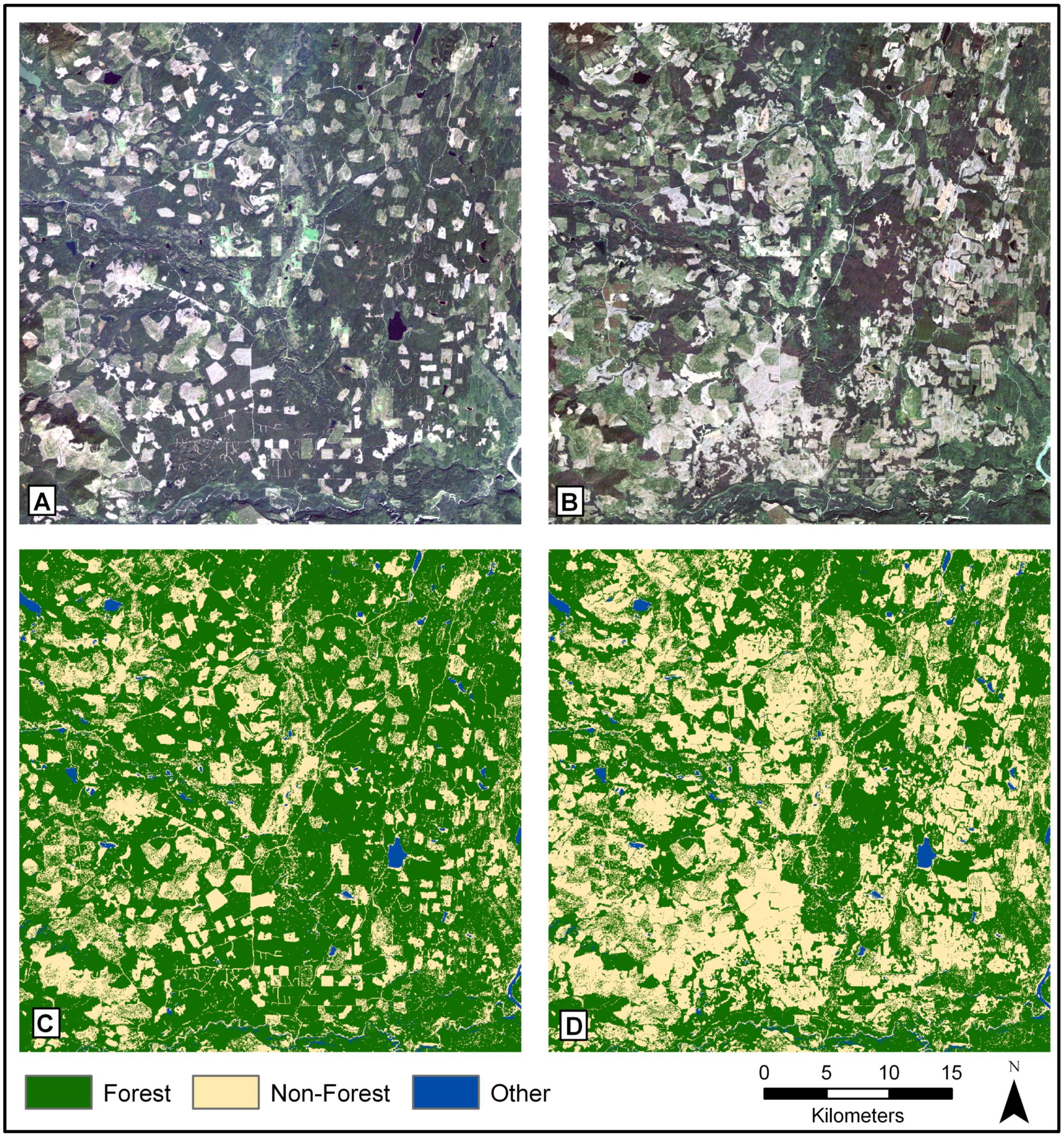


Figure 2.5: Images showing Landsat (Path: 48 Row: 23) representation of the study area in 2000 (A) and 2006 (B). Forest, non-forest, other data derived from the Landsat data for 2000 (C) and 2006 (D).

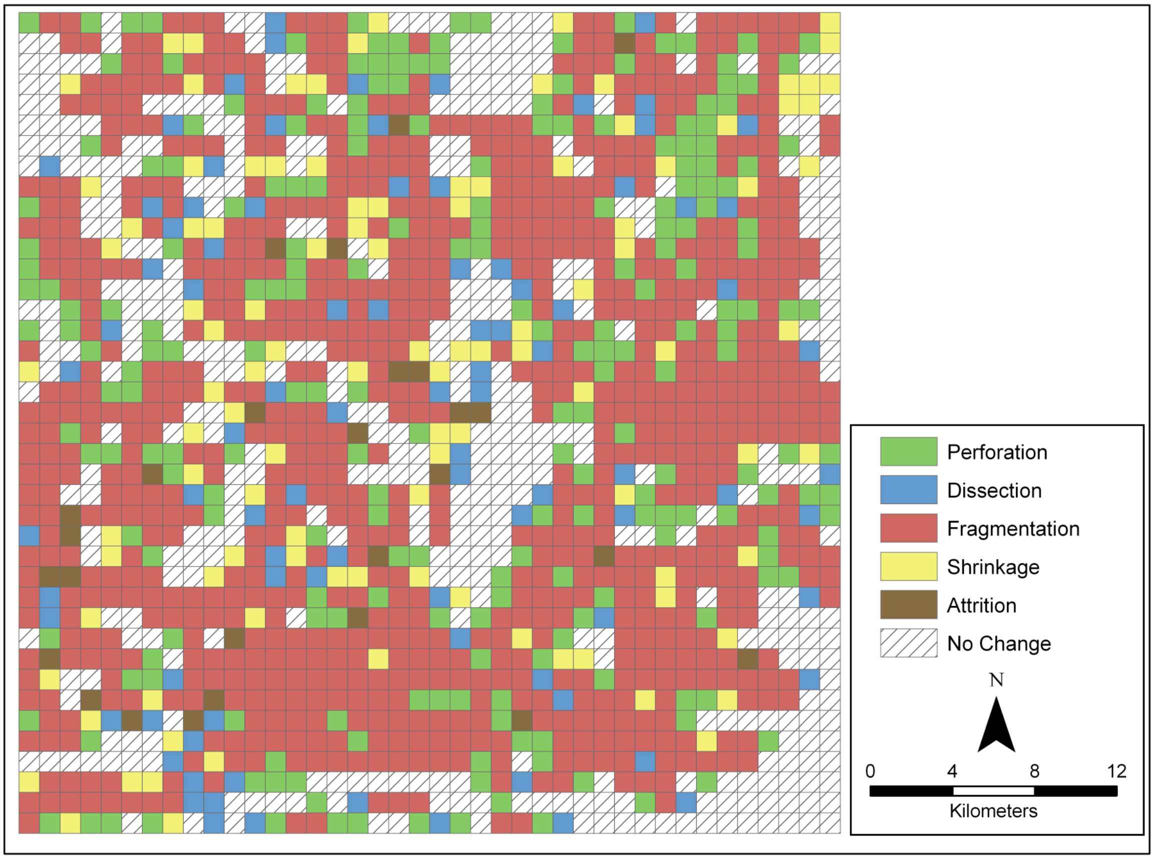


Figure 2.6: Spatial distribution of observed spatial processes of landscape change.

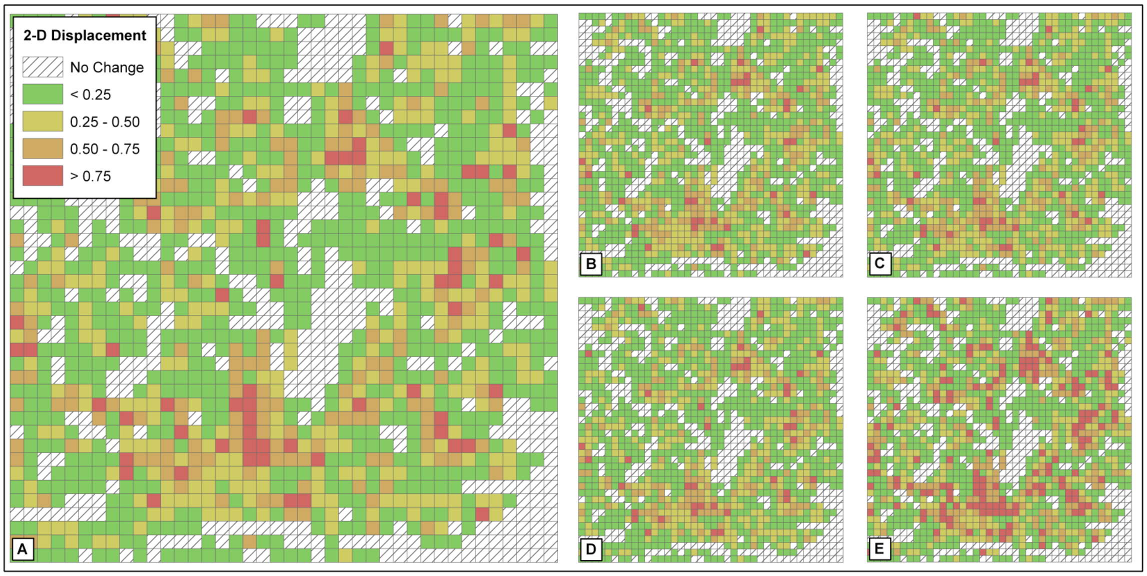


Figure 2.7: Spatial distribution of average 2-D displacement (A) as well as 2-D displacement for each of the four configuration measures used: ED (B), NP-F (C), NP-NF (D), LP-F (E).

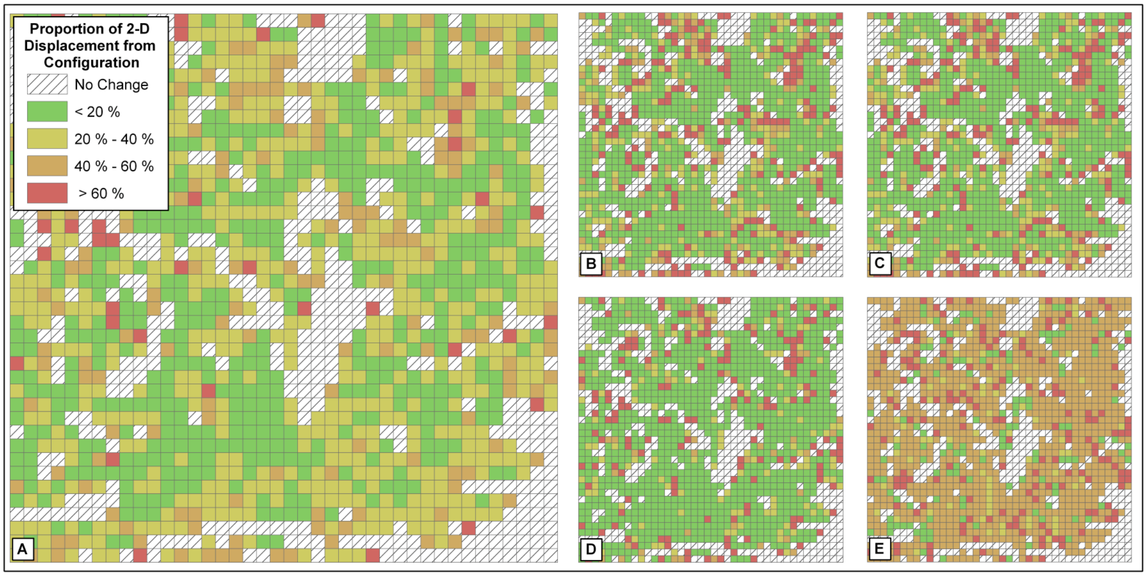


Figure 2.8: Spatial distribution of average proportion of 2-D displacement from configuration (A) as well as proportion of 2-D displacement from configuration for each of the four configuration measures used: ED (B), NP-F (C), NP-NF (D), LP-F (E).

3.0 REGIONALIZATION OF LANDSCAPE PATTERN INDICES USING MULTIVARIATE CLUSTER ANALYSIS

3.1 Abstract

Regionalization, or the grouping of objects in space, provides a useful tool for organizing, visualizing, and synthesizing information contained in multivariate spatial data. Landscape pattern indices can be used to quantify the spatial pattern (composition and configuration) of land cover features. Observable patterns can be linked to underlying processes affecting the generation of landscape patterns (e.g., forest harvesting). The objective of this research is to develop an approach for investigating spatial distribution of forest pattern across a broad region where the occurrence and causes of forest pattern is variable. I generate spatial pattern regions (SPR) using landscape pattern indices to describe forest pattern. Analysis of forest pattern is performed using a 2006 land cover dataset covering the Prince George and Quesnel forest districts, 5.5 million ha of primarily forested land base situated within the interior plateau of British Columbia, Canada. Currently, forest land cover in this region is being altered by increased forest harvesting related to insect salvage and mitigation activities. Multivariate cluster analysis using the CLARA (Clustering for LARge Applications) algorithm is used to group landscape objects, using a 1 km analysis unit containing forest pattern information, into SPR. Evaluative criteria are used to determine an optimal clustering level of six clusters. Output clusters are labelled to represent levels of forest fragmentation. Of the six generated SPR, SPR2 is the most prevalent covering 22% of the study area. On average landscapes in SPR2 are comprised of 55.5% forest cover, and contain the highest number of patches, and forest/non-forest joins of any of the SPR,

indicating highly fragmented landscapes. Underlying processes generating forest patterns such as topography and forestry can be investigated. The influence of topography on land cover classes is linked to fragmented landscapes located in the eastern part of the study area near the Rocky Mountains. In the central and western portions, anthropogenic disturbances (e.g., forestry, agriculture) are identified as shaping the forest patterns observed. The method presented can be applied across a large range of applications and spatial scales.

3.2 Introduction

Researchers in a wide variety of disciplines are often concerned with exploring patterns and trends in spatially referenced data. In practice this has led to a number of quantitative methods aimed at exploring and measuring the spatial structure of spatial data including: measures of spatial autocorrelation (Cliff and Ord 1981); geostatistics (Cressie 1993); geographically weighted regression (Fotheringham et al. 2002); and local measures of spatial association (Boots 2002). As well, a number of qualitative techniques for mapping and visualizing data have evolved, serving as valuable tools for viewing patterns and properties of spatial data (DiBiase 1990). When researchers are investigating spatial trends in one (or many) variables, it is often advantageous to group data. Typically this grouping process is termed classification (or clustering), referring to how objects are assigned to classes or clusters (Johnson and Wichern 1982).

Classification broadly refers to the grouping of entities based on common properties or relationships (Sokal 1974). Regionalization, or spatial classification, is a specialized form of classification that deals with geographic data (Chorley and Haggett

1967, Johnston 1968). The geographic entities (regions) created through the regionalization process are often used for multiple monitoring, mapping, and management activities. However, often classifications and related maps are best for a single purpose (Grigg 1965, Wood 1992). Moreover, there is considerable disagreement on how to delineate regions, which has led to a number of studies attempting characterize the same features with different regionalization processes (see Omernik 2004).

The spatial datasets used in regionalization are often large and contain several levels of detail making them difficult to view and interpret (Ng and Han 2002). The advantage of regionalization is that it allows large and detailed spatial datasets to be viewed and analyzed in a more manageable way. Cluster analysis has been used extensively with aspatial data and represents a useful tool for exploring groups in spatial data (Ng and Han 2002).

I implement multivariate cluster analysis as a quantitative approach to regionalizing landscape spatial pattern. Multivariate cluster analysis provides a new approach to the regionalization of landscape spatial pattern. Landscape pattern indices along with multivariate cluster analysis are used to generate Spatial Pattern Regions (SPR). SPR represent landscapes that exhibit similar spatial pattern characteristics. By mapping SPR I can explore the spatial distribution of forest pattern across a study area. A region of British Columbia, Canada where forest harvesting strategies have changed, a result of insect salvage and mitigation activities is used as a case study. SPR are used to identify the spatial distribution of forest pattern and its underlying cause.

3.3 Background

The practice of regionalization has developed through the creation of ecological zonations (sometimes referred to as ecoregions). Ecological zonations represent a holistic framework, integrating the significant or enduring environmental characteristics of the landscape into regions with similar properties and potentials that serves as a flexible, multipurpose spatial framework for a wide range of applications (Loveland and Merchant 2004). Table 3.1 lists regionalization examples from a number of disciplines, and illustrates the wide range of contexts for the creation and use of regions.

Ecologists have demonstrated the important linkages between landscape spatial pattern and ecological process for a number of processes (e.g., nutrient sediment loadings to streams, Jones et al. 2001; habitat occupancy by grassland birds, Helzer and Jelinski 1999; organism dispersal, Wiens et al. 1997; and the spread of natural disturbances, Turner et al. 1989). Humans impact landscape spatial pattern through urbanization (Luck and Wu 2002), agriculture (Agger and Brandt 1988), road-development (Riitters and Wickham 2003), forestry (Franklin and Forman 1987), and a number of other practices. In forested landscapes the spatial pattern of forest affects the occurrence and spread of natural disturbances, such as fire (Romme 1982, Agee 1998) and insect outbreaks (Radeloff et al. 2000, Barclay et al. 2005), which has a number of important implications for forest management and monitoring. Given important linkages between pattern and process, there are benefits to including a landscape pattern component when performing regionalization.

There are only a small number of examples that explore how landscape pattern can be used in regionalization. MacPhail (1971), used aerial photography to map landscape spatial patterns and relate them to fabric patterns and textures to aid the visual interpretation of different pattern regions. Similarly, Wickham and Norton (1994), created landscape pattern types defined as a kilometres-wide geographical area throughout which a limited number of land cover categories form a consistent pattern. Wickham and Norton (1994) employ visual interpretation of Landsat Thematic Mapper (TM) imagery in order to derive landscape pattern types. These studies took a qualitative approach using human interpretation and subjectivity for the regionalization process. A quantitative approach may be advantageous as it is more explicit, repeatable, transferable, and defensible (Hargrove and Hoffman 2004). Examples of quantitative approaches to mapping landscape spatial pattern also exist. Riitters et al. (2000) developed a classification of forest fragmentation using two indices of spatial pattern. Classified objects are mapped to examine the spatial distribution of forest fragmentation globally (Riitters et al. 2000) and in the United States (Riitters et al. 2002). Morphological image processing (see Soille 2003) has also been utilized for mapping forest components characterized as core, edge, or patch (Vogt et al. 2007).

3.4 Methods

3.4.1 Study Area

Two adjacent forest districts within British Columbia's interior plateau were chosen as the study area (Figure 3.1). The Prince George and Quesnel forest districts cover 5.5 million hectares of primarily forested land base. The climate in the Prince George and Quesnel forest districts is characterized by long, cold winters interspersed with hot, humid summers (Meidinger and Pojar 1991). Forests here are comprised primarily of lodgepole pine (*Pinus contorta*), white spruce (*Picea glauca*) and sub-alpine fir (*Abies lasiocarpa*).

Currently, the largest ever recorded mountain pine beetle (*Dendroctonus ponderosae*) infestation is occurring in this region, causing extensive mortality in lodgepole pine stands. The range of this infestation in British Columbia is estimated to have increased from 166 000 ha in 1999 to 10.1 million ha in 2007 (Westfall and Ebata 2008). Short-term increases to the provincial allowable annual cut (with concessions to come in the future) have been prescribed in the Prince George and Quesnel forest districts as a means to recover economic value from infested timber resources (British Columbia Ministry of Forests and Range 2007). Under previous management scenarios, harvesting practices generally consisted of a series of smaller (<60 ha) forest openings (Eng 2004). Salvage and mitigation activities in response to the mountain pine beetle have the potential to generate larger (>1000 ha) forest openings (Eng 2004).

3.4.2 Data

A 2006 forest land cover dataset was generated using a change detection method based on Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) data (Han et al. 2007), and an existing land cover dataset produced by the Earth Observation for Sustainable Development of Forests (EOSD) program (Wulder et al. 2003, 2008a). Land cover is represented at a spatial resolution of 25 m, with up to 23 classes of categorical detail which can be aggregated to: forest, non-forest and other classes (Wulder and Nelson 2003). The forest, non-forest, and other categories provide a useful set of land cover classes for examining the spatial pattern of forests in this region, and is comparable to land cover schemes used for forest fragmentation studies in Canada (Wulder et al. 2008b) and the United States (Riitters et al. 2002).

A regular squared partition (fishnet) was used to generate an encompassing set of smaller analysis units (landscapes) within the study region. A 1 km landscape was chosen to capture the impacts of forest harvesting and insect salvage and mitigation activities. Larger landscape sizes exhibit varying levels of spatial pattern, while smaller landscape sizes tend towards a bifurcation of forest patch or no patch. A 1 km landscape has been demonstrated as an effective analysis unit for monitoring forest fragmentation across Canada (Wulder et al. 2008b).

3.4.3 Analysis

Landscape Pattern Variables

A large number of metrics exist for quantifying the spatial pattern of land cover features. It is typically appropriate to choose a subset of metrics relevant to a specific application (Gergel 2007). Previous work has used correlation analysis to identify key components of landscape spatial pattern (e.g., Riitters et al. 1995, Hargis et al. 1997, Boots 2006), and for choosing relevant metrics. Often four to six primary components of spatial pattern are considered (e.g., Hargis et al. 1999, O'Neill et al. 1999, Lofman and Kouki 2001).

I select five indices of landscape pattern (Table 3.2) for regionalization in this context. Class proportion effectively defines the composition of the landscape in two class landscapes (Boots 2006), and researchers have demonstrated that class proportion is the driving factor of landscape spatial pattern (Remmel et al. 2002, Boots 2006). Join counts are useful in quantifying the level of spatial clustering (sometimes calculated as contagion; see Li and Reynolds 1993) in landscape components (Boots 2006) and can be related to edge amount, an important ecological feature in forested landscapes (Ranney et al. 1981). The number of patches is an important factor in monitoring the fragmentation of landscape components (Haines-Young and Chopping 1996). When quantifying patch area Boots (2006) suggests that the sum of squared area of patches provides more information than average patch area as it is more sensitive to patch size distribution (e.g., the difference between one large and one small patch, and two medium patches). I employ an area squared measure to quantify the areal properties of patches; a feature commonly used when monitoring habitat fragmentation (Fahrig 2003). Lastly I calculate the mean patch perimeter-area ratio, which is useful in monitoring the regularity/complexity of patch shapes. Natural landscapes frequently exhibit complex, irregular shapes (Forman 1995), while anthropogenic landscapes generally contain regular shapes and straight edges (Hammett 1992, Forman 1995).

Multivariate Cluster Analysis

Cluster analysis has been referred to as the art of finding groups in data (Kaufman and Rousseeuw 1990). More specifically, cluster analysis is a quantitative statistical method that uses unsupervised learning to explore, find and categorize features and to gain insight on the nature or structure of data (Duda et al. 2001). Clustering algorithms fall into two broad categories: hierarchical or flat-partition (Kaufman and Rousseeuw 1990). Hierarchical methods are advantageous when the initial number of clusters is unknown (Duda et al. 2001); however, hierarchical methods are most suited for the classification of variables rather then objects (Johnson and Wichern 1982) and are computationally constraining with large datasets. Flat-partition methods can better handle large datasets, but require that the user specify a pre-determined number of clusters (*k*).

The CLARA (Clustering for LARge Applications) algorithm (Kaufman and Rousseeuw 1990) was used to perform cluster analysis. CLARA is a flat-partition method that has been specifically designed for use with large datasets. User definition of the *k* parameter is required, and since *k* is unknown I implement the algorithm for a range of *k* values (2-10). An optimal clustering level (*k*) can be chosen iteratively using evaluative criteria (Milligan and Cooper 1985, Halkidi et al. 2002). Cluster analysis is performed using the R statistical software package (R Development Core Team 2008).

Normalization and Weighting

When performing cluster analysis it is often suggested that data be normalized. Normalization (standardization) assigns equal spacing for parameters of varying ranges and units by assigning a zero mean and a unit standard deviation to all data variables (Kaufman and Rousseeuw 1990). I normalize the data following Kaufman and Rousseeuw (1990):

$$z_{if} = \frac{x_{if} - m_f}{s_f} \qquad [6]$$

Where z_{if} is the normalized value for observation i of variable f, x_{if} is the original value for observation i of variable f, m_f is the mean of variable f and s_f is a measure of dispersion for variable f. I use the mean absolute deviation as the measure of dispersion which is defined as:

$$S_f = \frac{1}{n}\{ |x_{1f} - m_f| + |x_{2f} - m_f| + \cdots + |x_{nf} - m_f| \} \qquad [7]$$

Where; n is the number of observations and other variables as in [6]. This dispersion measure is more robust then the standard deviation and is therefore recommended (Kaufman and Rousseeuw 1990).

In many cases, particular attributes may have added meaning or importance for a given analysis. *A priori* knowledge can be a useful tool that can improve a clustering by adding weight to given attributes (e.g., Abrahamowicz 1985). In the absence of quantitative information expert opinion was used to assign weights to input variables on a case specific basis. The class proportion metric was weighted by a factor of two over the other metrics to generate output groups that contain similar levels of forest cover. The goal being to improve interpretability of output clusters.

With geographic data there is potential to include spatial weighting in subsequent analysis. Spatial weighting refers to increasing similarity, in attribute space, to objects that are spatially proximal to one another. In practice this is often incorporated by including the x and y coordinate values as attributes in the analysis; although other methods exist for creating spatial weights (see Oliver and Webster 1989 for a discussion). Often however, regions tend to be geographically cohesive without spatial weighting because of the spatial autocorrelation present in the data (Hargrove and Hoffman 2004).

Sometimes it is necessary to identify new/different locations that exhibit similar ecological (or other) characteristics of a chosen region for the placement of parks or industrial activities. Statistical methods for regionalization that do not include spatial weighting offer the opportunity for locating spatially disjoint regions with similar characteristics (Coops et al. 2009). Moreover, when it is expected that regions with similar characteristics are spatially distanced (e.g., separated by natural or anthropogenic features), the use of spatial weighting may be unwarranted. I expect forest patterns to portray similar characteristics in spatially distanced regions separated by developed areas or mountain ridges, and because of this expectation I did not include spatial weighting in the generation of SPR.

Measure of Separation

In cluster analysis it is necessary to calculate a measure of separation between objects. The use of the Euclidean distance measure is common in the regionalization examples (e.g., Fovell and Fovell 1993, Gong and Richman 1995), and is easily computed on standardized variables in attribute space. Euclidean distance was implemented as the measure of separation between objects and is calculated using [8].

$$d(i,j) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \cdots + (x_{ip} - x_{jp})^2} \qquad [8]$$

Where d is the distance in attribute space between the i_{th} and j_{th} objects and x is the value of p_{th} attribute. In this example I employ only interval-scaled variables; when using binary, ordinal, nominal or some mixture of variable types, other separation measures are more appropriate (Kaufman and Rousseeuw 1990).

Cluster Evaluative Criteria

Flat partition clustering methods require user definition of the number of clusters (k). When k is unknown, cluster evaluative criteria provide information for determining an optimal k. Measures of cluster strength frequently suggested are often tested on datasets with clearly defined clusters (e.g., Milligan and Cooper 1985). These measures are known to work well with clusters that are compact, however novel approaches to testing cluster validity when data does not exude compact clusters (e.g., spatial data) are needed (Halkidi et al. 2002). Strongly defined clusters are not expected here, as landscapes vary continuously over the range of metrics tested. The Davies-Bouldin index (DB) (Davies and Bouldin 1979) and average silhouette width (ASW) (Kaufman and Rousseeuw 1990) were chosen as evaluative criteria for selecting the optimal *k*.

ASW is calculated using [9], which is a measure of how well clusters are separated from their closest neighbour (Kaufman and Rousseeuw 1990).

$$ASW = \frac{1}{k}\sum_{i=1}^{k}\frac{b_i - a_i}{\max\{b_i, a_i\}} \tag{9}$$

Where; *a* is the average dissimilarity between objects in a cluster *i*, *b* is the average dissimilarity of the objects in *i* to those in its closest neighbour, and *k* is the number of clusters. The maximal ASW for all *k* is interpreted as the optimal or strongest cluster level (Kaufman and Rousseeuw 1990). Kaufman and Rousseeuw (1990, p. 88) suggest that ASW values of 0.71-1.00 indicate a *k* with well defined clusters, while ASW values of 0.26-0.50 indicate a *k* with weakly defined clusters, and cluster structure may be artificial.

DB uses a ratio of intra-cluster dispersion to inter-cluster separation divided by *k* to determine clustering strength for a given *k* [10] (Davies and Bouldin 1979).

$$DB = \frac{1}{k}\sum_{i=1}^{k}\frac{S_i + S_j}{m_{ij}} \tag{10}$$

Where; S_i is the dispersion of cluster *i*, S_j is the dispersion of the next closest cluster *j*, m_{ij} is the distance between the cluster centres of *i* and *j*, and *k* is the number of clusters. DB is advantageous in that it does not require user definition of parameters, such as minimum acceptable cluster distance or minimum acceptable standard deviation, which are often unknown (Davies and Bouldin 1979). Optimal k is found at the minimum DB value; when intra-cluster dispersion is low and inter-cluster separation is high.

Multivariate cluster analysis allows users to examine many statistical properties of each cluster. Descriptive statistics such as mean, median and coefficient of variation were computed for each SPR and landscape metric combination. The relative frequency histogram for each SPR and landscape pattern metric combination is generated to assess the distributional properties of each SPR. Examining the relative frequency histogram adds to interpretation of the landscape pattern properties of each SPR. Also, each cluster that is created by the CLARA algorithm has a *medoid* (or *centrotype*) which is a representative object for each cluster and has been used as a surrogate centre for each cluster during its creation (Kaufman and Rousseeuw 1987). Medoids are a good representation of cluster centres (the middle object in a cluster), that are less sensitive to outliers then other cluster profiles (Van Der Laan et al. 2003). With this algorithm medoid landscapes can be extracted and used as a spatial representation of each SPR.

3.5 Results

Using cluster evaluative criteria (DB and ASW) an optimal cluster level was identified at k = 6 (Figure 3.2). DB is minimal at k = 6 (Figure 3.2), and ASW is maximum at k = 2, but has a second peak when k = 6. I choose k = 6 as the optimal clustering over the case when k = 2 based on the evaluative criteria and because the case where k = 2 provides few unique insights on landscape processes (largely representing a bifurcation of landscapes with high and low forest composition).

The mean, median, and coefficient of variation for each of the 6 generated SPR are portrayed in Table 3.3. The mean and median forest proportion increases going from SPR1 to SPR5, and then decreases slightly to SPR6. The variation in forest proportion is highest when forest proportion is low (i.e., in SPR1 and SPR2). Number of patches is highest in SPR2 and SPR4 and lowest in SPR6. Forest/non-forest joins are substantially higher in SPR2 (mean = 629.5 joins) than in the others, but are most variable in SPR1, SPR5, and SPR6. Patch areas based on the area-squared measure are highest in SPR5 and lowest in SPR2. Average perimeter-area ratio is highest in SPR4, but the most notable result from this is the marked difference between the lowest SPR6 (mean = 527.6 m/ha) and the next lowest SPR3 (mean = 752.3 m/ha). SPR4, SPR5, and SPR6 all have high forest composition (mean > 80%), but SPR4 and SPR5 have high perimeter area ratios (mean = 955.0 m/ha, 879.6 m/ha, respectively), relative to SPR6.

Figure 3.3 shows the relative frequency histogram for each SPR-landscape metric combination. There is a gradient in forest proportion with SPR1 being low and SPR5 and SPR6 being high. SPR2 and SPR3 have similar distributions for forest proportion. Comparing the configurational attributes between SPR2 and SPR3 demonstrates that they differ considerably in number of patches and forest/non-forest joins. Based on Table 3.3 it would be expected that SPR4, SPR5, and SPR6 have similar forest proportions, but a clear difference is noticed in the distribution of SPR4 from SPR5 and SPR6. Similarly, the number of patches and forest/non-forest join count distributions are also noticeably different for SPR4 from SPR5 and SPR6. SPR5 and SPR6 have similar distributions for most of the spatial pattern metrics, but differ slightly in number of patches and substantially in average perimeter area ratio. The difference in average perimeter-area ratio between SPR6 and the rest of the SPR is clearly demonstrated by the relative frequency distributions.

Figure 3.4 contains a view of the medoid landscape of each SPR, as well as a summary of the expected spatial pattern properties for each. This information is useful in interpreting results, as it is a visual reference of the forest pattern expected in each SPR. SPR1 portrays landscapes with low forest composition, and high forest fragmentation. SPR2 and SPR3 contain similar forest composition, but in SPR3 forest is contiguous, while in SPR2 there are more numerous, smaller patches indicating increased forest fragmentation. SPR4 has patch shapes with very irregular edges. SPR5 is characterized by high forest composition with small perforations of non-forest. SPR6 is the least fragmented and has high forest composition and contiguous disturbances, indicative of patch harvests.

A map of the distribution of SPR is shown in Figure 3.5, and includes a digital elevation model (DEM) to aid in interpretation. SPR0 and SPR100 (0% and 100% forest respectively) are only a minor constituent across the study area representing 2% and 4% of the total area (Table 3.4). SPR2 is the most prevalent of the SPR (22%), while SPR1 (9%) has the lowest area of any of the generated SPR. Topography, especially along the eastern edge of the study area, plays an important role in landscape spatial pattern, as valleys contain predominantly SPR5 and SPR6, regions with high levels of forest composition, and low number of forest patches, while alpine areas are SPR0, SPR1, SPR2, and SPR3, those with low forest composition, high number of patches, high forest/non-forest joins. The topographic influence on land cover in alpine regions results in these regions being labelled the same as a naturally forested landscape that has similar pattern characteristics resulting from some form of disturbance (e.g., harvesting, natural disturbance). In reality, the patterns observed in alpine areas are natural and generally more static, and should be distinguished from low lying areas where landscape pattern originates from some other process. Anthropogenic activities are expected to be highest near the cities of Prince George and Quesnel (see study area, Figure 3.1). These areas appear as predominantly SPR1, SPR2, and SPR3, the SPR with the lowest forest proportion, and highest number of patches. In the western portion of the Quesnel forest district (the lower left portion of Figure 3.4), noticeable pockets of SPR100 (intact forest) and SPR5 and SPR6 (high forest proportion, low number of patches), are interspersed with pockets of SPR1, SPR2, and SPR3 (low forest proportion, high number of patches). This may be an indication of the types of forest harvesting occurring in this area. Here, where topography is less extreme and has less of an influence on the spatial pattern of the landscape, forest harvesting activities are expected to be the driving factor in shaping observed forest patterns.

3.6 Discussion

Multivariate clustering provides a quantitative method for the regionalization of spatial data (Hargrove and Hoffman 2004). Weighting of the class proportion metric compared to other metrics, facilitated the generation of output clusters that exhibit lower within cluster variation with respect to forest composition. This facilitates more appropriate comparisons between clusters as we can identify when they differ in composition, or an aspect of configuration.

Generation of relative frequency histograms for each SPR-metric combination is useful for interpretation of SPR properties. For example, based solely on tabulated results SPR4, SPR5, and SPR6 exhibit similar forest composition levels. Relative frequency histograms provide added information on SPR4 as it exudes a noticeably different distribution from SPR5 and SPR6. Similarly, extracting the medoid landscapes for each SPR provides a useful visualization tool. Medoid landscapes provide representative examples of the spatial pattern expected in each SPR.

Forest fragmentation can be broadly described as the breaking up of forest habitat into smaller and more numerous parcels (Forman 1995). A qualitative assessment of SPR properties was used to rank clusters with respect to forest fragmentation. Based on this ranking, SPR1 contains the highest level of forest fragmentation and SPR6 the lowest, with the others falling in between. SPR0 (0% forest) and SPR100 (100% forest) provide external bounds on this scale that represent no-forest and all-forest. Alternative interpretations of forest fragmentation may have considered SPR2 to be more fragmented then SPR1 based on its high number of patches and small patch areas. Forest composition has been used as a proxy for forest fragmentation (e.g., Wickham et al. 2008) and SPR5 would be interpreted as less fragmented then SPR6. Likewise interpretations of perimeter area ratio can be used to describe the complexity of landscape patch shapes, and relate to the source of forest fragmentation. Anthropogenic disturbance often result in regular shapes, while natural fragmentation processes may lead to more complex shapes (Forman 1995). SPR4, SPR5, and SPR6 were all found to have high forest composition but the small openings in SPR6 have regular shapes (low perimeter area ratio) while those in SPR4 and SPR5 have more complex shapes (high perimeter area ratio). Thus, the source of forest openings in SPR6 are likely the result of anthropogenic disturbance (e.g., harvest), while in SPR4 and SPR5, openings may be of natural origin (e.g., topography, wind-throw), or represent areas where anthropogenic disturbances more appropriately emulate natural patterns.

Any multivariate cluster analysis is dependant on the data, input parameters, and methods applied. I provide an example of multivariate clustering using the CLARA algorithm and two tests for determining the optimal clustering (DB and ASW). Changing the clustering algorithm or the evaluative criteria will impact results. As it was specifically designed for large datasets, the CLARA algorithm is suited for large spatial datasets, where other methods (e.g., hierarchical) are computationally constrained. It is up to the user to explore combinations of algorithms and criteria that are useful and relevant for their research.

The landscape pattern metrics employed in this study represent only a small subset of the suite of metrics available to researchers. Choice of metrics should be related to the ecological questions being investigated (Gergel 2007). Here I investigate effects of large-area forest harvests on landscape spatial pattern, and am interested in monitoring forest fragmentation. I employ metrics useful at quantifying the key components of landscape pattern related to forest fragmentation (Haines-Young and Chopping 1996, Wulder et al. 2008b).

This study was conducted in a region where increased forest harvesting has been prescribed in response to insect infestation (British Columbia Ministry of Forests and Range 2007). Examining the spatial distribution of SPR suggests that in the eastern parts of the study area topographical influence on land cover is the largest factor affecting forest patterns observed. In the areas with the most anthropogenic activity, located centrally within this study area, the highest levels of forest fragmentation are noticed. In the western portions, especially of the Quesnel forest district, parcels of fragmented landscapes (SPR1, SPR2, and SPR3) are interspersed with non-fragmented landscapes (SPR5, SPR6, and SPR100). Here, where mountain pine beetle infestation is widespread, salvage and mitigation harvesting activities may be the driving factor in shaping forest pattern, and this location may be most useful for investigating the potential impacts on various natural processes, such as wildlife habitat (Bunnell et al. 2004) and hydrologic regimes (Helie et al. 2005).

3.7 Conclusions

Multivariate cluster analysis provides a useful, quantitative approach for the regionalization of landscape spatial pattern. The CLARA clustering algorithm provides a suitable method for multivariate cluster analysis with large datasets (as is often the case with spatial data). When the desired number of clusters (k) is unknown, evaluative criteria can be used to determine an optimal k. Output clusters can be characterized by examining their statistical properties, and relative frequency histograms may provide added information. I found the medoid object (landscape) to be useful for representing each cluster visually. Mapping clusters presents a regionalization that provides information for management and decision-making that can be related to ancillary datasets (e.g., topography). The use of quantitative methods in regionalization projects has been advocated (Hargrove and Hoffman 2004) and this study provides an example.

Regionalization provides an effective framework for viewing and understanding the characteristics of spatial data. With regionalization I can evaluate the spatial distribution of data groups relatable to forest fragmentation rather then data objects. In this study I focus on a relatively small extent and investigate the effect of increased harvesting from mountain pine beetle salvage and mitigation activities on forest pattern. Recent international forest management protocol has advocated for national forest management practices that include consideration of forest pattern (Montreal Process Liaison Office 2000). In Canada, the spatial extent of forest monitoring limits how we can view and interpret forest pattern information. Similarly, the number of attributes required to effectively monitor forest pattern is not easily visualized with maps. Regionalization may provide an effective approach for meeting these monitoring directives.

Table 3.1: Examples using regionalization.

Regionalization	Context	Reference
Life Zone	Classify vegetation regions using elevation, temperature, precipitation, and evaporation.	Holdridge (1967)
Ecozone	Global regionalization of a set of five physical characteristics: climate, relief and drainage, soils, vegetation and animals, and land use.	Schultz (2005)
Ecoprovinces/Ecozones/ Ecoregions	Nested system of ecological zones covering Canada using various input parameters.	Wiken (1986)
Environmental Domain* (New Zealand)	To identify unique ecosystems for protection. Used climate and landform variables.	Leathwick et al. (2003)
Environmental Domain* (Canada)	For monitoring biodiversity. Used land cover, productivity, and elevation data.	Coops et al. (2009)
Spatially coherent regions*	Derive spatially contagious regions of crop yield, using crop yield data.	Lark (1998)
Geologic Regions*	For oil and gas exploration. Used structural, petrographic, and petrophysical features.	Harff and Davis (1990)
Climate Zones*	Extract climate zones for conterminous United States. Used long-term monthly temperature and precipitation data.	Fovell and Fovell (1993)

*Use multivariate cluster analysis.

Table 3.2: Metrics chosen for multivariate cluster analysis, their formulation and selected reference.

Metric	Units	Formulation	Selected Reference
Class Proportion	%	$\frac{\sum a_i}{A} \rightarrow \{i = F\}$	Hargis et al. 1997
Join Counts	#	$\sum g_{jk} \rightarrow \{j = F,\, k = N\}$	Boots 2006
Number of Patches	#	$\sum n_i \rightarrow \{i = F, N, O\}$	Haines-Young and Chopping 1996
Patch Area Squared	ha^2	$\sum a_i^2 \rightarrow \{i = F, N, O\}$	Boots 2006
Mean Patch Perimeter-Area Ratio	m/ha	$\frac{1}{n}\sum \frac{p_i}{a_i} \rightarrow \{i = F, N, O\}$	Riitters et al. 1995

A – total area of landscape, a – area of patch, g – join between two neighbouring cells, n number of patches, p – perimeter of patch, F – forest, N – non-forest, O – other.

Table 3.3: Mean, median and coefficient of variation for each metric-SPR combination.

	(units)	**Forest Proportion** (%)	**Number of Patches** (#)	**Forest/Non-Forest Joins** (#)	**Squared Area of Patches** (ha^2)	**Average Patch Perimeter Area Ratio** (m/ha)
SPR1	mean	18.9	14.9	277.3	5647	831.1
	median	19	15	284	5484	838.9
n = 5271	c.v.	0.60	0.40	0.49	0.24	0.14
SPR2	mean	55.5	24.0	629.5	3481	889.2
	median	57	23	616	3442	888.7
n = 12150	c.v.	0.25	0.26	0.21	0.21	0.08
SPR3	mean	65.7	12.7	367.6	4021	752.3
	median	68	13	362	3964	762.6
n = 11548	c.v.	0.19	0.29	0.28	0.22	0.14
SPR4	mean	84.7	21.4	371.1	5907	955.0
	median	85	20	365	5917	952.0
n = 8027	c.v.	0.07	0.28	0.27	0.13	0.08
SPR5	mean	93.5	9.7	153.4	7172	879.6
	median	95	10	148	7315	871.6
n = 10034	c.v.	0.05	0.35	0.50	0.09	0.11
SPR6	mean	88.3	5.2	137.6	6675	527.6
	median	92	5	128	6959	585.9
n = 5775	c.v.	0.15	0.49	0.62	0.18	0.34

Table 3.4: Area percentages of each SPR.

SPR	Area (%)
SPR0	2
SPR1	9
SPR2	22
SPR3	21
SPR4	14
SPR5	18
SPR6	10
SPR100	4

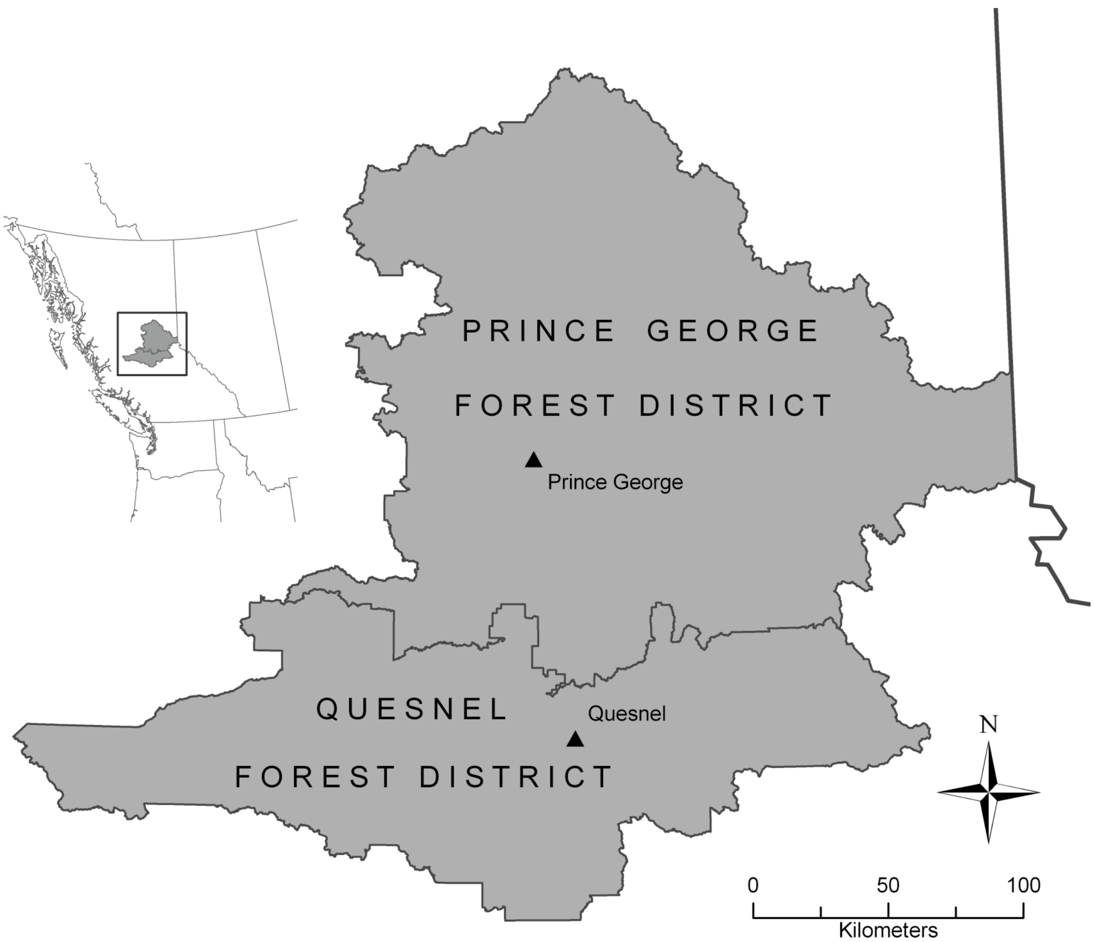


Figure 3.1: Study area, the Prince George and Quesnel forest districts located in British Columbia, Canada.

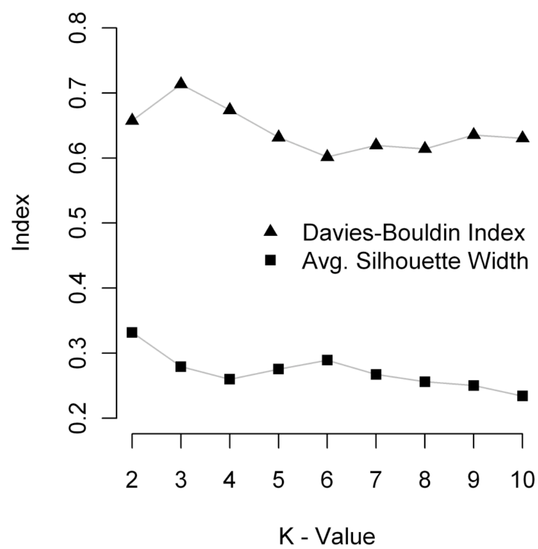


Figure 3.2: Davies-Bouldin Index (DB) and Average Silhouette Width (ASW) results for k values of 2 – 10. Optimal k is found at minimum DB and maximum ASW (in this case k = 6).

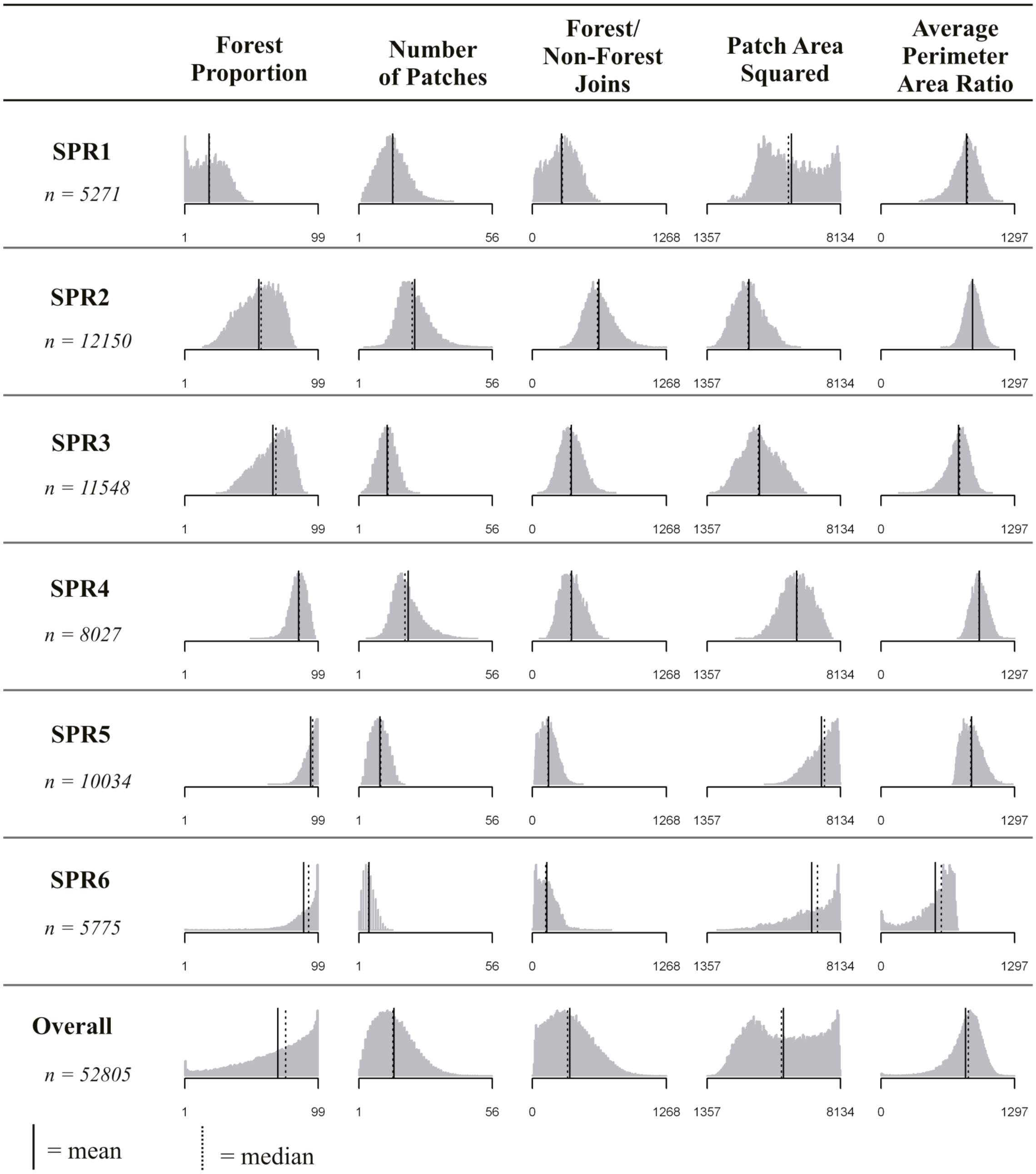
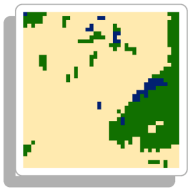
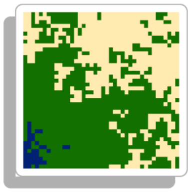


Figure 3.3: Relative frequency histogram for each metric-SPR combination. Included are the mean and median values for each histogram.



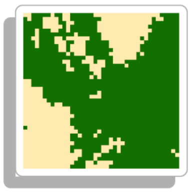
SPR1

SPR1 has the lowest level of forest proportion. It has moderate but variable number of patches and forest/non-forest join counts. It has high squared area of patches, but these are also quite variable. Perimeter-area ratio for SPR1 is very similar to the overall mean. This SPR has the highest level of forest fragmentation.



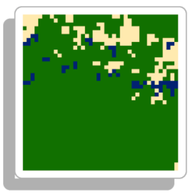
SPR2

SPR2 portrays medium levels of forest proportion, similar to that of SPR3. It has on average the most number of patches, which provide the lowest area squared value.The highest level of forest/non-forest joins was seen in this class indicating the least amount of spatial dependence in forest cover, and most forest edge.



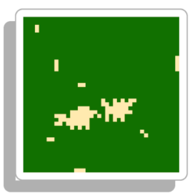
SPR3

SPR3 is comprised of similar forest proportion to SPR2. Conversely to SPR2 it has a low number of patches and lower number of forest/non-forest joins. Patch areas are comparable to SPR2, but low compared to other SPRs.



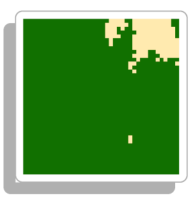
SPR4

SPR4 is characterized by relatively high forest composition, and high patch numbers but moderate forest/non-forest joins. Patch area squared measure for SPR4 is comparable to SPR1. SPR4 has the highest average perimeter area ratio of any of the SPRs.



SPR5

SPR5 has the highest mean forest proportion. It is characterized by a low number of patches and low forest/non-forest joins. SPR5 has high patch area squared measurements but similar perimeter area ratio to the overall mean.



SPR6

SPR6 has the second highest mean forest proportion, and is most comparable to SPR5. It has lower number of patches then SPR5. Forest/non-forest joins and patch area squared measure are highly variable for SPR6. It's distinguishing feature is that it contains the lowest average perimiter-ratio of all SPRs. It is the SPR with the lowest forest fragmentation.

Forest Non-Forest Other

Figure 3.4: Medoid landscapes for each SPR. Medoids are the central object in each cluster of the multivariate clustering. They are the representative landscape for each SPR. SPR0 and SPR100 are not shown but represent no forest and all forest respectively.

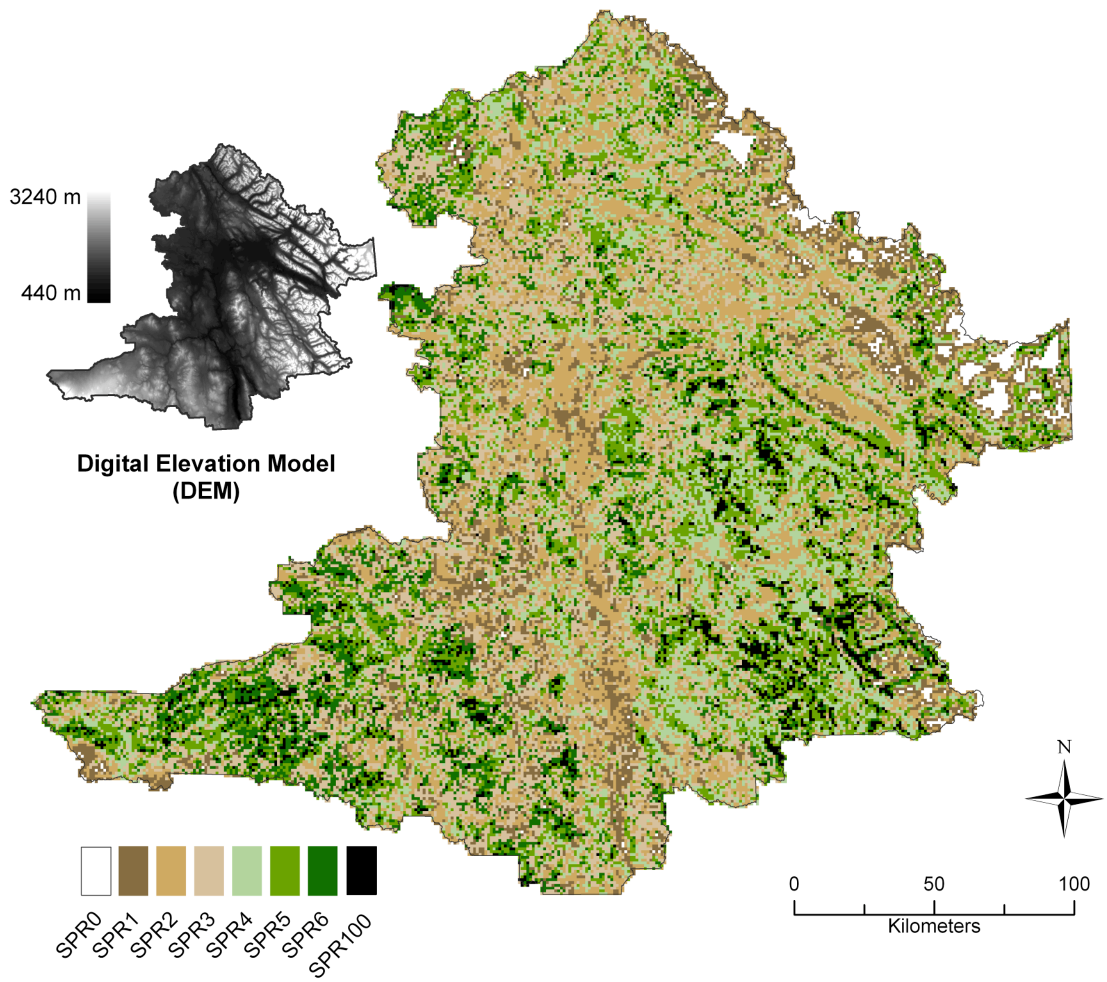


Figure 3.5: Map of SPR across the Prince George and Quesnel forest districts in British Columbia, Canada.

4.0 CONCLUSION

4.1 Discussion and Conclusions

Given the spatial extent of the current mountain pine beetle infestation, managing infested landscapes with minimal ecological impacts is challenging. Long-term it is desirable that management strategies generate a mosaic of forest species and age classes. Barclay et al. (2005) demonstrate that forest management and fire suppression leading up to the current mountain pine beetle infestation generated a forest structure (age and spatial distribution) that enhanced mountain pine beetle traversability, increasing the potential for infestation. Similarly, impacts to the ecological function of hydrologic regimes (Helie et al. 2005) and local terrestrial and aquatic vertebrates (Bunnell et al. 2004) associated with undesirable forest pattern should be minimized when implementing salvage and mitigation activities. Optimal forest management requires consideration of forest spatial pattern. As forest pattern is now a component of international forest monitoring agendas (Montreal Process Liaison Office 2000); effective methods for quantifying changes in forest pattern across temporal and spatial scales will help meet management and monitoring objectives. This research identifies two new approaches that improve upon existing techniques used for quantifying changes in forest pattern over time and space.

In Chapter 2, I demonstrate a new method for comparing forest pattern across two time periods and apply it to a 160 000 ha study area located in the Prince George forest district in British Columbia, Canada. Two measures, 2-D Displacement and Proportion of 2-D Displacement from Configuration, are used to quantify the impacts of increased harvesting from mountain pine beetle salvage and mitigation activities on forest pattern.

Forest cover information for 2000 and 2006 represent forest conditions at approximately the onset and peak of the mountain pine beetle epidemic for this part of British Columbia. In regions where increased harvesting is most prevalent; forest edge, and the number of forest and non-forest patches are increasing, an indication of forest fragmentation. With an increasing number of both forest and non-forest patches one might expect the areas of these patches to decrease. This is only true for forest patches which decrease in area, while non-forest patches increase in area. Using the 2-D Displacement and Proportion of 2-D Displacement from Configuration I identify composition as the primary component of spatial pattern that is changing in regions with the most intense harvest activity. In the peripheral areas, configurational changes are more prevalent and have a larger impact on the forest pattern occurring in these landscapes.

In Chapter 3, I present a new approach for mapping the spatial distribution of forest pattern. Regionalization using multivariate cluster analysis is performed on the Prince George and Quesnel forest districts partitioned into 1 km landscapes. Landscape pattern indices are used to generate forest pattern attributes for analysis. I find that in the eastern portion of the Prince George and Quesnel study area, the topographic influence on land cover may be the dominant factor shaping forest pattern. In the western and central parts of the study area, observed forest fragmentation is linked to anthropogenic activity. The western and central regions have been the most intensely infested by mountain pine beetle. Here increased salvage and mitigation activities are a contributing to greater forest fragmentation. Near the cities of Prince George and Quesnel it is likely that other anthropogenic activities (e.g., agriculture) are impacting observed forest pattern. Fragmented regions have higher number of patches, forest/non-forest join counts, and smaller forest patch areas. Perimeter-area ratios are highest in landscapes that have natural forest disturbances and lowest when forest disturbance is generated from anthropogenic activities.

4.2 Research Contributions

Current methods (i.e., landscape pattern indices) for examining the spatial patterns in categorical land cover datasets have a number of limitations (Turner et al. 2001, Li and Wu 2004). Through this research I develop new methods for quantifying; a) temporal change in landscape pattern, and b) spatial distribution of landscape pattern. Previous work has demonstrated the need to consider landscape configuration in the context of landscape composition (Remmel and Csillag 2003, Boots 2006), and my methods address this issue.

The 2-D Displacement and Proportion of 2-D Displacement from Configuration represent techniques for quantifying temporal change in landscape pattern indices while considering change in configuration explicitly within the context of change in composition. 2-D Displacement measures the magnitude of landscape change for a given configurational metric. Proportion of 2-D Displacement from Configuration can be used to quantify the amount of landscape change that can be attributed to configurational change, while accounting for changes in composition. These two measures improve temporal analysis of landscape pattern, and are appropriate for a wide range of applications where landscape pattern indices are employed. In particular, they will be beneficial when landscape change is driven by alteration in composition, as is the case in forest change resulting from mountain pine beetle salvage activities.

In Chapter 3, I use an existing method (regionalization using multivariate cluster analysis) with a new application (measures of landscape pattern). Output clusters are termed Spatial Pattern Regions (SPR). Multivariate cluster analysis allows multiple layers of landscape pattern information (e.g., metrics) to be combined into a single output level (e.g., SPR clusters). SPR can be mapped to investigate the spatial distribution of landscape pattern attributes. Statistical properties of SPR can be evaluated to provide both qualitative and quantitative information about each SPR. The similarities of each SPR can be qualitatively or quantitatively compared. I used a qualitative assessment of similarity, and related output SPR to forest fragmentation. The use of an SPR-like approach is applicable for monitoring landscape pattern for a variety of applications and at a wide range of spatial scales. Given demonstrated linkages between landscape pattern and wildlife habitat requirements (e.g., grassland birds, Helzer and Jelinski (1997); American marten, Hargis et al. (1999); caribou, Hansen et al. (2001)), it would be advantageous for management to include a landscape pattern component in the design of conservation reserves. SPR style methods can also aid in locating new conservation areas. Creating maps of key indicators (e.g., biodiversity) for conservation reserves is essential for locating new reserve areas (Margules and Pressey 2000). The SPR approach enables landscape pattern information to be considered when locating potential conservation areas.

4.3 Research Opportunities

This research provides new methods that improve the use of landscape pattern indices for quantifying change in landscape pattern across temporal and spatial scales.

Implementation of demonstrated methods with other applications may provide additional insight on the usefulness of these methods. The measures 2-D Displacement and Proportion of 2-D Displacement from Configuration consider composition explicitly when quantifying changes in configuration over time. Future work with these measures should focus on exploring the distributional properties associated with varying amounts of landscape change. A better understanding of the sensitivity of these measures to landscape changes will provide context for their use.

The SPR approach quantitatively identifies differences in observed spatial patterns over large spatial extents. Similarly, the SPR method is successful in identifying spatially disjoint or distant regions that portray similar landscape patterns. Landscape pattern information generated using the SPR method is useful for exploring the potential of new sites for conservation, recreation, or industrial activities. For example, if a new conservation region should contain landscape patterns similar to a known other location, an SPR like approach could help identify potential sites.

Future avenues of this research should focus on incorporating the concepts of temporal and spatial change into a single analysis. It would be interesting to use an SPR approach for examining the changes in landscape patterns over time identified using the 2-D Displacement and Proportion of 2-D Displacement from Configuration measures. Landscapes undergoing similar changes in landscape pattern could be linked to similar processes generating this change. Extending on the concept of multivariate cluster analysis for regionalization may provide the framework for quantifying temporal change in forest pattern across a large spatial extent.

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