

**MULTITEMPORAL REMOTE SENSING OF LANDSCAPE  
PATTERN DYNAMICS RESULTING FROM MOUNTAIN  
PINE BEETLE INFESTATION AND TIMBER HARVEST**

by

Steve Neil Gillanders

B.Sc. Royal Roads University, 2003

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF  
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

in

The Faculty of Graduate Studies

(Forestry)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

May 2009

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## **ABSTRACT**

Occurring over multiple years and impacting an area over 13 million hectares to date, the current epidemic of mountain pine beetle (*Dendroctonus ponderosae* Hopkins) in British Columbia lends itself to the use of remote sensing technologies for monitoring purposes. Change detection procedures based upon spectral values are common; however, monitoring changes in landscape pattern presents opportunities for the generation of unique and ecologically important information. Furthermore, while the use of two images may provide the means to identify change, the use of more than two images affords the ability for long-term monitoring and characterization of processes such as change rates and dynamics.

The initial component of this study consists of a literature review undertaken to investigate and summarize methods and applications of landscape pattern analysis using three or more image dates. This information was in turn used to make recommendations for the application of landscape pattern analysis of a time-series of remotely-sensed data to a case study involving mountain pine beetle infestation and timber harvesting.

Following the review, we focussed on the detection and monitoring of lodgepole pine stands in order to quantify the progression of forest fragmentation and loss of connectivity as a result of mountain pine beetle infestation and timber harvest. This was accomplished using a key set of landscape pattern indices applied to six Landsat satellite images spanning 1993 to 2006. Through our analysis we found that the impacts of the mountain pine beetle on forest spatial pattern consist of an increase in the number of

forest patches, shape complexity, and patch isolation, and a decrease in forest patch size and interspersion. In addition, we determined that in a spatial context, mountain pine beetle infestation plays a significantly greater role in forest fragmentation and loss of connectivity than timber harvest. However, we also discuss the limitations of these findings due to the differences between natural and anthropogenic disturbances and the inability of Landsat data to detect patch-level dynamics. This research demonstrates the unique information available from satellite image time-series combined with landscape pattern analysis to better understand the combined effects of insect infestation and forest harvesting.

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## ACKNOWLEDGEMENTS

This project is funded by the Government of Canada through the Mountain Pine Beetle Program administered by Natural Resources Canada, Canadian Forest Service, with additional information available at: <http://mpb.cfs.nrcan.gc.ca>. Special thanks to Dr. Nicholas Coops for his support and guidance. Dr. Michael Wulder, Dr. Sarah Gergel, and Dr. Trisalyn Nelson provided valuable advice on methods, results, and manuscript writing. Many thanks to Dr. Nicholas Goodwin for his considerable help in dealing with technical aspects of remote sensing. I would also like to thank Dr. Valerie LeMay for providing assistance with statistical analysis methods. In addition, thanks to my partner Martha and my daughter Olivia for their love and support. Finally, I would like to thank the students of the IRSS lab for their friendship, continual support, and ongoing exchange of knowledge.

*To Amanda Broadribb, Eva Reycraft, and Doug Broadribb for your  
encouragement*

## **CO-AUTHORSHIP STATEMENT**

This thesis is the combination of two scientific manuscripts for which I am the lead author. The initial project structure was provided by Dr. Nicholas Coops and Dr. Michael Wulder, from which multitemporal landscape pattern analysis as a tool to characterize forest cover dynamics due to mountain pine beetle infestation was identified as a key research opportunity. For these two scientific journal articles, I performed all research, data analysis, interpretation of results, and prepared the final manuscripts. Dr. Sarah Gergel provided assistance with experimental design and methodology. Dr. Nicholas Goodwin provided assistance with technical aspects of remote sensing. Co-authors provided advice on methodology and made editorial comments and suggestions where required.

# 1 INTRODUCTION

Forests provide critical habitat to a wide range of species but also provide important ecological services including the maintenance of biodiversity, soil and water resources, and the provision of timber and non-timber forest products. The composition and distribution of forests change not only through the slow and gradual process of growth and succession, but also through irregular and abrupt natural disturbances (Linke et al. 2007) and anthropogenic disturbances resulting from human activities. The associated changes in land cover resulting from anthropogenic disturbances are widely considered to be the primary drivers of biodiversity decline and species loss (Hansen et al. 2001). For instance, deforestation, typically associated with long-term or permanent loss of forest cover and its conversion to another land use, represents one of the key forces of global environmental change (Fearnside 1996, Justice et al. 2001, Zhang et al. 2001). Due to the importance of forested ecosystems, resource managers have increasingly relied on monitoring programs to evaluate land cover and forest changes, disturbance processes, and spatial pattern (Linke et al. 2007).

Forest disturbance includes processes such as wildfire, windthrow, insect attack, and timber harvesting. Each type of disturbance results in different impacts on ecosystems and landscapes, as well as on stand structure, species, and site conditions (Linke et al. 2007). Consequently, the impacts of different forest disturbance agents result in changes to spatial pattern, which can influence wildlife species, communities, and populations in addition to a range of abiotic processes.

## **1.1      *Landscape fragmentation***

A major consequence of forest disturbance is fragmentation, which can adversely affect a range of factors including wildlife habitat (Fleishman and Nally 2007), biodiversity (Olf and Ritchie 2002, Fahrig 2003), species extinction rates (Wilcox and Murphy 1985, Fahrig 2002), and abiotic processes (Pasher and King 2006). In general, fragmentation results in 1) an increase in the number of patches, 2) a decrease in the mean patch size, and 3) an increase in the total amount of edge (Rutledge 2003). Fragmentation affects ecosystems by modifying the conditions within a landscape patch and the flow of resources among landscape patches (Saunders et al. 1991).

When an ecosystem is fragmented the flow of physical resources is altered as a result of the changes in the size, number, shape, and configuration of patches. These impacts often decrease along a gradient away from the edge of a patch toward the interior, or core. Core areas tend to have similar abiotic conditions to those found in the interior of larger patches, while edge areas are more influenced by the conditions in neighbouring patches and tend to have a higher degree of alteration. In the case of forest fragmentation, edge is often the boundary between a forest patch and an area with a more open physical structure such as clearcut. As such, edge areas tend to receive more solar radiation, which can result in higher temperatures and drier conditions, as well as increased wind flow (Saunders et al. 1991).

Different species respond differently to fragmentation. For example, the influence of abiotic changes will have a more pronounced influence on some species, while changes in interspecific interactions will tend to have a greater affect on other species. In general, these differential responses to fragmentation will restructure community dynamics, often resulting in a lower species richness and a higher relative abundance of generalist species (Harrison and Bruna 1999). As abiotic changes occur resulting from fragmentation, plant species composition changes as competitive interactions cause a reshuffling to accommodate abiotic changes. Consequently, the composition of plant species will determine the resources available to herbivores, the herbivores available to predators, and the plant resources available to detrivores. Animals may be forced to expand their range in order to locate the resources required to meet their dietary needs, their body sizes may decrease as a result, or they may have fewer reserves available for reproduction (Rutledge 2003). Furthermore, reproduction and mortality rates will change according to resource availability, mating opportunities, competition, and the presence of predators.

Conversely, fragmentation may be beneficial to some species by providing an advantage, such as refuge from a predator or disease that has difficulty moving among the patches of a fragmented landscape. Thus, the effects of landscape fragmentation vary depending on the process or organism of interest, but in general a significantly altered and fragmented landscape would be expected to have significant impacts on remnant biota (Saunders et al. 1991).

Forests may be fragmented by a range of disturbance events such as logging, conversion to agricultural lands, wildfire, and insect outbreaks. Thus fragmentation can result from

both anthropogenic and natural activities. Although naturally occurring forest disturbances result in the discontinuity of forest stands, they are significant for the maintenance of biodiversity, age-stand heterogeneity, and forest stability (Waring and Running 1998). Understanding forest disturbance and spatial pattern is increasingly recognized as an integral component of sustainable forest management (Linke et al. 2007).

## **1.2 Mountain pine beetle**

The current mountain pine beetle (*Dendroctonus ponderosae* Hopkins) epidemic in British Columbia has altered lodgepole pine forests to an unprecedented scale (Chan-McLeod 2006) and represents the largest infestation on record for the province. As a result of anthropogenic and environmental influences such as forest wildfire suppression and a moderating trend in temperature extremes, populations of this native insect have reached epidemic proportions in the interior of British Columbia. The impacts of this outbreak are expected to continue for decades, directly affecting a range of socio-economic and environmental values. These include changes to timber supply, watershed hydrology, fish habitat, snow interception, wildfire fuel-load, coarse woody debris ground cover, and high-value and sensitive forest sites (i.e., critical wildlife habitat, conservation areas, etc.).

The mountain pine beetle population cycle consists of four stages: endemic populations; incipient epidemic populations; epidemic populations; and post-epidemic (declining) populations (Safranyik 2004). In the endemic phase local mountain pine beetle

populations are relatively benign infesting a few scattered trees within a forest (Carroll and Safranyik 2004). Incipient infestations represent the beginning of an outbreak and occur when beetle populations have grown such that they have the ability to mass attack the average large diameter component of a given forest stand (Safranyik 2004). Epidemic populations exist at the landscape level and develop as a result of the expansion of incipient and local endemic populations, and long-range insect dispersal. The post-epidemic stage represents a beetle population collapse resulting from factors such as a depletion of suitable hosts or a lethal low temperature event (Safranyik 2004). Outbreaks occur at irregular intervals and often persist for between five and twenty years resulting in tree mortality over vast areas (Carroll and Safranyik 2004).

Following mountain pine beetle attack, tree mortality is characterized by three distinct stages: green-attack, red-attack, and grey-attack. The green-attack stage refers to a tree that has been killed but still has green foliage. After a twelve-month period following the initial beetle attack, 90% of killed trees will have red needles, referred to as the red-attack stage. The grey-attack stage is characterized by defoliation, which typically occurs three-years following attack (Wulder et al. 2005a).

In managed forest stands the economic losses due to mountain pine beetle infestation are often greater than the volume loss reported because most tree mortality is among the larger-diameter trees (Carroll and Safranyik 2004). In addition to the tree mortality and timber losses, mountain pine beetle epidemics can result in an increase in fuel loading, promote succession to the climax forest, impact watershed drainage, wildlife ecology,

and recreational values (Carroll and Safranyik 2004). Even with a cold weather event of the magnitude required to produce beetle mortality rates resulting in a population collapse, the timber supply, community stability, and ecological dynamics of BC interior forest ecosystems will be significantly impacted by this current outbreak (Wilson 2004).

### **1.3      *Remote sensing***

Remote sensing provides a valuable record and analysis possibilities for studying long-term changes in vegetation. In addition to being the only data source available for many inaccessible areas, remote sensing provides the opportunity to acquire data with the spatial coverage and temporal frequency sufficient for studying and monitoring vegetation at a relatively low cost. Numerous studies using remote sensing for environmental monitoring and change detection demonstrate that remote sensing technologies are becoming increasingly important for studying the landscape at local, regional, and global scales (Coppin et al. 2004, Goetz et al. 2006, Schroeder et al. 2007).

Remote sensing applications have been investigated for the operational mapping of mountain pine beetle since the 1960s. Because vegetation attributes such as changes in leaf pigments, tissue structure, and moisture content are detectable using remote sensing technologies, these indicators provide a means of detecting and monitoring the impacts of a landscape disturbance agent such as mountain pine beetle infestation. These foliage characteristics have unique patterns of absorption and/or reflectance and can be used to develop algorithms to detect change (Wulder and Dymond 2004).

Each attack stage of mountain pine beetle infestation has unique spectral characteristics associated with it. Green-attack is a form of non-visual stress which is most likely the result of moisture stress and can be detected based on a decrease in near-infrared reflectance. Red-attack results in an increase in the spectral reflectance of red wavelengths and a decrease in green reflectance. In addition, red-attack foliage has a higher reflectance in the range of 850 – 1100 nm. Increasing levels of defoliation in the grey-attack stage are associated with an increase in visible wavelengths, a decrease in near-infrared reflectance, and an increase in mid-infrared reflectance (Wulder et al. 2005a).

The mapping of green and grey-attack has not been a common approach to mountain pine beetle mapping. However, a number of methods have been developed to successfully detect red-attack tree crowns and stands using remote sensing technology (Wulder et al. 2005a). Typically, the spectral properties associated with the red-attack stage of tree defoliation following beetle infestation are the signature used to identify mountain pine beetle disturbance. Image band combinations such as the Tasselled Cap Transformation wetness or normalised difference moisture index are often used as these have been shown to be particularly sensitive at detecting changes in forest structure and vegetation (Seto et al. 2002, Skakun et al. 2003, Healey et al. 2005, Jin and Sader 2005, Healey et al. 2006, Goodwin et al. 2008).

A range of remotely-sensed data types have been used for identifying and monitoring mountain pine beetle, from fine spatial resolution digital aerial imagery allowing an

ability to detect individual crowns (Coggins et al. 2008) to broad-scale satellite imagery capable of mapping at a regional scale (Coops et al. 2009). The application of moderate spatial resolution imagery such as Landsat to detect and monitor mountain pine beetle infestation at epidemic levels has proven to be useful and effective (Wulder et al. 2005a) for a number of reasons. First, with an archive spanning more than 30 years, Landsat imagery offers the longest-running time series of satellite-based remote sensing data available (Cohen and Goward 2004). Thus it provides the means to characterize historical mountain pine beetle outbreaks allowing for temporal observations and comparisons (Wulder et al. 2005b, Wulder et al. 2006, Goodwin et al. 2008). Second, the spatial resolution of Landsat is considered to be appropriate for applications associated with land management (Cohen and Goward 2004). Third, the spectral properties of Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) imagery include major portions of the visible, near-infrared, and mid-infrared electromagnetic spectrum, allowing for the detection and characterization of a range of land cover features including a host of vegetation properties. In addition, Landsat data are considered to be an affordable data source allowing for the acquisition of large volumes of data (Cohen and Goward 2004). With the recent announcement by the United States Geological Service (USGS) that the entire archive of Landsat imagery is now free to the public (Woodcock et al. 2008), the widespread use of Landsat imagery is expected to continue. While the majority of applications for detecting and monitoring mountain pine beetle have been based on the spectral response of pixels to identify red and grey-attack, there is additional information based on the arrangement and distribution of pixels which has not as readily been utilized; namely, landscape spatial pattern.

## **1.4      *Landscape pattern and process***

Landscape ecology is largely concerned with the notion that environmental patterns have a strong influence on ecological processes (Turner 1989). Processes such as population dynamics and community structure are largely driven by the interaction of organisms and the spatial structure, or pattern, of their habitat (Johnson et al. 1992). Thus changes in landscape pattern can result in changes to the functional integrity of an organism's habitat, thereby disrupting or modifying critical ecological processes (With and Crist 1995). As a result, quantitative measures of spatial pattern have been developed and are referred to as landscape metrics or landscape pattern indices. In general, landscape pattern indices measure landscape configuration (the specific arrangement of spatial elements) and composition (the number and amount of different spatial elements) for categorical data (Turner 2005). Measuring landscape pattern provides information related to ecological conditions and provides the ability to make inferences at both a species-specific and broader ecosystem-level context. When measured over time, changes in landscape pattern provide an indication of changes to ecological systems, which can in turn provide important information to land and resource managers.

The categorical data derived from classified raster or vector data essentially represent a given landscape as a mosaic of patches. Landscape pattern indices focus on the spatial character and the distribution of patches, and may be defined at three levels: 1) patch-level, 2) class-level, and 3) landscape-level. Patch-level indices characterize the spatial character and context of individual patches. Class-level indices measure the properties that result from the unique configuration of a given patch type (class) across the

landscape. Landscape-level pattern indices measure all patch types over the full extent of the landscape (McGarigal and Marks 1995).

Landscape pattern indices are commonly used to assess and/or monitor landscape fragmentation resulting from disturbance. While many studies have applied landscape pattern indices to a single categorical map, thereby characterizing the spatial pattern of a landscape for a 'snapshot' in time, other studies have attempted to apply landscape pattern indices to characterize both landscape disturbance and temporal landscape change (Sachs et al. 1998, Trani and Giles 1999, Henebry and Goodin 2002, Sohl et al. 2003, Yu and Ng 2006). Incorporating a temporal aspect into the analysis of spatial pattern moves beyond the treatment of fragmentation as a unitary event, allowing for the characterization of a continuum of changes that more accurately reflects the physical reality of a given landscape (Bissonette and Storch 2007).

## **1.5 Objectives**

A review of associated academic literature suggests that incorporating a temporal dimension to studies involving landscape ecology is a critical information need, both in order to gain an understanding of historic variability and landscape dynamics, but also to advance the field of ecology (Reynolds-Hogland and Mitchell 2007). The goals of Chapter 2 were to investigate and summarize the methods and applications of land cover spatial pattern analysis using three or more image dates. This included a literature review of academic research articles which met the above-mentioned criteria, as well as an in-depth summary of the potential applicability and limitations of spatial pattern analysis,

including caveats of their use as published by a variety of authors (Gustafson 1998, Turner et al. 2001, Li and Wu 2004, Gergel 2007). The findings of this review were used to inform both the selection and applicability of landscape pattern indices, and also to develop hypotheses of expected changes in forest landscape pattern due to the impacts of mountain pine beetle infestation and timber harvest.

The goals of Chapter 3 were to monitor changes in landscape pattern resulting from mountain pine beetle infestation and timber harvest in order to quantify and characterize the progression of forest fragmentation and loss of connectivity. The specific objectives of these analyses were to: 1) assess how the mountain pine beetle changes landscape spatial pattern, and 2) determine the relative impact of mountain pine beetle infestation and logging on habitat fragmentation and connectivity. This was accomplished using a data stack of six Landsat images spanning a period of 13 years (1993-2006), covering a study area in the central interior of British Columbia.

Chapter 4 discusses the significance and implications of this work, and makes suggestions for future research. Finally, to help guide the reader is a glossary located in Appendix A that lists many of the ecological terms referred to throughout this manuscript.

## **1.6      *References***

- Bissonette J. A., I. Storch. 2007. Temporal dimensions of landscape ecology: Wildlife responses to variable resources. Springer, New York, NY, USA. 284.
- Carroll A. L., L. Safranyik. 2004. The bionomics of the mountain pine beetle in lodgepole pine forests: Establishing a context. Pages 21-32 *In* T.L. Shore, J.E. Brooks, and J.E. Stone, editors. Mountain Pine Beetle Symposium: Challenges and Solutions. October 30-31, 2003, Kelowna, British Columbia.. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Information Report BC-X-399, Victoria, BC. 298.
- Chan-McLeod, A. C. A. 2006. A review and synthesis of the effects of unsalvaged mountain-pine-beetle-attacked stands on wildlife and implications for forest management. *BC Journal of Ecosystems and Management* 7:119-132.
- Coggins S., N. C. Coops, and M. A. Wulder. 2008. Parameterisation of insect infestation spread models using tree structure and spatial characteristics derived from high-spatial resolution digital aerial imagery. *Canadian Journal of Remote Sensing* 34:485-502.
- Cohen W. B., S. N. Goward. 2004. Landsat's Role in Ecological Applications of Remote Sensing. *Bioscience* 54:535-545.
- Coops N. C., M. A. Wulder and D. Iwanicka. 2009. Large area monitoring with a MODIS-based Disturbance Index (DI) sensitive to annual and seasonal variations. *Remote Sensing of Environment* 113: 1250-1261.
- Coppin P., I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin. 2004. Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing* 25:1565-1596.
- Fahrig L. 2002. Effect of Habitat Fragmentation on the Extinction Threshold: A Synthesis. *Ecological Applications* 12:346-353.

- Fahrig L. 2003. Effects of habitat fragmentation on biodiversity. *Annual Review of Ecology, Evolution, and Systematics* **34**:487-515.
- Fearnside P. M. 1996. Amazonian deforestation and global warming: carbon stocks in vegetation replacing Brazil's Amazon forest. *Forest Ecology and Management* **80**:21-34.
- Fleishman E., R. M. Nally. 2007. Measuring the response of animals to contemporary drivers of fragmentation. *Canadian journal of zoology* **85**:1080-1090.
- Gergel S. E. 2007. New directions in landscape pattern analysis and linkages with remote sensing. Pages 173-208 *In* M. A. Wulder and S. E. Franklin, editors. *Understanding Forest Disturbance and Spatial Pattern: Remote Sensing and GIS Approaches*, Taylor and Francis, Boca Raton, FL, USA.
- Goetz S. J., G. J. Fiske, and A. G. Bunn. 2006. Using satellite time-series data sets to analyze fire disturbance and forest recovery across Canada. *Remote Sensing of Environment* **101**:352-365.
- Goodwin N. R., N. C. Coops, M. A. Wulder, S. Gillanders, T. A. Schroeder, and T. Nelson. 2008. Estimation of insect infestation dynamics using a temporal sequence of Landsat data. *Remote Sensing of Environment* **112**:3680-3689.
- Gustafson E. J. 1998. Minireview: Quantifying Landscape Spatial Pattern: What Is the State of the Art? *Ecosystems* **1**:143-156.
- Hansen A. J., R. P. Neilson, V. H. Dale, C. H. Flather, L. R. Iverson, D. J. Currie, S. Shafer, R. Cook, and P. Bartlein. 2001. Global Change in Forests: Responses of Species, Communities, and Biomes. *Bioscience* **51**:765-779.
- Harrison S., E. Bruna. 1999. Habitat Fragmentation and Large-Scale Conservation: What Do We Know for Sure? *Ecography* **22**:225-232.
- Healey S. P., Z. Yang, W. B. Cohen, and D. J. Pierce. 2006. Application of two regression-based methods to estimate the effects of partial harvest on forest structure using Landsat data. *Remote Sensing of Environment* **101**:115-126.

- Healey S. P., W. B. Cohen, Y. Zhiqiang, and O. N. Krankina. 2005. Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment* **97**:301-310.
- Henebry G. M., D. G. Goodin. 2002. Landscape trajectory analysis: Spatio-temporal dynamics from image time series. *International Geoscience and Remote Sensing Symposium 2002 IEEE International*; Piscataway, N.J. USA. 2375-2378.
- Jin S., S. A. Sader. 2005. Comparison of time series tasseled cap wetness and the normalized difference moisture index in detecting forest disturbances. *Remote Sensing of Environment* **94**:364–372.
- Johnson A., J. Wiens, B. Milne, and T. Crist. 1992. Animal movements and population dynamics in heterogeneous landscapes. *Landscape Ecology* **7**:63-75.
- Justice C., D. Wilkie, Q. Zhang, J. Brunner, and C. Donoghue. 2001. Central African forests, carbon and climate change. *Climate Research* **17**:229-246.
- Li H., J. Wu. 2004. Use and misuse of landscape indices. *Landscape Ecology* **19**:389-399.
- Linke J., M. G. Betts, M. B. Lavigne, and S. E. Franklin. 2007. Introduction: Structure, function, and change of forest landscapes. Pages 1-29 *In* M. A. Wulder and S. E. Franklin, editors. *Understanding Forest Disturbance and Spatial Pattern: Remote Sensing and GIS Approaches*, CRC Press (Taylor and Francis), Boca Raton, FL.
- McGarigal K., B. J. Marks. 1995. FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. Portland, OR: U.S. Department of Agriculture, Forest Service. Pacific Northwest Research Station; 1995. Report nr Gen. Tech. Rep. PNW-GTR-351. 122.
- Oloff H., M. E. Ritchie. 2002. Fragmented nature: Consequences for biodiversity. *Landscape and Urban Planning* **58**:83-92.
- Pasher J., D. King. 2006. Landscape fragmentation and ice storm damage in eastern Ontario forests. *Landscape Ecology* **21**:477-483.

- Reynolds-Hogland M. J., M. S. Mitchell. 2007. Three Axes of Ecological Studies. Pages 174-194 *In* J. A. Bissonette and I. Storch, editors. Temporal dimensions of landscape ecology: wildlife responses to variable resources, Springer, New York, NY, USA.
- Rutledge D. 2003. Landscape indices as measures of the effects of fragmentation: Can pattern reflect process? Wellington, New Zealand: New Zealand Department of Conservation; 2003. Report nr DOC Science Internal Series 98. 27.
- Sachs D. L., P. Sollins, and W. B. Cohen. 1998. Detecting landscape changes in the interior of British Columbia from 1975 to 1992 using satellite imagery. *Canadian Journal of Forest Research* **28**:23-36.
- Safranyik L. 2004. Mountain pine beetle epidemiology in lodgepole pine. Pages 33-40 *In* T.L. Shore, J.E. Brooks, and J.E. Stone, editors. Mountain Pine Beetle Symposium: Challenges and Solutions. October 30-31, 2003, Kelowna, British Columbia.. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Information Report BC-X-399, Victoria, BC. 298.
- Saunders D. A., R. J. Hobbs, and C. R. Margules. 1991. Biological Consequences of Ecosystem Fragmentation: A Review. *Conservation Biology* **5**:18-32.
- Schroeder T. A., W. B. Cohen, and Z. Yang. 2007. Patterns of forest regrowth following clearcutting in western Oregon as determined from a Landsat time-series. *Forest Ecology and Management* **243**:259-273.
- Seto K. C., C. E. Woodcock, C. Song, X. Huang, J. Lu, and R. K. Kaufmann. 2002. Monitoring land-use change in the Pearl River Delta using Landsat TM. *International Journal of Remote Sensing* **23**:1985–2004.
- Skakun R. S., M. A. Wulder, and S. E. Franklin. 2003. Sensitivity of the thematic mapper enhanced wetness difference index to detect mountain pine beetle red-attack damage. *Remote Sensing of Environment* **86**:433-443.
- Sohl T. L., T. R. Loveland, J. A. Griffith, and S. V. Stehman. 2003. Detecting trends in landscape pattern metrics over a 20-year period using a sampling-based monitoring programme. *International Journal of Remote Sensing* **24**:175-181.

- Trani M. K., J. R. H. Giles. 1999. An analysis of deforestation: Metrics used to describe pattern change. *Forest Ecology and Management* **114**:459-470.
- Turner M. G. 1989. Landscape Ecology: The Effect of Pattern on Process. *Annual Review of Ecology and Systematics* **20**:171-197.
- Turner M. G. 2005. Landscape ecology: What is the state of the science? *Annual Review of Ecology, Evolution and Systematics* **36**:319-344.
- Turner M. G., R. H. Gardner, and R. V. O'Neill. 2001. *Landscape ecology in theory and practice: Pattern and process*. Springer, New York, NY, USA. 424.
- Waring R. H., S. W. Running. 1998. *Forest ecosystems: Analysis at multiple scales*. Academic Press, New York, NY, USA. 440.
- Wilcox B. A., D. D. Murphy. 1985. Conservation Strategy: The Effects of Fragmentation on Extinction. *The American Naturalist* **125**:879-887.
- Wilson B. 2004. An Overview of the Mountain Pine Beetle Initiative. Pages 3-9 *In* T.L. Shore, J.E. Brooks, and J.E. Stone, editors. *Mountain Pine Beetle Symposium: Challenges and Solutions*. October 30-31, 2003, Kelowna, British Columbia.. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Information Report BC-X-399, Victoria, BC. 298.
- With K. A., T. O. Crist. 1995. Critical thresholds in species' responses to landscape structure. *Ecology* **76**:2446-2459.
- Woodcock C. E., R. Allen, M. Anderson, A. Belward, R. Bindschadler, W. Cohen, F. Gao, S. N. Goward, D. Helder, E. Helmer, R. Nemani, L. Oreopoulos, J. Schott, P. S. Thenkabail, E. F. Vermote, J. Vogelmann, M. A. Wulder, and R. Wynne. 2008. Free Access to Landsat Imagery. *Science* **320**:1011-1011.
- Wulder M. A., J. C. White, N. C. Coops, T. Han, M. F. Alvarez, C. R. Butson, X. Yuan. 2006. A procedure for mapping and monitoring mountain pine beetle red attack forest damage using Landsat imagery. Victoria, BC: Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre. Information Report BC-X-404. 30.

- Wulder M.A., C. C. Dymond. 2004. Remote sensing technologies for mountain pine beetle surveys. Pages 146-153 *In* T.L. Shore, J.E. Brooks, and J.E. Stone, editors. Mountain Pine Beetle Symposium: Challenges and Solutions. October 30-31, 2003, Kelowna, British Columbia.. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Information Report BC-X-399, Victoria, BC. 298.
- Wulder M. A., C. C. Dymond, J. C. White. 2005a. Remote sensing in the survey of mountain pine beetle impacts: review and recommendations. Victoria, British Columbia: Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre. Information Report nr BC-X-401. 67.
- Wulder M. A., J. C. White, N. C. Coops, T. Han, M. F. Alvarez. 2005b. A protocol for detecting and mapping mountain pine beetle damage from a time-series of Landsat TM or ETM+ data. Victoria, British Columbia: Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre. Report nr Version 1.0. 70.
- Yu X., C. Ng. 2006. An integrated evaluation of landscape change using remote sensing and landscape metrics: A case study of Panyu, Guangzhou. *International Journal of Remote Sensing* **27**:1075-1092.
- Zhang H., A. Henderson-Sellers, and K. McGuffie. 2001. The Compounding Effects of Tropical Deforestation and Greenhouse Warming on Climate. *Climatic Change* **49**:309-338.

## **2 MULTITEMPORAL REMOTE SENSING OF LANDSCAPE DYNAMICS AND PATTERN CHANGE: DESCRIBING NATURAL AND ANTHROPOGENIC TRENDS<sup>1</sup>**

### ***2.1 Introduction***

Land cover change may be the most significant cause of global environmental change (Skole et al. 1997). Land cover refers to the physical materials on the surface of a given tract of land (Treitz and Rogan 2004) such as fields, lakes, trees, or concrete. Impacts of land cover modification such as habitat loss and degradation are known to impair ecosystem function and reduce ecosystem services (Kerr and Ostrovsky 2003). Balancing the human need for these ecological services (i.e., agriculture, forestry, urbanization) while maintaining ecosystem function requires explicit knowledge about ecosystem responses to land cover change. The ability to monitor these trends at a variety of scales provides critical information required to assist in sustainable resource management decisions.

With a growing understanding of the linkages between land use and land cover change and impacts upon populations, communities, and ecosystem and environmental processes, long-term monitoring over large areas is increasingly important. Because

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<sup>1</sup> A version of this chapter has been published. Gillanders, S.N., N.C. Coops, M.A. Wulder, S.E. Gergel, and T. Nelson. Multitemporal remote sensing of landscape dynamics and pattern change: Describing natural and anthropogenic change. *Progress in Physical Geography* 32: 503-528.

traditional field data are limited to a local extent and are not readily applicable to regional or global extents, remote sensing is considered an essential technology for ecological and conservation-related applications (Kerr and Ostrovsky 2003). For many studies, it represents the only data source available for measuring habitat characteristics and for detecting and monitoring environmental change (Kerr and Ostrovsky 2003; Turner et al. 2003; Wulder et al. 2004a). The use of satellite-based remotely-sensed data has been determined to be a cost-effective approach to identifying change over large areas (Lunetta et al. 2004). Furthermore, remotely-sensed data can provide a synoptic record of land cover changes and may represent the only means to obtain multitemporal datasets for some monitoring applications, particularly for those projects located in remote areas.

Many satellite-based remote sensing platforms provide data at a spatial and temporal resolution that are suitable for detecting and monitoring land cover changes. For instance, the grain size (or spatial resolution) of the Landsat-5 Thematic Mapper (TM) sensor allows for land cover characterization and change detection consistent with the grain of land management (Cohen and Goward 2004). Furthermore, the orbital revisit period of 16 days and an archive of over 30 years of imagery provide a rich context for land cover monitoring. As a result of the repeat imaging capabilities of many sensors, and the subsequent increase in multitemporal datasets in recent years, there is a growing need for multitemporal analysis methods.

While the focus of many change detection studies is on the areal extent of landscape disturbance (Yen et al. 2005; Lunetta et al. 2006), terrestrial ecosystems are inherently

heterogeneous, and thus maintaining the existing mosaic in the size, shape, and distribution of patches within a landscape has important ecological implications (Riitters et al. 2000). This variability is considered a critical element which drives the flow of species and materials within a landscape (Southworth et al. 2002). Thus, in addition to calculating the amount of land cover change over time it becomes important to quantify changes in landscape spatial pattern.

The location and arrangement of vegetation across a landscape is an expression of varied ecological processes at work in the natural environment. Some of these ecological processes vary spatially and influence spatial patterns on the landscape. Landscape spatial pattern is the result of dynamic abiotic and biotic processes operating on the landscape over time. Consequently, existing and future landscape patterns are the manifestation of the processes that produced them and therefore, contain information related to these processes (Peterson 2002). Both anthropogenic and natural disturbances lead to changes in landscape spatial pattern and these changes can be measured using landscape pattern indices, also referred to as landscape metrics.

Ecological processes operate within various spatial and temporal scales (Turner et al. 2001). Furthermore, structure in ecological systems is scale specific. While the spatial aspect of scale is often the focus in the field of landscape ecology, it is important to recognize that scale also has a temporal dimension and that the consideration of one without the other fails to describe the complete system (Gunderson et al. 2007). This is partly due to the relative lack of long-term datasets but is also driven by the ease with

which spatial analysis can be performed using technologies such as geographic information systems (GIS) (Reynolds-Hogland et al. 2007). Reynolds-Hogland & Mitchell (2007) present a concept of designing ecological studies that integrates three axes: i) temporal resolution; ii) spatial resolution; and iii) the resolution of the ecological process under consideration. The authors suggest that ecological studies that fail to consider these three components can produce misleading results. Gunderson et al. (2007) argue that landscape ecology and ecology in general will advance considerably when both spatial and temporal aspects of process and structure are analyzed simultaneously.

The main objective of this paper is to review studies that have performed multitemporal landscape pattern analysis of 'natural' landscapes using three or more image dates.

Studies based on the use of simulated landscapes or landscape models have been excluded in an effort to focus on ecological land cover monitoring applications. Using the information gained through the reviewed literature, recommendations for both suitable landscape pattern indices and analysis methods are applied to a case study involving the monitoring of spatial and temporal dynamics associated with the impacts of mountain pine beetle infestation on lodgepole pine forests in the central interior of British Columbia, Canada.

## **2.2      *Land cover change detection mapping***

Digital change detection is a method of identifying and quantifying differences in the state of an object or phenomenon from multi-date imagery (Singh 1989), which is typically acquired from multispectral remote sensing platforms. Depending on the scale

of the imagery utilized (Wulder et al. 2004b), this approach to land surface monitoring provides an effective means of evaluating change at the landscape or regional scale by analysing an archive of remotely-sensed data (Cohen and Goward 2004). Traditional field or aerial photo interpretation-based methods of monitoring generate empirical data to quantify land use and land cover change; however, extending fine-scale data methods to a broader landscape or regional scale presents a number of methodological challenges. Furthermore, change detection methods based on the use of satellite imagery provide the ability to use consistent and repeatable procedures and to utilize the non-visible regions of the electromagnetic spectrum (Coppin et al. 2004). While a wide range of change detection approaches are possible (Collins and Woodcock 1996; Skole et al. 1997; Lu et al. 2004; Treitz and Rogan 2004), Coppin et al. (2004) present digital change detection approaches with an emphasis on ecosystem monitoring and describe two primary approaches based on spectral information from the visible and infrared domain: bi-temporal change detection and temporal trajectory analysis.

Bi-temporal change detection utilizes the spectral differences between two images to identify change (Coppin et al. 2004). In essence, the differentiation of change and no-change pixels depends on the pixel values of co-registered images representing the same area at different times (Singh 1989; Liu et al. 2004). The selection of imagery acquisition dates is a critical component of bi-temporal change detection procedures. Both calendar acquisition dates and the image temporal interval are important considerations that will dictate the magnitude of change detectability. To minimize discrepancies in reflectance

caused by differences in seasonal vegetation and sun angle, anniversary dates or anniversary windows are often used (Coppin et al. 2004).

Temporal trajectory analysis involves the use of an image time-series to monitor indicators of land surface attributes (Coppin et al. 2004). The temporal frequency, linked to the process of interest, will dictate the spatial and temporal resolutions. For instance, within-year trends to vegetation phenology over broad areas may be captured with coarse spatial resolution instruments that have short revisit intervals. Applications of the temporal trajectory approach are often based on daily image acquisitions provided by sensors such as the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR), Moderate-Resolution Imaging Spectroradiometer (MODIS), and Systeme Probatoire de l'Observation de la Terre (SPOT) VEGETATION (Coppin et al. 2004). The temporal frequency of available imagery using these sensors provides the means to compare seasonal profiles, thereby reducing the influence of phenology on change detection performance (Coppin et al. 2004). However, imagery available with fine temporal frequency is currently limited to coarse spatial resolution sensors, acting to restrict the categories of land cover that can be detected with temporal trajectories. Thus, multitemporal change detection studies are typically applied at regional, continental, or global scales.

More commonly, investigators are interested in capturing land dynamics at the landscape scale based on an annual time-step using moderate spatial resolution (approx. 10 – 100m spatial resolution) imagery such as Landsat, and in some cases SPOT. Data from Landsat

TM imagery is most commonly utilized for trajectory-based analysis of land cover change over time due to the spatial and spectral qualities of the imagery and the long-term image archive (Goward et al. 2001). Further, the United States Geological Survey (USGS) (the agency that populates and maintains the Landsat archive) is poised to reprocess the entire archive to new standards and to make the entire holdings of the archive available at no cost (Woodcock et al. 2008). With cost limitations removed, applications with dense time-series of Landsat imagery are expected to proliferate. The Landsat TM and ETM+ (Enhanced Thematic Mapper Plus) series of sensors provide imagery from 1984 to present, with the MSS (Multispectral Scanner) sensor furthering the time-series to 1972 (Cohen and Goward 2004).

Although the use of moderate spatial resolution imagery allows for the detection of objects that coarser resolution imagery does not, there are challenges in applying these data to the evaluation of spatial and temporal trends. For instance, obtaining cloud-free imagery for some areas of the Earth can be difficult even on an anniversary basis (Hansen et al. 2008; Ju and Roy 2008). If the gap between sequential images is too long or there are not enough scenes available to represent the process under investigation, identifying disturbance events in time can be difficult. Thus, distinguishing discontinuities resulting from disturbance events from environmental variation may not be possible when there is a mismatch between the rate of change and the availability of imagery (de Beurs and Henebry 2005).

Another challenge that affects both bi-temporal and multitemporal change detection studies is determination of what constitutes significant change. Assumptions of stationarity, image quality, sensor noise, and the complexity of many change detection methods can lead to difficulties in distinguishing the influence of the signal from notable land cover change. Although a wide range of methods have been developed to detect and describe changes found in image time series, there remains a lack of general techniques to assess statistical significance of change (de Beurs and Henebry 2005).

Multitemporal change detection procedures utilizing dense data stacks have been applied to a range of studies. Pax-Lenney et al. (1996) used ten Landsat-5 TM images with dates ranging from 1984 to 1993 to assess the status of agricultural lands in the Nile Delta and Western Desert of Egypt. Temporal changes in NDVI (Normalized Difference Vegetation Index) values were used to determine the presence and vigour of vegetation. Data were then classified into a number of land use categories and areal statistics were calculated to determine land cover dynamics over the spatial and temporal extent of the study area. Lawrence and Ripple (1999) used eight dates of Landsat TM imagery over a range of 11 years to analyse trends of vegetation recovery over the Mount St. Helens, Washington, volcano blast zone. The authors demonstrated the applicability of change curve analysis to extract specific change parameters including number of years to reach ten percent cover, greatest rate of cover increase during the study period, and time-integrated cover. Schroeder et al. (2007) utilized a time-series consisting of nineteen near-anniversary Landsat TM and ETM+ images to characterize forest regrowth patterns in Western Oregon, USA. Similar to Lawrence and Ripple (1999), the authors used continuous

spectral trajectories to obtain estimates of forest regrowth for five distinct cover classes. Kennedy et al. (2007) used a stack of eighteen Landsat TM images spanning a period of twenty years to test an automated trajectory-based change detection procedure that provided estimates of both discontinuous (i.e., stand replacing disturbance) and continuous phenomena (i.e., growth, recovery).

Change detection of land cover features is an important application of remote sensing, providing critical information to make better informed decisions regarding resource management and predictions of future environmental conditions. However, typical change detection procedures are restricted in scope by solely relying on spectral information to identify and characterize change. Read and Lam (2002) outline three of the primary limitations related to exclusively relying on spectral data for land cover analyses: i) difficulty separating indistinct land covers and change classes; ii) resolving differences between change detection images for pixel by pixel comparisons; and iii) controlling for the changing spectral properties of land cover changes through time. Furthermore, the authors argue that pixel-by-pixel classifiers do not consider the spatial context of pixels and, therefore, fail to utilize all the information available in the data. By using the spatial arrangement of differences in pixel values to characterize a scene, the ability to detect change takes on an ecological element by incorporating the spatial pattern of landscape features. By identifying, measuring, and characterizing landscape pattern, insight into past, current, and future ecological conditions is possible. Integrating change detection with information regarding spatial pattern will provide a rich context

with which to interpret landscape change; whereby, change in pattern over time will inform the noted change with spatial context.

### **2.3      *Landscape ecology and spatial pattern***

Landscape patterns result from complex biotic and abiotic interactions operating at various spatial and temporal scales (Turner 2005; Bolliger et al. 2007). The habitats occupied by various organisms are spatially structured at a range of scales, and the interaction of these organisms on patch and boundary features drives ecological processes such as population dynamics and community structure (Johnson et al. 1992; Irish et al. 2006). Landscape ecology has many definitions but the key concepts that seem to tie these interpretations together are spatial heterogeneity and how this influences ecological processes. Landscape ecology is principally concerned with the notion that landscape patterns influence ecological processes (McGarigal 2002). A landscape can be defined from many points of view but typically refers to a land surface at a relatively large scale (hectares to square kilometres). Turner (2005) defines a landscape as “an area that is spatially heterogeneous in at least one factor of interest.” This broad definition encompasses a range of spatial scales from the domain of small organisms to the level of ecosystems and regions.

Since landscape ecology is concerned with the interaction between spatial pattern and ecological process, methods to describe and quantify spatial pattern are required (Turner et al. 2001). Landscape pattern indices are measures of landscape composition and configuration. Indices of landscape composition measure which land use/land cover

classes are present on the landscape and their relative amounts. These landscape pattern indices are thus aspatial but can provide important information related to the variety and abundance of patch types within the landscape (McGarigal et al. 2002). Spatial configuration refers to the arrangement, position, or orientation of patches within the landscape or within a given class (McGarigal 2002). Landscape pattern indices that measure configuration attempt to quantify aspects of spatial distribution such as the location of patch types relative to other patches. These indices correspond to the recognition that organisms and ecological processes are affected by the overall configuration of patches and patch types within the landscape mosaic (McGarigal 2002).

Landscape pattern indices are commonly defined at three levels: i) patch-level; ii) class-level; and iii) landscape-level. Patch-level indices are calculated for every patch in the landscape and characterize the spatial character and context of patches. Class-level indices represent an assimilation of all the patches of a given class. Landscape-level indices are measures of all patch types or classes over the full extent of the data (McGarigal 2002). In the broad field of landscape monitoring, the most commonly applied landscape pattern indices are those that quantify edge and shape (Lausch and Herzog, 2002). These indices measure the occurrence of ecotones and are often associated with patch area and fractal dimension. The number and size of patches are also often measured (Lausch and Herzog 2002) and represent two commonly used indices to quantify fragmentation (McGarigal 2002; McGarigal et al. 2002).

## **2.4      *Application of landscape pattern indices***

Landscape pattern analysis can help to explain relationships between ecological processes and spatial pattern. However, it is important to recognize that spatial pattern analysis is a tool used to accomplish specific objectives, rather than a goal of its own. These objectives must be specified prior to analysis and should include an ecological justification for the use of specific measures of spatial pattern (Turner 2005; Gergel 2007).

Since many landscape pattern indices are correlated and thus may not measure unique qualities of spatial pattern (McGarigal 2002), it is desirable to use the least number of indices possible to characterize a landscape (Turner et al. 2001; Gergel 2007). Hence, it is important to understand the theoretical and empirical relationships among pattern indices before choosing a set of landscape measures for a given application. Landscape pattern indices should be chosen which are relatively independent of each other and which are able to quantify ecologically meaningful information. Several authors have attempted to define the unrelated components and describe the major attributes of landscape structure (Riitters et al. 1995; Cushman et al. 2008), thereby eliminating the redundancy and difficulty in interpretation that plagues the common use of large sets of landscape pattern indices, but there is no consensus of an applicable minimum set.

A variety of issues and limitations related to the use and interpretation of landscape pattern indices are well understood (Gustafson 1998; Turner et al. 2001; Li and Wu 2004; Gergel 2007). Li & Wu (2004) outline conceptual flaws in landscape pattern analysis that

permit special consideration. These include i) unwarranted relationships between pattern and process; ii) ecological irrelevance of landscape indices; and iii) confusion between the scales of observation and analysis. The authors argue that the assumption that pattern and process are reciprocal is applied to most landscape ecological studies without a critical evaluation of the specific processes under investigation. Failure to recognize the existence of non-interactive relationships between pattern and process may result in conceptual flaws in landscape pattern analysis (Li and Wu 2004). The use of landscape pattern indices is valid only if the indices are chosen according to their ecological relevance (Gergel 2007). Furthermore, Li & Wu (2004) suggest that the indiscriminate use of pattern indices hinders efforts to establish associations between spatial pattern and process, particularly in correlation analysis. Understanding the role of scale in landscape pattern analysis requires distinguishing between the scale of observation and the scale of analysis (Gustafson 1998; Li and Wu 2004). Once data are collected, the scale of observation is constrained by the data. The scale of analysis is determined by the original scale of observation and the methods of data transformation. Thus, landscape pattern indices should be computed at multiple scales in order to adequately quantify spatial pattern (Li and Wu 2004).

While a number of concerns related to the use and interpretation of pattern indices should be taken into account, the classification scheme used to represent a given landscape will directly influence the numerical results of pattern analysis (Wickham et al. 1997; Gergel et al. 2001). All classifications of remote sensing data are subject to error, and these errors can be broadcast or propagated throughout the subsequent pattern analysis

(Langford et al. 2006; Gergel 2007; Shao and Wu 2008). Thus, without an understanding and recognition of the magnitude of errors and uncertainties in classified data, inferences related to pattern / process relationships, and even the characterization of landscape pattern itself, may be flawed (Shao and Wu 2008). This has obvious implications for the study of ecology but limited progress has been made in addressing these issues and generalizing the impacts of classification errors on landscape pattern analysis (Gergel 2007; Shao and Wu 2008). However, a professional knowledge of the landscape under study (Shao and Wu 2008) and rigorous classification accuracy assessment using field validation data can provide the means to minimize classification errors, thereby allowing for more accurate and reliable pattern analyses.

Another consideration associated with landscape pattern analysis is the criteria that will be used to determine whether a change in landscape pattern is significant or not. While statistical techniques can be used to detect significant changes of a landscape pattern index with known variation, determining ecologically significant change is much more difficult (Gustafson 1998). For example, the pattern / process relationship in some ecological systems is believed to be associated with critical thresholds in which small changes in spatial pattern produce abrupt shifts in ecological response (With and Crist 1995; Fahrig 2002; Peterson 2002; Folke et al. 2004). Thus, without a thorough understanding of the ecological system and the historical variability of landscape pattern, determining significant change can be challenging.

## **2.5      *Multitemporal spatial pattern analyses***

There are many examples of change detection applications using spatial pattern based on two dates of imagery (Sachs et al. 1998; Franklin et al. 2003a; Wang et al. 2005; Yang and Liu 2005; Stueve et al. 2007). These typically involve pairwise comparisons of landscape pattern indices derived from thematic maps representing a beginning, or reference point in time, and an end point in time. Where two sampling dates may allow for the evaluation of change, multiple dates permit the evaluation of trend. Thus, the use of multitemporal data for long-term monitoring of landscape spatial pattern can provide the means to identify a greater range of processes of landscape modification. Furthermore, a more complete multitemporal image sequence consisting of consecutive time steps allows for a more inclusive and informative trajectory of change.

Advances in spatio-temporal analysis are critical in order to gain insights and to develop a mature ecological understanding of spatial and temporal dynamics (Fortin et al. 2005). Gustafson (1998) argues that it is essential to any study investigating the link between spatial pattern and ecological process to recognize the temporal dynamics of pattern and to understand that a range of pattern conditions may be identified. A number of works identify the need for further research to develop tools that will effectively characterize spatio-temporal patterns based on an image time series (Henebry and Goodin 2002; Lausch and Herzog 2002; Fortin et al. 2005; Wagner and Fortin 2005). Although a multitemporal approach to landscape pattern analysis presents considerable challenges in data processing, analysis, and interpretation, it provides an opportunity to characterize and quantify the complexity of spatial and temporal patterns and processes.

A review of the literature shows that a variety of multitemporal change detection methods based on spatial pattern utilizing three or more time steps have been applied at a range of scales (Table 2.1). The majority of these studies focus on land use and land cover change and typically employ the use of three or four images. Many of these studies involve either monitoring changes in forest cover or land use and land cover dynamics as a result of urbanization. The spatial extent of the studies reviewed ranges from 16 km<sup>2</sup> to over 7,600 km<sup>2</sup>. Studies operating at a fine scale typically used aerial photography and GIS to conduct spatial pattern analysis, while those studies concerned with landscape or regional scales used satellite imagery, typically with Landsat as the primary data source.

**Table 2.1 Literature review summary of studies utilizing a time-series of three or more dates to conduct landscape spatial pattern analysis.**

Application	Study area	Size (sq km)	Number of images in time series	Temporal resolution	Data source	Landscape pattern indices (LPI) and spatial statistics used	Software used	Reference
Agricultural land change	Finland	24	4 (1958, 1977, 1993, 1997)	39 years	Aerial photographs	Landscape percentage, mean patch size, patch density, mean shape index, total edge lengths	LPIs calculated using FRAGSTATS ARC	(Hietala-Koivu 1999)
Forest cover change	USA	1,350	3 (1973, 1987, 1999)	26 years	Landsat MSS ETM+	Fragmentation index, center-versus-neighbors, perimeter-to-area ratio, square pixel metric	LPIs calculated using GIS.	(Fuller 2001)
	Honduras	1,000	3 (1987, 1991, 1996)	9 years	Landsat TM	Percentage land cover, largest-patch index, number of patches, mean patch size, edge density, mean shape index, interspersions and juxtaposition index	LPIs calculated using FRAGSTATS 2.0.	(Southworth et al. 2002)
	USA	1,540	13 (1989 to 2001)	13 years	Aerial detection survey GIS data	Nearest neighbour distances, number of infestation patches	Analyses conducted using ArcView 3.2.	(Dodds et al. 2006)
	Turkey	1,019	3 (1975, 1987, 2000)	26 years	Landsat MSS/TM/E TM+	Class area, patch density, largest patch index, number of patches, mean patch size, percent of landscape, patch size coefficient of variation, area-weighted mean shape index	LPIs calculated using FRAGSTATS 3.3.	(Çakır et al. 2008)
Land use / land cover change	USA	400	4 (1973, 1979, 1985, 1992)	19 years	Landsat MSS/TM	Number of patches, number of forest patches, forest mean patch size, perimeter/area fractal dimension, forest percentage like adjacencies, Simpson's diversity index	LPIs calculated using FRAGSTATS 3.01.02.	(Griffith et al. 2003)

Application	Study area	Size (sq km)	Number of images in time series	Temporal resolution	Data source	Landscape pattern indices (LPI) and spatial statistics used	Software used	Reference
	USA	100	> 4 (1940, 1961, 1964, 1990s DOQQs, 2001)	61 years	Aerial photographs, Digital Orthophotograph Quarter Quadrangles (DOQQ), IKONOS	Class area, number of patches, mean patch size, area weighted mean patch fractal dimension	LPIs calculated using FRAGSTATS.	(Narumalani et al. 2004)
	China	63	5 (1973, 1976, 1986, 1994, 2000)	27 years	Landsat MSS/TM/ETM+, SPOT 1 HRV	Patch per unit, perimeter-area fractal dimension, mean shape index, Shannon's diversity index, dominance index	Unknown	(Zhou et al. 2004)
Rangeland cover change	USA & Mexico	7,600	3 (1973, 1986, 1992)	19 years	Landsat MSS	Number of patches, largest patch, average patch size, connectivity	Unknown	(Kepner et al. 2000)
	USA	700	3 (1973, 1985, 1999)	26 years	Landsat MSS TM ETM+	Patch density, edge density, interspersions and juxtaposition index, contagion	LPIs calculated using FRAGSTATS.	(Wallace et al. 2003)
Urbanization	Malaysia	16	3 (1974, 1982, 1990)	16 years	Aerial photographs, GIS data	Number of patches, mean patch size, mean shape index, mean patch fractal dimension, mean nearest neighbour, mean proximity index, interspersions and juxtaposition index, class area, total landscape area, edge density, Shannon's evenness index	LPIs calculated using ArcView GIS extension Patch Analyst.	(Rainis 2003)
	China	3,600	8 (1978, 1988, 1991, 1992, 1995, 2000, 2001, 2002)	24 years	Landsat MSS TM ETM+	Mean patch size, landscape shape index	LPIs calculated using FRAGSTATS	(Schneider et al. 2003)

Application	Study area	Size (sq km)	Number of images in time series	Temporal resolution	Data source	Landscape pattern indices (LPI) and spatial statistics used	Software used	Reference
Experimental	China	149	3 (1989, 1996, 2004)	15 years	SPOT, Landsat TM, topographic and urban planning data	Class area, patch density, percent of landscape, mean patch size, largest patch index, landscape shape index, Euclidian mean nearest neighbour distance, patch richness	LPIs calculated using FRAGSTATS 3.3.	(Kong et al. 2006)
	China	1,230	4 (1988, 1993, 1998, 2002)	14 years	Landsat TM	Number of patches, mean patch size, largest patch index, edge density, landscape shape index, mean shape index, area-weighted mean patch fractal dimension, Shannon's diversity index, contagion index, cohesion	LPIs calculated using FRAGSTATS.	(Yu et al. 2006)
	Germany	700	4 digital maps (1912, 1944, 1973, 1989); 3 satellite images (1990, 1994, 1996); 2020 digitized landscape development plan	108 years; 6 years	Topographic maps, aerial photos, SPOT-XS	Mean patch size, number of patches, largest patch index, patch size standard deviation, patch size coefficient of variation, area-weighted mean patch fractal dimension, landscape shape index, mean shape index, area-weighted mean shape index, double log fractal dimension, edge density, Simpson's diversity index, patch richness density, patch richness, Simpson's evenness index, interspersion and juxtaposition index	LPIs calculated using FRAGSTATS 2.0.	(Lausch et al. 2002)

Application	Study area	Size (sq km)	Number of images in time series	Temporal resolution	Data source	Landscape pattern indices (LPI) and spatial statistics used	Software used	Reference
	Costa Rica	1,400	3 (1986, 1996, 1997)	11 years	Landsat TM	Fractal dimensions (isarithm and modified TPSA methods), spatial autocorrelation, Shannon's diversity index, contagion, fractal dimension, patch richness	LPIs calculated using FRAGSTATS.	(Read et al. 2002)
	Brazil	944	6 (1984, 1989, 1993, 1995, 1998, 2000)	16 years	Landsat TM	Class area, percent land, patch density, largest patch index, mean patch size, patch size standard deviation, patch size coefficient of variation, edge density, mean nearest neighbour distance, landscape shape index, square pixel, mean shape index, area weighted mean shape index, mean patch fractal dimension, area weighted mean patch fractal dimension, double log fractal dimension	LPIs calculated using ArcView GIS extension Patch Analyst 2.2 (Grid).	(Frohn et al. 2006)

The conversion of agricultural lands for other land uses is an important subject in many areas of the world. Hietala-Koivu (1999) used a series of four digitized black and white aerial photographs spanning a period of 39 years to describe structural changes in a 24 km<sup>2</sup> agricultural landscape in southwest Finland. In addition to the percentage of the total area occupied by each relevant class through the time series, changes at the class and landscape level were assessed using the FRAGSTATS\*ARC program (Berry et al. 1998). By using a suite of five landscape pattern indices (landscape percentage, mean patch size, patch density, mean shape index, and total edge length) it was concluded that the study area has become more homogenous through the intensification of agriculture.

Using a suite of landscape pattern indices to characterize changes in forest cover is a common application. For instance, Dodds et al. (2006) used annual aerial detection survey data to examine spatial patterns of Douglas-fir beetle infestations in northern Idaho, USA over a 13-year period. The authors concluded that pattern analysis can provide information that is relevant to forecasting Douglas-fir beetle related forest damage. Using a series of Landsat MSS and ETM+ images from 1973, 1987, and 1999, Fuller (2001) characterized spatial and temporal patterns of forest fragmentation in Virginia, USA. Changes in forest area and spatial patterns were quantified using a set of four pattern indices and their relationship to radiance values of the Landsat thermal band was examined. Southworth et al. (2002) also used Landsat data but based their time series on three Landsat TM images spanning a nine-year period to monitor forest cover change in the mountains of western Honduras. Seven pattern indices were used to describe changes in spatial pattern, and these trends were explained using biophysical environmental parameters and socio-economic data. The authors employed techniques which provided linkages between land cover, land use, and biophysical structure, thereby permitting an analysis that related pattern and process. In a study

based in northeast Turkey, Çakir et al. (2008) used Landsat MSS, TM, and ETM+ satellite imagery to monitor forest cover change. The use of three images covering a temporal range of 25 years provided the basis to classify the imagery at the 1975, 1987, and 2000 time-steps and to evaluate both spatial and temporal trends in forest cover.

Monitoring changes in land use and land cover is a common theme of the reviewed literature. For example, Narumalani et al. (2004) used a variety of data types to quantify changes in land cover / land use and to monitor the ecological impacts of these changes at the Effigy Mounds National Monument, Iowa, USA. A post-classification change detection algorithm was used to determine pixel-by-pixel differences between the three periods (1940s, 1960s, 1990s). In order to identify changes in the geometry and fragmentation of land cover classes, four pattern indices were used and were examined in three-dimensional landscape pattern space in an attempt to assess the direction and magnitude of change through time. Similarly, Zhou et al. (2004) investigated land use and land cover changes but used five image dates consisting of Landsat MSS, TM, ETM+ and SPOT 1 HRV data over a 27 year period in China. The authors used a post-classification change detection approach and then derived class area statistics and temporal trajectories. In addition, a set of five pattern indices were used to evaluate changes in spatial pattern associated with land use and land cover trends. Likewise, Griffith et al. (2003) used four Landsat MSS and TM images covering a range of 20 years to evaluate temporal trends in landscape patterns resulting from changes in land cover and land use in the Middle Atlantic Coastal Plain Ecoregion of the USA. Data were classified and a set of six pattern indices were selected to describe the number, size, shape and spatial relationship of patches of land cover types. A repeated measures analysis was then applied to determine whether there were statistically significant trends in the indices over time. Results

indicated that all pattern indices showed evidence of a trend toward an increasingly fine-grained landscape, and statistically significant trends were detected in five of the six indices.

The monitoring of changes in rangeland vegetation has also been conducted using a multitemporal landscape pattern approach. Kepner et al. (2000) monitored changes in rangeland vegetation cover in a semi-arid region of southeast Arizona, USA and northeast Sonora, Mexico. Using Landsat MSS data covering an area of approximately 7,600 km<sup>2</sup>, three periods (1973-1986, 1986-1992, 1973-1992) were utilized to assess changes in four pattern indices in an effort to document land cover changes and determine ecosystem vulnerability. Also focussing on an area of southeast Arizona, Wallace et al. (2003) used Landsat MSS, TM, and ETM+ imagery to evaluate rangeland conditions over a period of 26 years. The authors examined the utility of remote sensing as a tool for ecological assessment by quantifying land use and land cover change and evaluating the spatial arrangement and complexity of land cover types.

Another common application of multitemporal landscape pattern analysis is to evaluate changes in land cover due to urbanization. Many of these studies are focussed on urban growth and development in China. For example, in an effort to gain an understanding of changes in urban green space in Jinan, China, Kong and Nakagoshi (2006) used both gradient analysis and landscape pattern indices to evaluate trends over a period of 15 years. The authors relied on SPOT and Landsat imagery collected for three image dates (1989, 1996, 2004) to create categorical urban green space maps. Ancillary data included a topographic map and census data. A set of eight class and landscape-level indices were used to generate curves based on an eight-direction gradient from the urban center of the study area. By using a ``moving window`` method, the authors attempted to provide a more informative link between pattern and process. Yu and Ng (2006) used four Landsat

TM images spanning a period of 14 years to evaluate the impacts of urbanization on land cover in Panyu, Guangzhou, China. By using a set of ten class and landscape-level indices, the authors analyzed aspects of landscape heterogeneity and fragmentation with respect to urbanization. Similarly, Schneider et al. (2003) used eight image dates of Landsat MSS, TM, and ETM+ spanning 24 years to monitor urban growth in Chengdu, China. The authors used a decision tree change detection method to map land use trends and then quantified the density and pattern of land use over space and time using a combination of pattern indices and gradient analysis. Focussing on a 16 km<sup>2</sup> study area centred on Butterworth, Malaysia, Rainis (2003) used a set of pattern indices to quantify spatial and temporal trends of urban land use. The author utilized aerial photographs and GIS data to develop land use classes for three time-steps (1974, 1982, and 1990) over a period of 16 years. Land use statistics and pattern indices were used as an urban land use monitoring tool. The author concluded that while the use of landscape pattern indices can provide information related to land use structure, their meaning and interpretation in the urban planning context requires further research.

Several studies employed an experimental approach to multitemporal landscape pattern analysis. For instance, Lausch and Herzog (2002) used a variety of vector and raster data from a range of sources including digital maps, aerial photos, prospective planning materials, and SPOT-XS imagery to monitor land-use changes in a region of eastern Germany where open cast coal mining has resulted in far-reaching environmental changes. Using a time-series of four classified maps for each of two independent study areas, the applicability of pattern indices for landscape monitoring was evaluated. For the two study areas the authors used 24 and 27 indices, respectively, and confirmed the findings of Riitters et al. (1995) and Cain et al. (1997) that there are many redundancies among landscape pattern indices and that relatively few indicators are required to

capture landscape pattern. Read and Lam (2002) used three unclassified Landsat TM images spanning 11 years to investigate the performance of a set of spatial statistics and pattern indices as techniques for land cover discrimination and change detection for a lowland tropical site in north-eastern Costa Rica. Their results indicated that the fractal dimension (based on calculations using the triangular prism surface area method) and measures of spatial autocorrelation were useful for distinguishing differing quantities of spatial complexity, while standard landscape pattern indices were not particularly useful for this application. Frohn and Hao (2006) used six Landsat TM images centered on a deforested area in Rondonia, Brazil spanning a period of 17 years to evaluate the performance of sixteen pattern indices with respect to spatial aggregation. Their research built on prior work related to the influence of scale on pattern indices by using two different spatial aggregation methods and assessing the sensitivity of indices under these different data representations.

Fragmentation is a complex process that is both a consequence of habitat loss and an independent process in and of itself. In the case of a continuous matrix, the fragmentation process begins with a reduction in habitat area and an increase in the proportion of edge habitat (Neel et al. 2004). The majority of habitat will initially be connected but will increasingly become perforated and incised. When sufficient habitat is lost, or when the initial continuous matrix appears as a patch mosaic (~ 50 – 60% of the landscape), remaining habitat often becomes detached into isolated patches (Jaeger, 2000).

The significance of landscape and habitat fragmentation is a prominent ecological issue (Wilcox and Murphy 1985; Hargis et al. 1998; With and Crist 1995; Trani and Giles 1999; With and King 1999; Riitters et al. 2000; Wickham et al. 2007). Thus, many of the landscape pattern indices

employed in the reviewed literature were used to measure aspects of fragmentation. The indices which were most commonly used in the reviewed literature are shown in Table 2.2. Of the 17 articles reviewed, 11 used mean patch size (MPS) and 10 used number of patches (NP). Landscape fragmentation is commonly characterized using pattern indices such as number of patches (NP), mean patch size (MPS), the distance between patches, and measures of edge habitat (Langford et al. 2006). NP and MPS are often used complementary since high NP and low MPS values support an interpretation of fragmented landscape conditions (Matsushita et al. 2006). Largest patch index (LPI) was used in seven of the articles. When used at the class level this landscape pattern index represents a measure of dominance as it quantifies the percentage of total landscape area comprised by the largest patch (Weng 2007). Edge density (ED) and mean shape index (MSI) were each used in six of the studies. Edge density (ED) is calculated as the length of all borders between different classes in a reference area divided by the total area of the reference unit and is a measure of the complexity of the shapes of patches and an indicator of the spatial heterogeneity of a landscape. Mean shape index (MSI) is also used as a fragmentation index (Young et al. 2006) as it denotes the average patch shape, or average perimeter-to-area proportion for all patches in a landscape. Class area (CA), patch density (PD), and landscape shape index (LSI) were each used in five of the studies. Class area (CA) equals the sum of the areas of all patches of the corresponding patch type. Patch density (PD) is also considered a fragmentation index (Trani and Giles 1999). Patch density (PD) increases with a greater number of patches and serves as an indication of the extent to which a landscape is fragmented. Landscape shape index (LSI) provides a standardized measure of total edge or edge density and can be interpreted as a measure of patch aggregation or disaggregation (McGarigal et al. 2002).

**Table 2.2 The most commonly used landscape pattern indices in the reviewed literature.**

<b>Landscape pattern index (LPI)</b>	<b>Number of times used</b>
Mean patch size	11
Number of patches	10
Largest patch index	7
Edge density	6
Mean shape index	6
Class area	5
Patch density	5
Landscape shape index	5

## **2.6 Case study**

### **2.6.1 The mountain pine beetle**

Major transformations of forest ecosystems at global, regional, and local scales are occurring with increasing frequency and, in many cases, result in losses in timber values along with a reduction in biodiversity (Laurance 1999; Simberloff 2000; Hoekstra et al. 2005). Thus, ecological applications of remote sensing involving land cover are often associated with forest management and conservation. Changes in forest cover resulting from both anthropogenic and natural causes are increasingly important and remote sensing represents an effective means of monitoring these dynamics (Aplin 2005).

The mountain pine beetle (*Dendroctonus ponderosae* Hopkins) is a native insect to the pine forests of western North America. As a result of anthropogenic and environmental influences on the lodgepole pine ecosystem, such as forest wildfire suppression and a moderating trend in temperature extremes, mountain pine beetle populations in the central interior of British Columbia, Canada have reached epidemic proportions. The current beetle epidemic is the province's leading cause of tree mortality (Westfall 2007) and represents the largest insect infestation on record in British Columbia. Due to the broad spatial extent of the current infestation, remotely-sensed data

provide opportunities to effectively monitor and evaluate the impacts of the mountain pine beetle (Wulder et al. 2006b).

Mountain pine beetles attack susceptible pine in large numbers (mass-attack) to overcome the defensive system of a healthy tree. Once the tree is killed but still has green foliage it is referred to as being in the green-attack stage. The foliage gradually changes colour and after a twelve-month period following attack over 90% of killed trees will have red needles (red-attack stage). The grey-attack stage occurs when the needles are shed following red-attack, typically 2 or 3 years following the initial attack (Wulder et al. 2006c). Given the distinct changes in spectral reflectance from green to red, the majority of remote sensing applications utilize the red-attack stage for identifying and monitoring the impacts of mountain pine beetle (Wulder et al. 2005a).

Monitoring the magnitude and tracking the leading edge of mountain pine beetle infestation is critical to forest resource managers. Due to the large area of the current epidemic, monitoring strategies utilizing remotely-sensed data have been developed and successfully applied (Wulder et al. 2005b; Coops et al. 2006; Wulder et al. 2006a; Wulder et al. 2006c). The Landsat TM and ETM+ sensors have proven to be useful for several MPB red-attack mapping applications (Franklin et al. 2003b; Skakun et al. 2003; Wulder et al. 2005b). The spectral resolution of these sensors is sufficient to detect a range of radiation levels allowing for the differentiation of red-attack crowns from healthy trees and other stages of mountain pine beetle-related tree mortality. Furthermore, there have been a number of studies which have relied on time-series analysis to identify spatial and temporal trends of infestation (Nelson et al. 2003; Skakun et al. 2003; Aukema et al. 2006; Goodwin et al. 2008). A developing approach for the mapping and characterization of MPB red-attack is landscape spatial pattern analysis. Since the impacts of mountain pine beetle

infestation are expressed at both a spatial and temporal scale and are inherently linked to ecological processes, this natural disturbance agent represents an excellent candidate for monitoring via multitemporal spatial pattern analysis.

### **2.6.2 Multitemporal spatial pattern analysis**

As a landscape disturbance agent, mountain pine beetle-induced tree mortality leads to habitat fragmentation at both a landscape and local scale depending on the severity and extent of infestation. This has important ecological implications related to habitat abundance, biodiversity, and the influence that changes in spatial pattern have on a variety of ecological processes. For instance, population dynamics of many species are influenced by not only the amount of available habitat but also on the spatial arrangement of habitat (Hughes et al. 2006). In a forested landscape, fragmentation can be quantified as a reduction in the average size of forest patches, an increase in the distance between patches, and an increase in the ratio of edge to interior (Allan et al. 2003). Fragmentation of previously continuous forest can result in a reduction of species diversity in remnant forest patches (Allan et al. 2003). Some species in landscapes with low forest cover experience increases in stress and a greater risk of predation while gaining access to food (Belisle et al. 2001). Likewise, many avian species have a high propensity to utilize forest edges but may also be reluctant to move among forest patches which are surrounded by open area (Bélisle 2005).

While the mountain pine beetle represents a contagious disturbance agent that can contribute to forest fragmentation, operational and salvage logging play an important role as well. For instance, the removal of dead trees which represent potential nest sites for woodpeckers will limit the distribution of this effective mountain pine beetle predator. Likewise, extensive logging at the regional level would be expected to result in a systematic fragmentation of forested landscapes and

may disrupt or destabilize other forest processes in unpredictable ways (Franklin and Forman 1987) which could potentially result in outbreaks of other insects or other unforeseen and undesirable effects (Hughes et al. 2006).

In order to monitor the rate and magnitude of landscape fragmentation and loss of connectivity resulting from both mountain pine beetle disturbance and operational and salvage logging, a number of key landscape pattern indices will be applied to the time series (Table 2.3). The pattern indices in Table 2.3 were chosen to represent key aspects of landscape fragmentation which include changes in composition, shape, and configuration of patches as well as loss of area (Saunders et al. 1991; Harrison and Bruna 1999; Olf and Ritchie 2002). Furthermore, these indices were selected in an effort to assess ecosystem integrity, rather than a single species with specific habitat needs. Thus, these select pattern indices represent measures of quantifiable landscape changes associated with habitat fragmentation: reduced habitat area, increased edges, reduced interior area, patch isolation, and increased number of patches (Davidson 1998).

**Table 2.3 Landscape pattern indices selected to measure aspects of habitat fragmentation for the case study.**

<b>Name</b>	<b>Symbol</b>	<b>Description</b>	<b>Interpretation</b>	<b>Reference(s)</b>
Number of patches	<i>NP</i>	Number of patches of a particular class	Higher values indicate more fragmentation	(McGarigal et al., 2002; Turner et al., 1989)
Area-weighted mean patch size	<i>AWMPS</i>	Measures patch area multiplied by proportional abundance of the patch (or patch type)	Lower values indicate more fragmentation	(McGarigal et al., 2002)
Fractal dimension	<i>FD</i>	Measures patch shape complexity	Higher values indicate an increase in shape complexity	(McGarigal et al., 2002)
Edge density	<i>ED</i>	Ratio of total edges (number of cells at patch boundary) and total area (total cells)	Higher values indicate more fragmentation	(Hargis et al., 1998; Li et al., 2005; McGarigal et al., 2002)
Patch richness density	<i>PRD</i>	Patch richness expressed as the number of patch types per unit area	Used to compare patch richness among different landscapes	(McGarigal et al., 2002)
Mean proximity index	<i>MPI</i>	At class level, measures the degree of isolation and fragmentation of the corresponding patch type	Lower values indicate an increase in patch isolation and/or patch size	(Gustafson et al., 1994; McGarigal et al., 2002)
Interspersion / juxtaposition	<i>IJI</i>	Measures the degree of aggregation or 'clumpiness' of a map based on adjacency of patches	Lower values characterize landscapes in which the patch types are poorly interspersed (i.e., disproportionate distribution of patch type adjacencies)	(McGarigal et al., 2002)

To measure changes in landscape composition, number of patches (NP) and area-weighted mean patch size (AWMPS) will be used. Number of patches functions as both a landscape level and class level index and is often used in habitat analysis (Li et al. 2005). An increase in the number of patches of a given land cover type may indicate progression towards a more fragmented landscape. Area-weighted mean patch size is ecologically important because it quantifies the fragmentation

levels of a variety of landscapes and can be used to compare measurements of different classes (Li et al. 2005). Because this landscape pattern index is spatially explicit at the level of the individual patch, it should provide a measure of the progression of disturbance resulting from both MPB infestation and salvage logging. Patch richness density (PRD) is also a measure of landscape composition but will be used to measure the proportional abundance of mountain pine beetle infestation and logging to provide us with an indication of the relative impacts of these classes to landscape fragmentation and connectivity. Patch richness density quantifies the number of different patch types within a landscape boundary divided by the total landscape area. PRD standardizes patch richness (the number of patch types present) to a per area basis that facilitates comparison among landscapes (McGarigal et al., 2002). Patch richness is a key component of landscape structure because the variety of landscape elements present in a landscape can have an important influence on a range of ecological processes (McGarigal et al., 2002).

Shape indices attempt to measure patch complexity, which can be important for different ecological processes (Rutledge, 2003). Fractal dimension (FD) measures the degree of shape complexity with values ranging from 1, which indicates relatively simple shapes such as squares, to 2, which indicates more complex shapes (McGarigal et al., 2002). To quantify changes in patch shape, fractal dimension will be used.

Measures of landscape configuration that will be used for these analyses include edge density (ED), mean proximity index (MPI), and interspersion / juxtaposition (IJI). Edge density quantifies the amount of edge between landscape elements and may be important as a measure of fragmentation in terms of the movement of organisms or material across ecotones (Turner et al. 1989) with increases in edge density suggesting greater complexity of patches. Total edge density

provides an indication of the fragmentation level of either an entire landscape or a class (Li et al. 2005). Mean proximity index measures the degree of patch isolation and fragmentation; it is equal to 0 if all patches of the corresponding patch type have no neighbours of the same type within the specified search radius; it increases as patches become less isolated and the patch type becomes less fragmented in distribution (McGarigal et al. 2002). The interspersion / juxtaposition index measures the extent to which patch types are interspersed; higher values result from landscapes in which the patch types are well interspersed (i.e., equally adjacent to each other), whereas lower values characterize landscapes in which the patch types are poorly interspersed (i.e., disproportionate distribution of patch type adjacencies). The interspersion / juxtaposition index is calculated in percentage units and approaches 100% when all classes are equally adjacent to all other classes, and approaches zero when patch adjacency becomes uneven (McGarigal et al. 2002).

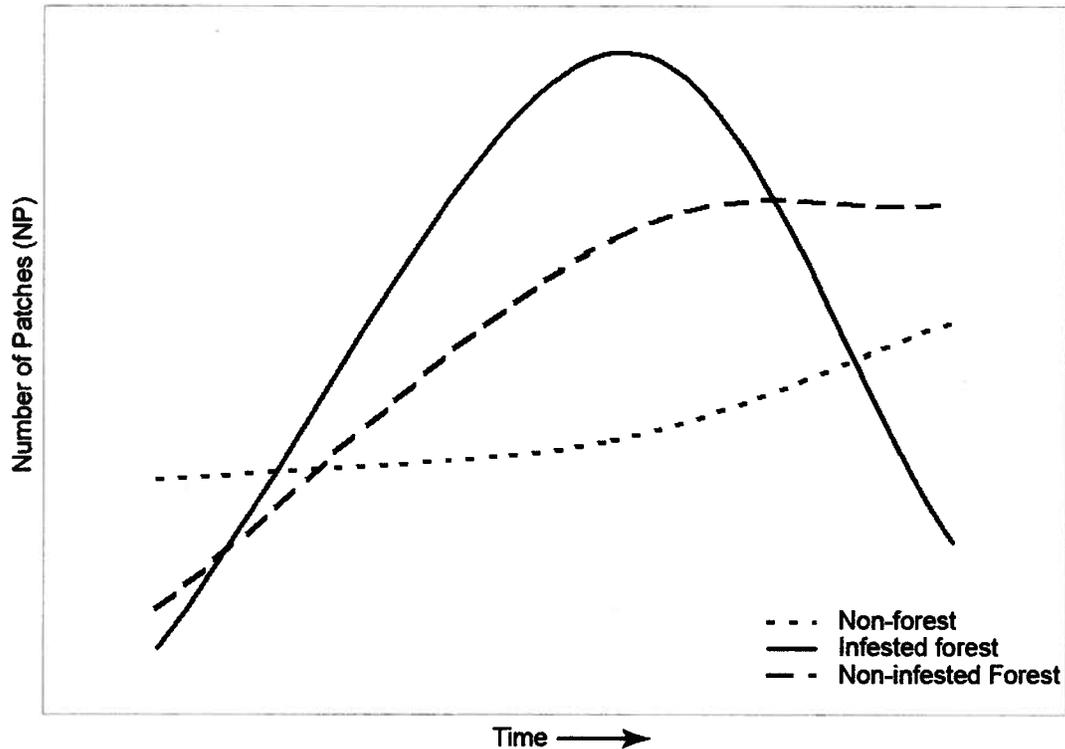
Monitoring this set of landscape pattern indices provides an alternative to monitoring the spectral response alone, which would simply show the changes of a given pixel (or group of pixels) through time. For example, a pixel which represents forest attributes that are subsequently impacted by the mountain pine beetle would change from a spectral response representing forest to one representing a disturbed, or damaged forest. While a spectral trajectory can be useful for monitoring changes in land cover, the use of these select landscape pattern indices to track changes in landscape pattern will provide additional information related to the ecological conditions of the landscape.

### **2.6.3 Hypotheses**

Due to the severity and extent of mountain pine beetle infestation in the study area, it is expected that the relative impact on fragmentation and connectivity from logging is less than that of the

mountain pine beetle. However, the combination of these two landscape disturbances is expected to result in a heavily fragmented landscape with a significantly reduced degree of connectivity.

For example, Figure 2.1 illustrates a landscape trajectory based on the landscape pattern index number of patches (NP) for the above scenario. Early in the time series it is expected that the matrix will consist of a mostly contiguous forest comprised of large patches of continuous, non-infested trees. Beetle-infested forest patches are expected to be few and distributed across the landscape in small patches. As the mountain pine beetle infestation progresses, the number and size of infested forest patches increases across the landscape. While the non-forest class consisting of logging clearcuts and roads (and other non-vegetated features) begins as a relatively stable trajectory, the number of non-forest patches also increases in response to beetle-impacted timber salvaging. Both mountain pine beetle-induced tree mortality and logging contribute to the fragmentation of the forested matrix and an increase in the number of forest patches. Eventually, infested forest patches expand in size and coalesce to form larger patches which are indicated by a reduction in the number of patches. At the peak of mountain pine beetle infestation, the number of patches of forest would be expected to level off as most pine trees have been killed and remaining conifers are non-target species such as spruce and fir.



**Figure 2.1** Expected results for number of patches (NP) landscape trajectory of non-forest, infested forest, and non-infested forest classes.

Figure 2.2 shows an example landscape trajectory based on edge density (ED) for non-forest, infested forest, and non-infested forest. Initially the impacts of the mountain pine beetle are limited to small infested forest patches scattered throughout the landscape represented by a slightly higher edge density value than the continuous, non-infested forest. Non-forest has a relatively high ED value due to the presence of linear features such as roads. As the impacts of the beetle progress, the amount of edge relative to area increases significantly for both infested forest and non-infested forest. This is due to an increase in the number of infested patches and the fragmentation of continuous forest into a number of forest patches with complex and irregular edges. As efforts to salvage standing dead timber increase, ED values for non-forest also increase due to additional road building and clearcuts on the landscape. At the peak of mountain pine beetle infestation, large

contiguous patches on infested forest will result in a decrease in ED values. Edge density values for non-infested forest will be high due to the large number and complex shape of patches.

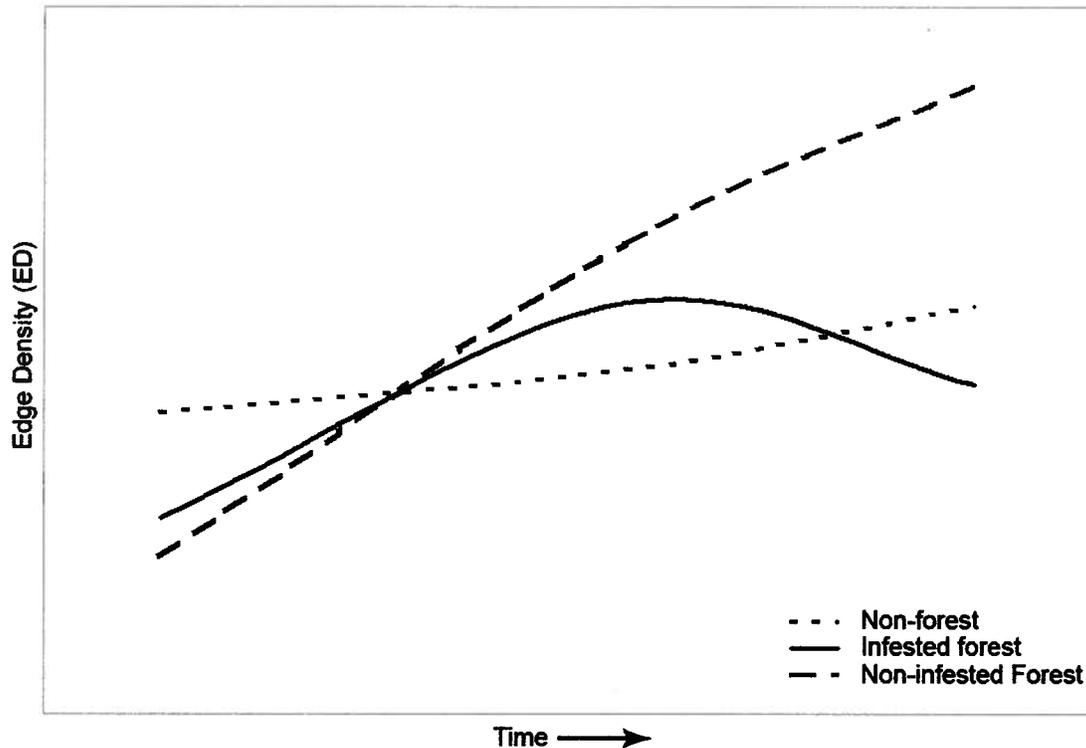


Figure 2.2 Expected results for edge density (ED) landscape trajectory of non-forest, infested forest, and non-infested forest classes.

## 2.7 Conclusion

While various change detection methods based on spectral information from remotely-sensed imagery have been developed as landscape monitoring applications, landscape pattern analysis provides an ecological context for spatial and temporal analysis. Extensive research has been conducted into the use of landscape pattern indices to assess and monitor changes in land cover. The focus of most of this work has been on the comparison of reference conditions to those at a later date. While the comparison of landscape pattern between two dates provides the means to detect change, incorporating a more complete time sequence allows for the investigation of trends.

Landscape patterns result from complex biotic and abiotic interactions and influence ecological processes. This relationship is the basis of landscape ecology and has led to the development of methods to describe and quantify spatial pattern. Landscape pattern indices measure landscape composition and configuration of classified data and provide the means to interpret spatial pattern in an ecologic context. However, it is important to recognize that the use of landscape pattern indices requires specific research objectives with ecological significance. Thus, the selection of measures of spatial pattern must have ecological relevance in order to be meaningful in an ecological context. Furthermore, since many measures of spatial pattern are correlated, it is desirable to use the least number of landscape pattern indices possible.

The current mountain pine beetle epidemic in British Columbia, Canada, provides a contemporary example of a massive ecological disturbance which has resulted in significant changes to forest structure and is expected to have far-reaching ecological, environmental, and economic ramifications. Due to the broad spatial extent of the current infestation, remotely-sensed data provide opportunities to monitor the impacts of the mountain pine beetle. By monitoring changes in spatial pattern using a time-series of remotely-sensed data, insights into past, present, and future ecological conditions can be derived. For instance, by focussing on the relative impacts of mountain pine beetle-induced tree mortality and logging on forest fragmentation and connectivity, an understanding of landscape integrity can be gained.

Future multitemporal landscape pattern analysis research should focus on the interpretation of landscape pattern indices and the linkages to temporal change. Cushman and McGarigal (2007) emphasized the importance of incorporating temporal variability into ecological studies by using

landscape trajectories to measure landscape pattern dynamics over time. The authors compared the impacts of different simulated forest harvest regimes on the extent and configuration of American marten habitat through time by assessing the displacement, divergence, velocity, and acceleration of landscape change. The forest harvest regimes included both differences in harvest rotation scenarios and cutting pattern/intensity. Their unique approach provided the means to not only quantify the impacts of different cutting regimes compared to initial conditions and relative to each other, but also the rates and directions of changes in landscape structure. By doing so, the authors argue that these measures can be used for linking patterns of change to mechanistic drivers, as well as for revealing ecological thresholds.

With growing availability of archives of remotely-sensed data and an increasing need for long-term monitoring strategies, the development of reliable and repeatable change-detection analysis methods will continue to gain importance. The use of multitemporal data sets to conduct landscape pattern analysis represents an exciting opportunity to not only conduct change-detection analysis, but to advance the disciplines of both landscape ecology and remote sensing.

## **2.8      *References***

- Allan B. F., F. Keesing, and R. S. Ostfeld. 2003. Effect of Forest Fragmentation on Lyme Disease Risk. *Conservation Biology* **17**:267-272.
- Aplin P. 2005. Remote sensing: ecology. *Progress in Physical Geography* **29**:104-113.
- Aukema B. H., A. L. Carroll, J. Zhu, K. F. Raffa, T. A. Sickley, and S. W. Taylor. 2006. Landscape level analysis of mountain pine beetle in British Columbia, Canada: Spatiotemporal development and spatial synchrony within the present outbreak. *Ecography* **29**:427-441.
- Bélisle M. 2005. Measuring landscape connectivity: The challenge of behavioral landscape ecology. *Ecology* **86**:1988-1995.
- Belisle M., A. Desrochers, and M. Fortin. 2001. Influence of Forest Cover on the Movements of Forest Birds: A Homing Experiment. *Ecology* **82**:1893-1904.
- Berry J. K., D. J. Buckley, K. McGarigal. 1998. Fragstats\*arc: Integrating ARC-INFO with the FRAGSTATS landscape analysis program. Proceedings of the 1998 ESRI User Conference. San Diego, CA, U.S.A. ESRI; URL: <http://proceedings.esri.com/library/userconf/proc98/PROCEED/TO450/PAP401/P401.HTM>. Date accessed 21 February 2008.
- Bolliger J., H. Wagner, and M. Turner. 2007. Identifying and Quantifying Landscape Patterns in Space and Time. Pages 177-194 *In* F. Kienast, S. Ghosh, and O. Wildi, editors. *A Changing World: Challenges for Landscape Research*, Springer Netherlands, 297.
- Cain D. H., K. Riitters, and K. Orvis. 1997. A multi-scale analysis of landscape statistics. *Landscape Ecology* **12**:199-212.
- Çakır G., F. Sivrikaya, and S. Keleş. 2008. Forest cover change and fragmentation using Landsat data in Maçka State Forest Enterprise in Turkey. *Environmental monitoring and assessment* **137**:51-66.

- Cohen W. B., S. N. Goward. 2004. Landsat's Role in Ecological Applications of Remote Sensing. *Bioscience* **54**:535-545.
- Collins J. B., C. E. Woodcock. 1996. An assessment of several linear change detection techniques for mapping forest mortality using multitemporal Landsat TM data. *Remote Sensing of Environment* **56**:66-77.
- Coops N. C., M. A. Wulder, and J. C. White. 2006. Integrating remotely sensed and ancillary data sources to characterize a mountain pine beetle infestation. *Remote Sensing of Environment* **105**:83-97.
- Coppin P., I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin. 2004. Digital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing* **25**:1565-1596.
- Cushman S., K. McGarigal. 2007. Multivariate landscape trajectory analysis. Pages 119-140 *In* J. A. Bissonette and I. Storch, editors. *Temporal dimensions of landscape ecology: Wildlife responses to variable resources*, Springer US, New York, NY, USA. 284.
- Cushman S. A., K. McGarigal, and M. C. Neel. 2008. Parsimony in landscape metrics: Strength, universality, and consistency. *Ecological Indicators* **8**:691-703.
- Davidson C. 1998. Issues in Measuring Landscape Fragmentation. *Wildlife Society Bulletin* **26**:32-37.
- de Beurs K. M., G. M. Henebry. 2005. A statistical framework for the analysis of long image time series. *International Journal of Remote Sensing* **26**:1551-1573.
- Dodds K. J., S. L. Garman, and D. W. Ross. 2006. Landscape analyses of Douglas-fir beetle populations in northern Idaho. *Forest Ecology and Management* **231**:119-130.
- Fahrig L. 2002. Effect of Habitat Fragmentation on the Extinction Threshold: A Synthesis. *Ecological Applications* **12**:346-353.
- Folke C., S. Carpenter, B. Walker, M. Scheffer, T. Elmqvist, L. Gunderson, and C. S. Holling. 2004. Regime shifts, resilience, and biodiversity in ecosystem management. *Annual Review*

of Ecology, Evolution and Systematics **35**:557-581.

Fortin M. J., M. R. T. Dale. 2005. *Spatial Analysis: A Guide for Ecologists*. Cambridge University Press, Cambridge, UK. 365.

Franklin S. E., M. G. Betts, and R. G. Taylor. 2003. Interpretation of landscape pattern and habitat change for local indicator species using satellite imagery and geographic information system data in New Brunswick, Canada. *Canadian Journal of Forest Research* **33**:1821-1831.

Franklin J. F., R. T. T. Forman. 1987. Creating landscape patterns by forest cutting: ecological consequences and principles. *Landscape Ecology* **1**:5-18.

Franklin S. E., M. A. Wulder, R. S. Skakun, and A. L. Carroll. 2003. Mountain Pine Beetle Red-Attack Forest Damage Classification Using Stratified Landsat TM Data in British Columbia, Canada. *Photogrammetric Engineering & Remote Sensing* **69**:283-288.

Frohn R. C., Y. Hao. 2006. Landscape metric performance in analyzing two decades of deforestation in the Amazon Basin of Rondonia, Brazil. *Remote Sensing of Environment* **100**:237-251.

Fuller D. O. 2001. Forest fragmentation in Loudoun County, Virginia, USA evaluated with multitemporal Landsat imagery. *Landscape Ecology* **16**:627-642.

Gergel S. E., M. G. Turner. 2001. *Learning Landscape Ecology: A Practical Guide to Concepts and Techniques*. Springer-Verlag, New York, N.Y. USA. 336.

Gergel S. E. 2007. New directions in landscape pattern analysis and linkages with remote sensing. Pages 173-208 *In* M. A. Wulder and S. E. Franklin, editors. *Understanding Forest Disturbance and Spatial Pattern: Remote Sensing and GIS Approaches*, Taylor and Francis, Boca Raton, FL. 246.

Goodwin N. R., N. C. Coops, M. A. Wulder, S. Gillanders, T. A. Schroeder, and T. Nelson. 2008. Estimation of Insect Infestation Dynamics using a Temporal Sequence of Landsat Data. *Remote Sensing of Environment* **112**: 3680-3689.

Goward S. N., J. G. Masek, D. L. Williams, J. R. Irons, and R. J. Thompson. 2001. The Landsat 7 mission: Terrestrial research and applications for the 21st century. *Remote Sensing of*

Environment **78**:3-12.

Griffith J. A., T. L. Sohl, T. R. Loveland, and S. V. Stehman. 2003. Detecting trends in landscape pattern metrics over a 20-year period using a sampling-based monitoring programme. *International Journal of Remote Sensing* **24**:175-181.

Gunderson L., C. R. Allen, and D. Wardwell. 2007. Temporal scaling in complex systems: resonant frequencies and biotic variability. Pages 78-89 *In* J. A. Bissonette and I. Storch, editors. *Temporal dimensions of landscape ecology: Wildlife responses to variable resources*, Springer US, New York, NY, USA. 284

Gustafson E. J. 1998. Minireview: Quantifying Landscape Spatial Pattern: What Is the State of the Art? *Ecosystems* **1**:143-156.

Hansen M. C., D. P. Roy, E. Lindquist, B. Adusei, C. O. Justice, and A. Altstatt. 2008. A method for integrating MODIS and Landsat data for systematic monitoring of forest cover and change in the Congo Basin. *Remote Sensing of Environment* **112**:2495-2513.

Hargis C. D., J. A. Bissonette, and J. L. David. 1998. The behavior of landscape metrics commonly used in the study of habitat fragmentation. *Landscape Ecology* **13**:167-186.

Harrison S., E. Bruna. 1999. Habitat Fragmentation and Large-Scale Conservation: What Do We Know for Sure? *Ecography* **22**:225-232.

Henebry G. M., D. G. Goodin. 2002. Landscape trajectory analysis: Spatio-temporal dynamics from image time series. *International Geoscience and Remote Sensing Symposium 2002 IEEE International*; Piscataway, N.J. USA. 2375-2378.

Hietala-Koivu R. 1999. Agricultural landscape change: A case study in Ylane, southwest Finland. *Landscape and Urban Planning* **46**:103-108.

Hoekstra J. M., T. M. Boucher, T. H. Ricketts, and C. Roberts. 2005. Confronting a biome crisis: Global disparities of habitat loss and protection. *Ecology Letters* **8**:23-29.

Hughes J, A. Fall, L. Safranyik, K. Lertzman. 2006. Modeling the effect of landscape pattern on mountain pine beetles. Victoria, BC: Natural Resources Canada, Canadian Forest Service,

Pacific Forestry Centre. Report nr BC-X-407. 64.

Irish R. R., J. L. Barker, S. N. Goward, and T. Arvidson. 2006. Characterization of the Landsat-7 ETM Automated Cloud-Cover Assessment (ACCA) Algorithm. *Photogrammetric Engineering & Remote Sensing* **72**:1179-1188.

Jaeger J. A. G. 2000. Landscape division, splitting index, and effective mesh size: new measures of landscape fragmentation. *Landscape Ecology* **15**:115-130.

Johnson A., J. Wiens, B. Milne, and T. Crist. 1992. Animal movements and population dynamics in heterogeneous landscapes. *Landscape Ecology* **7**:63-75.

Ju J., D. P. Roy. 2008. The availability of cloud-free Landsat ETM+ data over the conterminous United States and globally. *Remote Sensing of Environment* **112**:1196-1211.

Kennedy R. E., W. B. Cohen, and T. A. Schroeder. 2007. Trajectory-based change detection for automated characterization of forest disturbance dynamics. *Remote Sensing of Environment* **110**:370-386.

Kepner W. G., C. J. Watts, C. M. Edmonds, J. K. Maingi, S. E. Marsh, and G. Luna. 2000. A Landscape Approach for Detecting and Evaluating Change in a Semi-Arid Environment. *Environmental Monitoring and Assessment* **64**:179-195.

Kerr J. T., M. Ostrovsky. 2003. From space to species: Ecological applications for remote sensing. *Trends in Ecology & Evolution* **18**:299-305.

Kong F., N. Nakagoshi. 2006. Spatial-temporal gradient analysis of urban green spaces in Jinan, China. *Landscape and Urban Planning* **78**:147-164.

Langford W., S. Gergel, T. Dietterich, and W. Cohen. 2006. Map misclassification can cause large errors in landscape pattern indices: Examples from habitat fragmentation. *Ecosystems* **9**:474-488.

Laurance W. F. 1999. Reflections on the tropical deforestation crisis. *Biological Conservation* **91**:109-117.

- Lausch A., F. Herzog. 2002. Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability. *Ecological Indicators* **2**:3-15.
- Lawrence R. L., W. J. Ripple. 1999. Calculating change curves for multitemporal satellite imagery: Mount St. Helens 1980-1995. *Remote Sensing of Environment* **67**:309-319.
- Li H., J. Wu. 2004. Use and misuse of landscape indices. *Landscape Ecology* **19**:389-399.
- Li X., H. S. He, R. Bu, Q. Wen, Y. Chang, Y. Hu, and Y. Li. 2005. The adequacy of different landscape metrics for various landscape patterns. *Pattern Recognition* **38**:2626-2638.
- Liu Y., S. Nishiyama, and T. Yano. 2004. Analysis of four change detection algorithms in bi-temporal space with a case study. *International Journal of Remote Sensing* **25**:2121-2139.
- Lu D., P. Mausel, E. Brondizio, and E. Moran. 2004. Change detection techniques. *International Journal of Remote Sensing* **25**:2365-2401.
- Lunetta R. S., D. M. Johnson, J. G. Lyon, and J. Crotnell. 2004. Impacts of imagery temporal frequency on land-cover change detection monitoring. *Remote Sensing of Environment* **89**:444-454.
- Lunetta R. S., J. F. Knight, J. Ediriwickrema, J. G. Lyon, and L. D. Worthy. 2006. Land-cover change detection using multi-temporal MODIS NDVI data. *Remote Sensing of Environment* **105**:142-154.
- Matsushita B., M. Xu, and T. Fukushima. 2006. Characterizing the changes in landscape structure in the Lake Kasumigaura Basin, Japan using a high-quality GIS dataset. *Landscape and Urban Planning* **78**:241-250.
- McGarigal K., S. A. Cushman, M. C. Neel, and E. Ene. 2002. Fragstats: Spatial Pattern Analysis Program for Categorical Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst, USA. URL: [www.umass.edu/landeco/research/fragstats/fragstats.html](http://www.umass.edu/landeco/research/fragstats/fragstats.html). Date accessed 20 April 2008.
- McGarigal K. 2002. Landscape pattern metrics. Pages 1135-1142 *In* A. H. El-Shaarawi and W. W. Piegorsch, editors. *Encyclopedia of Environmetrics*, volume 2, John Wiley & Sons, Sussex,

England.

- Narumalani S., D. R. Mishra, and R. G. Rothwell. 2004. Change detection and landscape metrics for inferring anthropogenic processes in the greater EFMO area. *Remote Sensing of Environment* **91**:478-489.
- Neel M. C., K. McGarigal, and S. A. Cushman. 2004. Behavior of class-level landscape metrics across gradients of class aggregation and area. *Landscape Ecology* **19**:435-455.
- Nelson T, B. Boots, and M. A. Wulder. 2003. Spatial-temporal analysis of mountain pine beetle infestations to characterize pattern, risk, and spread at the landscape level. Victoria, BC: Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre; 2003. Report nr BC-X-399. 164.
- Olf H., M. E. Ritchie. 2002. Fragmented nature: Consequences for biodiversity. *Landscape and Urban Planning* **58**:83-92.
- Pax Lenney M., C. E. Woodcock, J. B. Collins, and H. Hamdi. 1996. The status of agricultural lands in Egypt: The use of multitemporal NDVI features derived from Landsat TM. *Remote Sensing of Environment* **56**:8-20.
- Peterson G. D. 2002. Estimating resilience across landscapes. *Conservation Ecology* **6**:1-17.
- Rainis R. 2003. Application of GIS and landscape metrics in monitoring urban land use change. Pages 267-278 *In* N. M. Hashim and R. Rainis, editors. *Urban Ecosystem Studies in Malaysia-A study of change*, Universal Publishers, Florida.
- Read J. M., N. S. N. Lam. 2002. Spatial methods for characterising land cover and detecting land-cover changes for the tropics. *International Journal of Remote Sensing* **23**:2457-2474.
- Reynolds-Hogland M. J., M. S. Mitchell. 2007. Three Axes of Ecological Studies. Pages 174-194 *In* J. A. Bissonette and I. Storch, editors. *Temporal dimensions of landscape ecology: Wildlife responses to variable resources*, Springer, New York, NY, USA. 284.
- Riitters K., J. Wickham, R. O'Neill, B. Jones, and E. Smith. 2000. Global-scale patterns of forest fragmentation. *Conservation Ecology* **4**:1-22.

- Riitters K. H., R. V. O'Neill, C. T. Hunsaker, J. D. Wickham, D. H. Yankee, S. P. Timmins, K. B. Jones, and B. L. Jackson. 1995. A factor analysis of landscape pattern and structure metrics. *Landscape Ecology* **10**:23-39.
- Rutledge D. 2003. Landscape indices as measures of the effects of fragmentation: can pattern reflect process? Wellington, New Zealand: New Zealand Department of Conservation; 2003. Report nr DOC Science Internal Series 98. 27.
- Sachs D. L., P. Sollins, and W. B. Cohen. 1998. Detecting landscape changes in the interior of British Columbia from 1975 to 1992 using satellite imagery. *Canadian Journal of Forest Research* **28**:23-36.
- Saunders D. A., R. J. Hobbs, and C. R. Margules. 1991. Biological consequences of ecosystem fragmentation: A review. *Conservation Biology* **5**:18-32.
- Schneider, A., K. C. Seto, and C. E. Woodcock. 2003: Spatial and temporal patterns of land cover change in Chengdu, China, 1978-2002. *Geoscience and Remote Sensing Symposium, 2003. IGARSS '03. Proceedings. 2003 IEEE International, July 21-25, 2003, Toulouse, France, 3365-3367.*
- Schroeder T. A., W. B. Cohen, and Z. Yang. 2007. Patterns of forest regrowth following clearcutting in western Oregon as determined from a Landsat time-series. *Forest Ecology and Management* **243**:259-273.
- Shao G., J. Wu. 2008. On the accuracy of landscape pattern analysis using remote sensing data. *Landscape Ecology* **23**:505-511.
- Simberloff D. 2000. Global climate change and introduced species in United States forests. *The Science of the total environment* **262**:253-261.
- Singh A. 1989. Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing* **10**:989-1003.
- Skakun R. S., M. A. Wulder, and S. E. Franklin. 2003. Sensitivity of the thematic mapper enhanced wetness difference index to detect mountain pine beetle red-attack damage. *Remote Sensing of Environment* **86**:433-443.

- Skole D., C. Justice, J. Townshend, and A. Janetos. 1997. A land cover change monitoring program: Strategy for an international effort. *Mitigation and Adaptation Strategies for Global Change* **2**:157-175.
- Southworth J., H. Nagendra, and C. Tucker. 2002. Fragmentation of a Landscape: Incorporating landscape metrics into satellite analyses of land-cover change. *Landscape Research* **27**:253-269.
- Stueve K. M., C. W. Lafon, and R. E. Isaacs. 2007. Spatial patterns of ice storm disturbance on a forested landscape in the Appalachian Mountains, Virginia. *Area* **39**:20-30.
- Trani M. K., J. R. H. Giles. 1999. An analysis of deforestation: Metrics used to describe pattern change. *Forest Ecology and Management* **114**:459-470.
- Treitz P., J. Rogan. 2004. Remote sensing for mapping and monitoring land-cover and land-use change: an introduction. *Progress in Planning* **61**:269-279.
- Turner M. G. 2005. Landscape ecology: What is the state of the science? *Annual Review of Ecology, Evolution and Systematics* **36**:319-344.
- Turner M. G., R. V. O'Neill, R. H. Gardner, and B. T. Milne. 1989. Effects of changing spatial scale on the analysis of landscape pattern. *Landscape Ecology* **3**:153-162.
- Turner M. G., R. H. Gardner, and R. V. O'Neill. 2001. *Landscape ecology in theory and practice: Pattern and process*. Springer, New York, NY, USA.
- Turner W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling, and M. Steininger. 2003. Remote sensing for biodiversity science and conservation. *Trends in Ecology and Evolution* **18**:306-314.
- Wagner H. H., M. Fortin. 2005. *Spatial analysis of landscapes: concepts and statistics*. *Ecology* **86**:1975-1987.
- Wallace O. C., J. Qi, P. Heilma, and R. C. Marsett. 2003. Remote Sensing for Cover Change Assessment in Southeast Arizona. *Journal of Range Management* **56**:402-409.

- Wang S. Y., G. Q. Wang, and Z. X. Chen. 2005. Study on landscape pattern change of soil erosion in Yellow River Basin, China. *Geoscience and Remote Sensing Symposium, 2005. IGARSS '05. Proceedings. 2005 IEEE International* **8**:5390-5393.
- Weng Y. 2007. Spatiotemporal changes of landscape pattern in response to urbanization. *Landscape and Urban Planning* **81**:341-353.
- Westfall J. 2006 Summary of forest health conditions in British Columbia. British Columbia Ministry of Forests and Range, Forest Practices Branch; 2007. Report nr 15. 64.
- Wickham J. D., R. V. O'Neill, K. H. Riitters, T. G. Wade, and K. B. Jones. 1997. Sensitivity of selected landscape pattern metrics to land-cover misclassification and differences in land-cover composition. *Photogrammetric Engineering and Remote Sensing* **63**:397-402.
- Wickham J. D., K. H. Riitters, T. G. Wade, and J. W. Coulston. 2007. Temporal change in forest fragmentation at multiple scales. *Landscape Ecology* **22**:481-489.
- Wilcox B. A., D. D. Murphy. 1985. Conservation strategy: The effects of fragmentation on extinction. *The American Naturalist* **125**:879-887.
- With K. A., A. W. King. 1999. Extinction thresholds for species in fractal landscapes. *Conservation Biology* **13**:314-326.
- With K. A., T. O. Crist. 1995. Critical thresholds in species' responses to landscape structure. *Ecology* **76**:2446-2459.
- Woodcock C. E., R. Allen, M. Anderson, A. Belward, R. Bindschadler, W. Cohen, F. Gao, S. N. Goward, D. Helder, E. Helmer, R. Nemani, L. Oreopoulos, J. Schott, P. S. Thenkabail, E. F. Vermote, J. Vogelmann, M. A. Wulder, and R. Wynne. 2008. Free access to Landsat imagery. *Science* **320**:1011-1011.
- Wulder M. A., C. C. Dymond. 2004a. Remote sensing technologies for mountain pine beetle surveys. Victoria, BC: Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre; 2004. Report nr BC-X-399. 146.
- Wulder M. A., C. C. Dymond, and J. C. White. 2005a. Remote sensing in the survey of mountain pine beetle impacts: review and recommendations. Victoria, British Columbia: Natural

Resources Canada, Canadian Forest Service, Pacific Forestry Centre; 2005 2005. Report nr BC-X-401. 67.

Wulder M. A., J. C. White, B. Bentz, M. F. Alvarez, and N. C. Coops. 2006a. Estimating the probability of mountain pine beetle red-attack damage. *Remote Sensing of Environment* **101**:150-166.

Wulder M. A., J. C. White, B. J. Bentz, and T. Ebata. 2006b. Augmenting the existing survey hierarchy for mountain pine beetle red-attack damage with satellite remotely sensed data. *The Forestry Chronicle* **82**:187-202.

Wulder M. A., J. C. White, N. C. Coops, T. Han, M. F. Alvarez. 2005b. A protocol for detecting and mapping mountain pine beetle damage from a time-series of Landsat TM or ETM+ data. Victoria, British Columbia: Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre; 2005. Report nr Version 1.0. 70.

Wulder M. A., C. C. Dymond, J. C. White, D. G. Leckie, and A. L. Carroll. 2006c. Surveying mountain pine beetle damage of forests: A review of remote sensing opportunities. *Forest Ecology and Management* **221**:27-41.

Wulder M. A., R. J. Hall, N. C. Coops, and S. E. Franklin. 2004b. High spatial resolution remotely sensed data for ecosystem characterization. *Bioscience* **54**:511-521.

Yang X., Z. Liu. 2005. Quantifying landscape pattern and its change in an estuarine watershed using satellite imagery and landscape metrics. *International Journal of Remote Sensing* **26**:5297-5323.

Yen P., S. Ziegler, F. Huettmann, and A. I. Onyehialam. 2005. Change detection of forest and habitat resources from 1973 to 2001 in Bach Ma National Park, Vietnam, using remote sensing imagery. *International Forestry Review* **7**:1-8.

Young J. E., G. A. Sanchez-Azofeifa, S. J. Hannon, and R. Chapman. 2006. Trends in land cover change and isolation of protected areas at the interface of the southern boreal mixedwood and aspen parkland in Alberta, Canada. *Forest Ecology and Management* **230**:151-161.

Yu X., C. Ng. 2006. An integrated evaluation of landscape change using remote sensing and landscape metrics: a case study of Panyu, Guangzhou. *International Journal of Remote*

Sensing 27:1075-1092.

Zhou Q., B. Li, and C. Zhou. 2004. Detecting And modelling dynamic landuse change using multitemporal and multi-sensor imagery. International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences **35, Part 2**:697-702.

### **3 EVALUATION OF FOREST FRAGMENTATION AND LOSS OF CONNECTIVITY USING MULTITEMPORAL LANDSAT IMAGERY: QUANTIFYING NATURAL AND ANTHROPOGENIC DISTURBANCE<sup>2</sup>**

#### **3.1 *Introduction***

The role of disturbance in altering landscapes and modifying ecosystems over a range of spatial and temporal scales is well recognized in ecology (Perry 2002, Drever et al. 2006, Noss and Lindenmayer 2006, Jentsch 2007). Pickett and White (1985) define disturbance as “any relatively discrete event in time that disrupts ecosystem, community, or population structure and changes resources, substrate availability, or the physical environment”. While natural disturbance events contribute to the maintenance of biodiversity (Connell 1978) and heterogeneity (Turner et al. 2003), anthropogenic disturbance events are widely considered the primary drivers of declines in biodiversity and species endangerment (Hansen et al. 2001). A greater understanding of the interaction of natural and anthropogenic disturbance regimes provides the ability to make better-informed management decisions, by gaining insight related to landscape dynamics and the historic range of variability in ecosystems.

##### **3.1.1 Forest fragmentation**

Both natural and anthropogenic disturbances occurring in forested landscapes can lead to forest fragmentation. Wilcove et al. (1986) define fragmentation as a process during which “a large

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<sup>2</sup> A version of this chapter has been submitted for publication. Gillanders, S.N., N.C. Coops, M.A. Wulder, S.E. Gergel, T. Nelson, and N.R. Goodwin. (Submitted). Evaluation of forest fragmentation and loss of connectivity using multitemporal Landsat imagery: Quantifying natural and anthropogenic disturbance. *Ecological Applications*.

expanse of habitat is transformed into a number of smaller patches of smaller total area, isolated from each other by a matrix of habitats unlike the original". Two major effects of this process are a modification of the microclimate within and surrounding the remnant, intact forest patch and the isolation of these patches from other remnant forest patches in the surrounding landscape (Saunders et al. 1991). Thus, forest fragmentation can lead to changes in forest ecosystem function and condition (Wickham et al. 2008).

Natural disturbances tend to alter forest pattern differently from anthropogenic impacts such as timber harvesting (Mladenoff et al. 1993). For instance, natural disturbances often result in patches with less edge effect between patches as compared with timber harvesting (Tinker et al. 1998). In a study conducted to characterize and compare the patch characteristics of stand replacing harvest and fire disturbances in a coniferous forest landscape, the authors found that clearcutting results in forest patterns characterized by smaller patch sizes, smaller patch perimeter lengths, greater inter patch distances, more edge habitat, and less interior habitat when compared to landscape patterns created by natural disturbance processes (Hudak et al. 2007). Similarly, Tinker et al. (1998) observed that timber harvesting fragments the landscape through a distinct suite of structural changes including a decrease in forest patch core area and mean patch size, and an increase in edge density and patch density. Furthermore, timber harvesting tends to remove a larger amount of biomass from a forest than most natural disturbances, and results in the removal of those select stands with high timber volume and quality (Tinker et al. 1998).

Fragmentation is significant from both an ecological and management perspective. For instance, population dynamics of many species are influenced by not only the amount of available habitat but also the spatial arrangement of habitat (Hughes et al. 2006). For birds and mammals that

require specific habitat characteristics, such as interior forest or late-successional forest stands, forest fragmentation can result in a reduction of both habitat quality and quantity. For some species, predation decreases with distance from edge (Tellería et al. 2001) while other species require habitat features such as large interior forest patches for successful reproduction (Murcia 1995). Roads and clearcuts may reduce the quality of habitat for some species and increase competition for resources in remaining forest patches.

### **3.1.2 Mountain pine beetle**

The mountain pine beetle (*Dendroctonus ponderosae* Hopkins) is a native insect to the forests of western North America and is considered a major cause of mortality in lodgepole pine (Taylor and Carroll 2004). As a result of influences on the lodgepole pine ecosystem such as an absence of extreme winter temperatures, an abundance of suitable hosts, and a moderating trend in temperature extremes mountain pine beetle populations in the central interior of British Columbia, Canada, have reached epidemic proportions and represent a critical management and ecological concern. As of January 2008, the cumulative area of British Columbia that has been affected (red or grey-attack) by the mountain pine beetle was 13.5 million hectares (British Columbia Ministry of Forests and Range 2008).

Lodgepole pine ecosystems in British Columbia have historically developed from the interaction of mountain pine beetle and fire events to produce a mix of tree age classes. However, a number of large fires in the early 1900s followed by management-based fire suppression produced a large inventory of mature lodgepole pine in the central interior of British Columbia. Because vulnerability to mountain pine beetle infestation increases with timber age, approximately 70% of

British Columbia's lodgepole pine inventory (1 billion cubic metres of timber) is considered to be at risk of mountain pine beetle infestation (Wilson 2004). This abundance of the ideal food source for mountain pine beetle and a decline in cold weather events required to bring beetle populations back to endemic or incipient levels has led to the current outbreak (Wilson 2004).

Due to the spatial extent of the current infestation, remotely-sensed data provide opportunities to effectively monitor and evaluate the impacts of the mountain pine beetle over a range of scales (Wulder et al. 2005b). Typically, the mapping of mountain pine beetle using remote sensing technologies relies on the spectral response of a given band combination or vegetation index for red-attack identification (Franklin et al. 2003, Skakun et al. 2003, Wulder et al. 2005a, Wulder et al. 2006b, Wulder et al. 2006a). For instance, indices such as the tasseled cap transformation wetness index and the normalized difference moisture index (NDMI) have both been successfully applied to detect mountain pine beetle red-attack (Han et al. 2007, Goodwin et al. 2008). This unique spectral response resulting from changes in foliage moisture characteristics in mountain pine beetle-impacted forest stands forms the basis for most mountain pine beetle mapping using remotely-sensed imagery.

In addition to these physiological changes, a forested landscape with an extensive lodgepole pine inventory impacted by the mountain pine beetle at the epidemic stage of its population cycle would be expected to become increasingly fragmented, exhibiting a reduction in forest patch connectivity and patch size, and an increase in patch complexity in terms of both edge and shape. Prior to extensive beetle infestation, large contiguous patches of forest would be dominant but would include isolated patches of natural disturbance (i.e., wildfire, windthrow, endemic insect infestation) as well as roads and clearcuts. Functional connectivity may be compromised

depending on the extent of these disturbances, but it would be expected that forest would be the dominant matrix component. As beetle populations increase, small isolated clusters of infested trees impacted by the beetle would appear on the landscape. Over time, as beetle populations continued to expand, trees neighbouring these small patches of beetle-impacted timber would be attacked, and new isolated patches would appear. In the case of the central interior of British Columbia where lodgepole pine is a predominant coniferous species, these patches of beetle-impacted trees would eventually coalesce and would replace an otherwise functional, live forest as the dominant matrix component. Based on the severity of the current epidemic in British Columbia, this trend would continue until the beetle had largely exhausted the availability of its food source.

The extent and severity of the current mountain pine beetle infestation in British Columbia results in an expectation that this disturbance agent will have a significant impact on forest fragmentation and connectivity. However, in concert with the beetle infestation are anthropogenic disturbances such as timber harvesting in the form of operational logging, otherwise referred to as green logging, and salvage logging consisting of the removal of dead or dying trees in an effort to recover economic value that would otherwise be lost (Lindenmayer and Franklin 2008). When the impacts of timber harvesting are combined with those of the current mountain pine beetle infestation, the cumulative impact of these landscape disturbances is expected to result in a heavily fragmented landscape with a significantly reduced degree of connectivity.

In this research we evaluate changes in selected landscape pattern indices over a number of forest stands that have undergone disturbance by both mountain pine beetle and timber harvest. Analysis of a temporal sequence of Landsat data at the forest stand level allowed for the development of

spatial trajectories based on a number of Landsat-derived landscape pattern indices, and provided an ability to quantify the effects of both natural and anthropogenic fragmentation in order to characterize forest stand conditions during infestation. The specific objectives of this research are to:

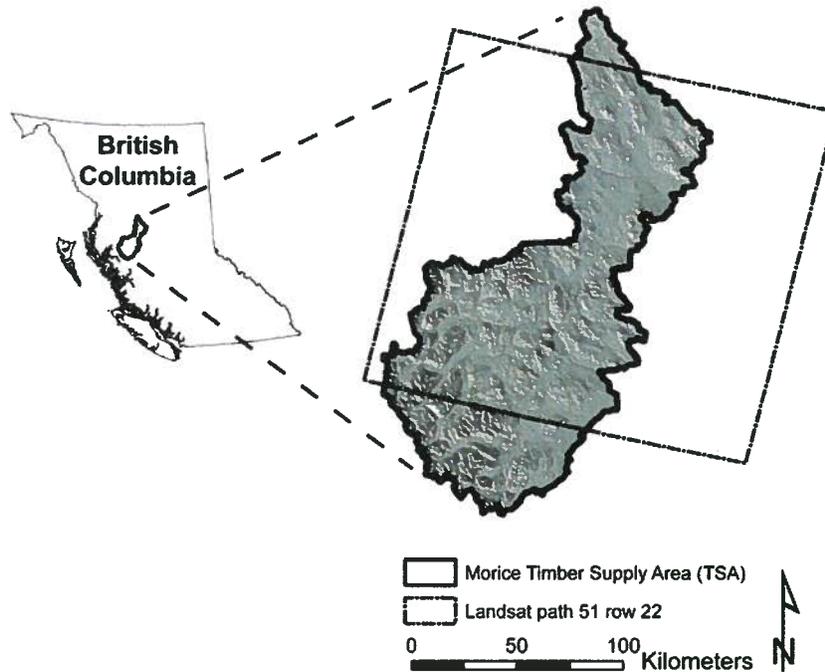
1. Assess how the mountain pine beetle changes landscape spatial pattern, and
2. Determine the relative impact of mountain pine beetle infestation and timber harvesting on forest fragmentation and connectivity.

The results from this analysis will help to inform resource managers of the changes in landscape pattern occurring in the British Columbia interior as a result of mountain pine beetle infestation and timber harvesting, and will provide much needed information to help guide future forest and land base management decisions.

## **3.2      *Methods***

### **3.2.1      Study area**

The study area is situated in the Morice Timber Supply Area (TSA) which is part of the British Columbia Ministry of Forests and Range (MoFR) Nadina Forest District located in the central interior of British Columbia (Figure 3.1).



**Figure 3.1 Location of Morice Timber Supply Area (TSA) and Landsat path 51 row 22 in relation to the province of British Columbia, Canada.**

The Morice TSA is located on the western edge of the Central Interior Plateau and covers approximately 1.5 million hectares (Tesera Systems Inc. 2006). The main forest species in the area include lodgepole pine (*Pinus contorta* var. *latifolia*), hybrid spruce (*Picea engelmannii* x *glauca*), and subalpine fir (*Abies lasiocarpa*). Trembling aspen (*Populus tremuloides*), amabilis fir (*Abies amabilis*), western hemlock (*Tsuga heterophylla*), and mountain hemlock (*Tsuga mertensiana*) are also present in lesser amounts. In the north and central areas of the Morice TSA, mountain pine beetle infestation occurred in the mid-1990s while in the southern region the infestation occurred in the late 1990s (Nelson et al. 2006). The Morice TSA has undergone extensive harvesting and management including mountain pine beetle treatment and salvaging efforts. Traditionally, the Morice TSA has represented the northern extent for mountain pine beetle. It is estimated that 80%

of the pine forest in the Morice TSA will be subject to some level of attack by 2013 and dead by 2018 (Tesera Systems Inc. 2006).

### 3.2.2 Data sources

Landsat TM and ETM+ satellite imagery were the primary data source for this study. The Landsat scene chosen was Path 51 / Row 22, which covers the extent of the area of interest. Scenes were chosen which were largely cloud-free and within the seasonal window of July to September when available. The data stack consists of six Landsat-5 TM and Landsat-7 ETM+ scenes covering the range of 1993 – 2006 (Table 3.1).

**Table 3.1 Image dates and Landsat sensor types used for the data stack.**

<b>Image acquisition date</b>	<b>Landsat sensor</b>
3 October, 1993	TM
24 August, 1996	TM
29 July, 1998	TM
14 August, 2001	ETM+
29 September, 2003	TM
20 August, 2006	TM

For stratification purposes, a 25 m digital elevation model (DEM) covering the extent of the study area was obtained and used to derive elevation values. In addition, vegetation resource inventory (VRI) data were used to analyze forest cover attributes.

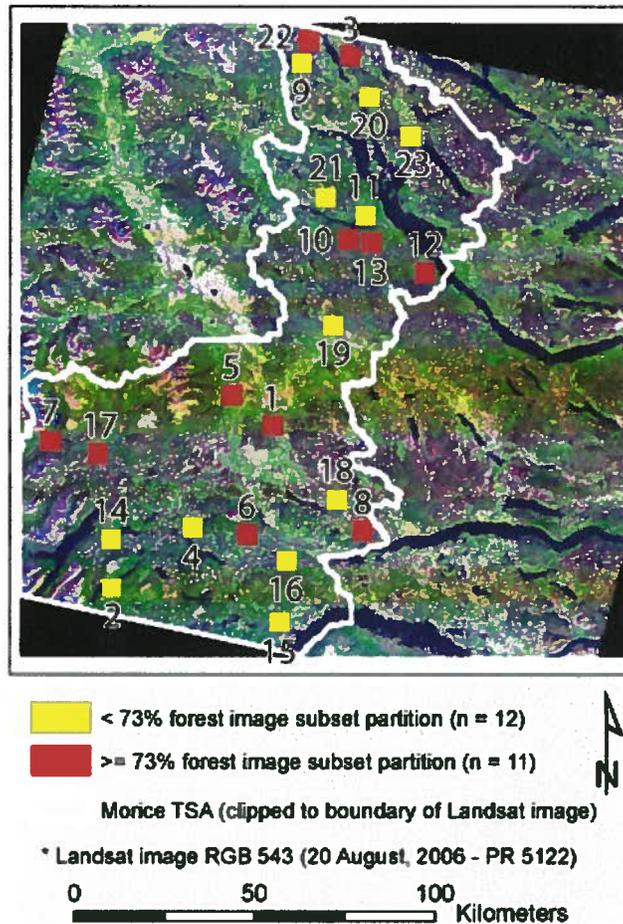
### 3.2.3 Pre-processing and classification

Data pre-processing included image-to-image geometric registration and radiometric normalisation. These are critical processing steps required to ensure that detected land cover changes are not artifacts of atmospheric conditions, imaging and viewing conditions, sensor degradation, or pixel misalignment but actually represent changes to surface conditions (Coops et al. 2006). A detailed examination of these processing steps, and the implementation to the datastack used in this paper are detailed in Goodwin et al. (2008) and as a result the issues and processing will only be touched on briefly here. Image registration was performed using a nearest-neighbour 2<sup>nd</sup> order polynomial transformation using the 2001 Landsat TM scene as the reference image due to its lack of cloud cover. The remaining five images were registered with a root mean square error (RMSE) < 0.5 pixels. Following registration, any cloud and shadow in the images were manually removed via masking. Radiometric normalisation was then applied, which is performed in order to account for differences in atmospheric conditions, solar angle, and satellite sensor characteristics. This step reduces the variability between images so that detectable changes between image dates correspond to land cover changes rather than variability due to differences in satellite solar acquisition. To achieve this, the 2001 image date was atmospherically corrected using the COST (cosine of the solar zenith angle) model (Chavez 1996). A relative normalisation procedure was then applied to the remaining five images using the Multivariate Alteration Detection (MAD) algorithm (Canty et al. 2004, Schroeder et al. 2006). MAD is an automated approach that normalises multiple images via regression analysis based on pseudo-invariant pixels in a base image. Again, the atmospherically corrected 2001 image was used as the base image for this procedure. Following these steps, data were converted to NDMI values for each image. A low-pass filter (3 x 3 pixel window) was then applied to the NDMI images in order to minimize the influence of any pixel mis-registration. Data were then classified based on the spectral trajectory

of the NDMI through time as developed and detailed by Goodwin et al. (2008). The output produced four classes at each time step: forest, harvest, mountain pine beetle-infested forest, and the non-forest mask.

### **3.2.4 Stratification**

The NDMI image data stack was stratified in an effort to obtain a sample of landscape replicates with similar levels of mountain pine beetle susceptibility. In order to accomplish this data were selected using an elevation range of 800 m – 1200 m and forest inventory attributes including stand age greater than 60 years , crown closure between 66 and 75%, and a lodgepole pine component between 30 – 80%. In general, low-elevation stands are more likely to be attacked due to the warmer temperatures being more favourable for insect survival. Forests stands between the age of 80 to 100 years are considered to be highly susceptible to mountain pine beetle (Carroll and Safranyik 2004), but due to the infestation severity in the study area we increased the stand age range to begin at greater than 60 years. Likewise, crown closure between 66 – 75% has been identified as highly susceptible to mountain pine beetle attack (Wulder et al. 2005). These attributes correspond to a high susceptibility to mountain pine beetle infestation and allowed for the retention of enough data that met these criteria in order to collect samples throughout the extent of the study area. Stratification provided the means to extract twenty-three 200 x 200 pixel (3,249 ha) image subset samples with similar conditions and mountain pine beetle susceptibility (Figure 3.2). Furthermore, in an effort to account for considerable variability in landscape pattern index values we partitioned the data by the percentage of forest in the initial classified image date.



**Figure 3.2** Location of the twenty-three 200 x 200 pixel (3,249 ha) image subset samples in relation to the Morice TSA boundary clipped to the northern and southern extents of Landsat path 51 row 22. Data were stratified by elevation and forest inventory attributes in order to collect replicates with similar initial conditions and mountain pine beetle susceptibility. Image subsets were partitioned into two groups based on the percentage of forest in the initial classified image date.

### 3.2.5 Landscape pattern indices

Landscape pattern indices can be grouped into categories of area, shape, isolation/proximity, contagion/interspersion, and diversity (McGarigal and Marks 1995). The following pattern indices were used to evaluate the progression of forest fragmentation and loss of connectivity in the study area (Table 3.2):

**Table 3.2 A listing and description of the landscape pattern indices (LPI) applied to the classified image subsets.**

LPI	Description	Category	Class	Landscape	Reference
Class area (CA)	total class area (ha)	area	√		(McGarigal and Marks 1995)
Number of patches (NP)	total number of patches in a particular class or an entire landscape	area	√	√	(McGarigal and Marks 1995, Turner et al. 1989)
Edge density (ED)	ratio of total edges (number of cells at patch boundary) and total area (total cells) (m/ha)	shape	√	√	(McGarigal and Marks 1995, Hargis et al. 1998, Li et al. 2005)
Area-weighted mean patch size (AREA_AM)	patch area multiplied by proportional abundance of the patch (or patch type) (ha)	area	√	√	(McGarigal and Marks 1995)
Area-weighted mean fractal dimension (FRAC_AM)	provides a measure of patch shape complexity by quantifying the mean fractal dimension of patches of the corresponding patch type, weighted by patch area	shape	√		(McGarigal and Marks 1995)
Mean proximity index (PROX_MN)	the degree of isolation and fragmentation of the corresponding patch type	isolation/proximity	√	√	(McGarigal and Marks 1995, Gustafson and Parker 1994)
Interspersion & juxtaposition index (IJI)	the degree of aggregation or 'clumpiness' of a map based on adjacency of patches	contagion/interspersion	√	√	(McGarigal and Marks 1995)
Simpson's diversity index (SIDI)	the probability that any pixels selected at random would be different types	diversity		√	(McGarigal and Marks 1995)

The indices of number of patches, class area, and area-weighted mean patch area correspond to area metrics. In concert with edge density, these pattern indices provide an indication of the degree of fragmentation for the different land-cover classes. Area-weighted mean fractal dimension, mean proximity index, and interspersion/juxtaposition index provide the means to measure shape, patch

isolation/proximity, and contagion/interspersion, respectively. Simpson's diversity index is a measure of diversity that measures the relative proportions of land cover classes. These landscape pattern indices were chosen due to their relevance to the research objectives.

Using an eight-neighbour rule we applied these landscape pattern indices to the classified maps measure changes in fragmentation and connectivity for each individual classification subset and image date. Select landscape pattern indices were applied at both the landscape and class (patch type) levels. Landscape-level pattern indices provide a measure of the ecological conditions of the landscape as a whole, irrespective of class. This same approach was applied at the class level, where we compared descriptive landscape pattern indices between the forest, mountain pine beetle-infested forest, and timber harvest classes over each of the twenty-three image subsets and six image dates. The twenty-three image subsets were then partitioned based on the median percentage of forest (73%) within each initial image date (1993).

### **3.2.6 Statistical analysis**

For each image subset, t-tests were used to determine whether there were statistically significant trends in the landscape pattern indices at both the landscape and class level over time. This analysis involved calculating a t statistic for each landscape pattern index trend in order to test if the slope differed significantly from zero. An alpha level of 0.05 was applied to test a two-tailed alternative hypothesis.

### 3.3 Results

Statistically significant trends were identified in the majority of the landscape-level pattern indices over time (Table 3.3). The exception is the < 73% forest trendline for the mean proximity index with a t-value of 1.652, which may be explained by the abundance of harvest and non-forest mask patches present in these image subsets, thereby limiting the number of patches available within the search radius of this index. Furthermore, the t-values of the < 73% partition are consistently lower than those of the >= 73% partition, which supports the notion that the proportion of forest within each image subset will in part dictate the behaviour of the pattern indices.

**Table 3.3 Test data for significant trends in landscape-level pattern indices over time. T-statistic values are based on 11 degrees of freedom for the < 73% forest partition (critical value of 2.201) and 10 degrees of freedom for the >= 73% forest partition (critical value of 2.228) and were evaluated using a two-sided alternate hypothesis with a significance level of 0.05%. Bold values are t-statistic values that represent landscape pattern index trends not significantly different from zero.**

<b>PARTITION</b>	<b>NP <i>t</i></b>	<b>ED <i>t</i></b>	<b>AREA_AM <i>t</i></b>	<b>PROX_MN <i>t</i></b>	<b>IJI <i>t</i></b>	<b>SIDI <i>t</i></b>
< 73% forest	11.297	11.361	7.686	<b>1.652</b>	4.240	9.447
>= 73% forest	12.774	15.928	11.144	5.167	5.407	14.765

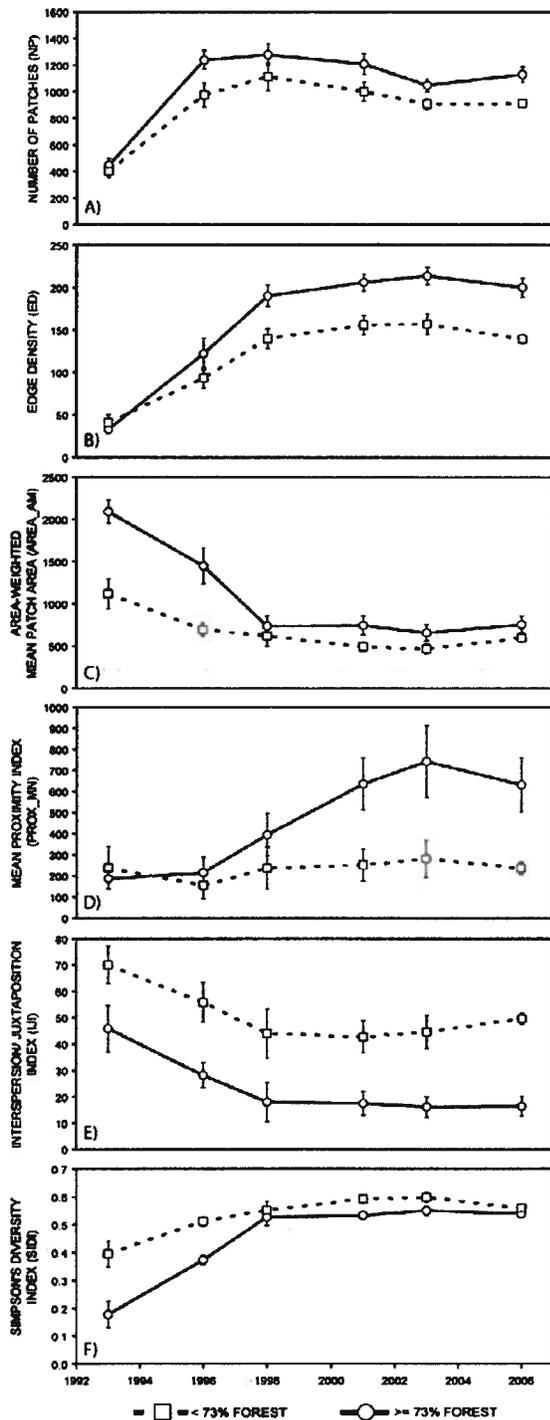
The t statistic values for the class-level pattern indices are shown in Table 3.4. Statistically significant trends were identified for all of the forest and mountain pine beetle-infested class-level pattern indices over time. Trends that were not significantly different from zero were identified in both partitions of the harvest class. In particular, the >= 73% forest partition harvest class had insignificant trends for all landscape pattern indices except for the interspersed/ juxtaposition index, although the t-value for this trendline (2.431) was only slightly greater than the critical value of 2.228. The harvest class of the < 73% forest partition had insignificant trends for the edge density and area-weighted mean fractal dimension trendlines.

**Table 3.4 Test data for significant trends in class-level pattern indices over time. T-statistic values are based on 11 degrees of freedom for the < 73% forest partition (critical value of 2.201) and 10 degrees of freedom for the >= 73% forest partition (critical value of 2.228) and were evaluated using a two-sided alternate hypothesis with a significance level of 0.05%. Bold values are t-statistic values that represent landscape pattern index trends not significantly different from zero.**

<b>PARTITION</b>	<b>CLASS</b>	<b>NP <i>t</i></b>	<b>ED <i>t</i></b>	<b>AREA_AM <i>t</i></b>	<b>FRAC_AM <i>t</i></b>	<b>PROX_MN <i>t</i></b>	<b>IJI <i>t</i></b>	<b>CA <i>t</i></b>
< 73% forest	forest	14.293	8.489	7.695	5.886	5.460	7.504	13.969
< 73% forest	harvest	2.239	<b>2.036</b>	2.517	<b>1.489</b>	2.715	8.167	2.422
< 73% forest	mpb	10.636	8.940	6.527	11.365	7.000	4.594	12.030
>= 73% forest	forest	17.299	14.818	13.662	10.962	8.839	9.211	17.882
>= 73% forest	harvest	<b>1.337</b>	<b>1.280</b>	<b>0.927</b>	<b>1.605</b>	<b>1.773</b>	2.431	<b>1.440</b>
>= 73% forest	mpb	11.984	15.145	15.570	16.193	13.761	2.260	16.382

### **3.3.1 How does the mountain pine beetle change landscape spatial pattern?**

Plotting the mean landscape-level pattern indices as shown in Figure 3.3 clearly indicates a landscape that has become more complex and fragmented through the time-series. A clear and distinct trajectory of change can be observed beginning from low levels of infestation through to a stand-replacing disturbance. For instance, increasing trends are observed for number of patches (Figure 3.3A), edge density (Figure 3.3B), the mean proximity index >= 73% forest partition (Figure 3.3D), and the Simpson’s diversity index in Figure 3.3F. Alternatively, decreasing trends are observed for area-weighted mean patch area (Figure 3.3C) and for the interspersed/juxtaposition index in Figure 3.3E. In addition, the majority of the trendlines tend to plateau following 1998 with the exception of the mean proximity index for the >= 73% forest partition in Figure 3.3D.

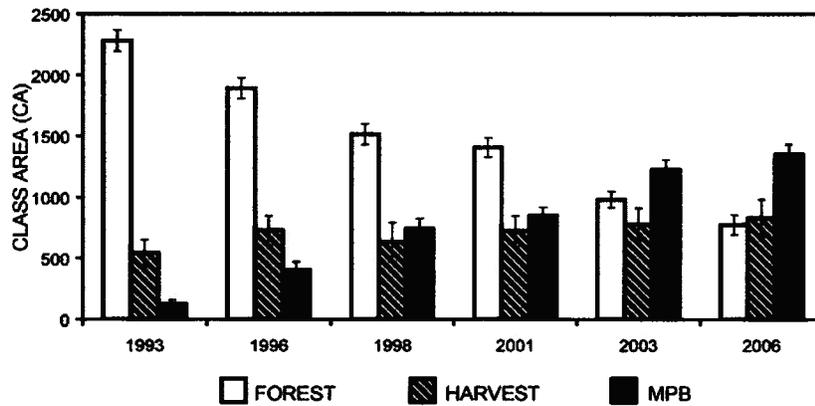


**Figure 3.3 Landscape-level spatial trajectory plots for image subsets showing changes in landscape pattern through time. Data are partitioned by percentage of forest in the initial image date (partition 1 < 73% forest; partition 2 ≥ 73% forest). Data points represent mean and standard error values for the two partitions based on landscape-level pattern indices vs. image date: a) number of patches; b) edge density; c) area-weighted mean patch area (ha); d) mean proximity index (100 m radius); e) interspersion/juxtaposition index; f) Simpson's diversity index.**

Several of the trendlines show considerable increases and decreases in landscape pattern index values. For instance, number of patches increased from approximately 400 to greater than 1100 in the span of 1993-1998. Similarly, edge density values increased by as much as 600% during the same period. The area-weighted mean patch area values for the  $\geq 73\%$  forest partition decreased from more than 2000 ha in 1993 to approximately 700 ha in 1998. Variance of the pattern index values for each partition, as indicated by the standard error bars at each point on the trendlines, is of a consistently small range with the exception of the mean proximity index and interspersion/juxtaposition index values. In general, there is a clear distinction between both partitions in each of the landscape-level figures.

### **3.3.2 What is the relative impact of mountain pine beetle infestation and timber harvesting on forest fragmentation and connectivity?**

Pattern analysis at the class-level allows for an assessment of the role that forest, timber harvest, and mountain pine beetle infestation play in contributing to fragmentation and loss of connectivity. For instance, Figure 3.4 shows the changes in class area (CA) (measured in hectares) for the forest, harvest, and mountain pine beetle infestation classes through the time series. In 1993 the forest class is clearly the dominant class with a value of 2282 ha compared to harvest with 542 ha and mountain pine beetle infestation with a value of 125 ha. While the harvest class tends to show a gradual increase through the time series with a value of 831 ha in 2006, the forest and mountain pine beetle infestation classes are much more dynamic. For instance, class area for the forest class steadily decreases to a value of 774 ha in 2006, while the mountain pine beetle infestation class increases to a maximum value of 1351 ha in 2006.



**Figure 3.4** Plot of class area (ha) vs. time for forest, harvest, and mountain pine beetle infestation land cover classes through time. Class area values represent the mean class area for the 23 image subsets and include standard error bars.

Figure 3.5 shows the remainder of the class-level pattern indices including number of patches (Figure 3.5A), edge density (Figure 3.5B), area-weighted mean patch area (Figure 3.5C), area-weighted mean fractal dimension (Figure 3.5D), mean proximity index (Figure 3.5E), and the interspersed/ juxtaposition index (Figure 3.5F). Similar to the landscape-level plots in Figure 3.3, the majority of the trendlines show dynamic increases or decreases through the time-series.

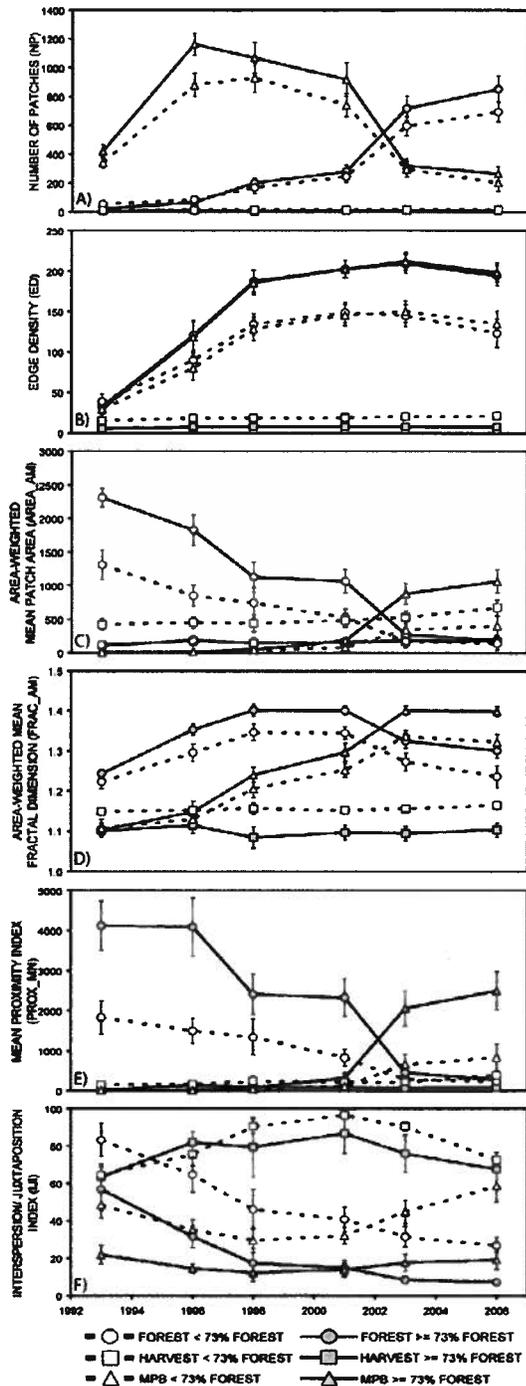


Figure 3.5 Class-level spatial trajectory plots for image subsets showing changes in landscape pattern through time for the forest, timber harvest, and mountain pine beetle-infested (MPB) classes. Data are partitioned by percentage of forest in the initial image date (partition 1 < 73% forest; partition 2  $\geq$  73% forest). Data points represent mean and standard error values for the two partitions based on landscape-level pattern indices vs. image date. a) number of patches; b) edge density; c) area-weighted mean patch area; d) area-weighted mean fractal dimension; e) mean proximity index (100 m radius); f) interspersed/juxtaposition index.

For example, in Figure 3.5A the number of patches of the forest class for both partitions ( $< 73\%$  forest and  $\geq 73\%$  forest) increases more than ten-fold through the time-series. Alternatively, the mountain pine beetle-infested class rapidly increases from 1993 to 1996 and then decreases through the time-series to lower values than the initial time step. Compared to the forest and mountain pine beetle-infested classes, the harvest class remains static with low values throughout the time-series.

Similar to the trend line for the number of patches of harvest in the previous figure, the edge density values for the harvest class in Figure 3.5B for both partitions are characterized by relatively low values and a stable trajectory throughout the time series. However, the forest and mountain pine-beetle infested classes show large increases from initial values of approximately 35 m/ha to between approximately 120 and 200 m/ha by 2006.

The area-weighted mean patch area plot in Figure 3.5C is characterized by a decrease in patch area of the forest class and an increase in patch area for the mountain pine beetle-infested class and the harvest class through the time-series. The forest class of the  $> 73\%$  forest partition declines from approximately 2300 ha in 1993 to a minimum value of less than 190 ha in 2006. The harvest class patch area increases through the time series but at a more modest rate.

The area-weighted mean fractal dimension plot in Figure 3.5D shows a relatively stable trajectory for the harvest, an increase for the mountain pine beetle-infested class, and an initial increase for the forest class followed by a decline through to 2006 to similar values as the initial image date.

The mountain pine beetle-infested class shows the most dynamic change with initial values in 1993 of 1.1 increasing to over 1.3 by 2006.

The plot for mean proximity index based on a 100 m radius in Figure 3.5E suggests a trend of increasing forest patch isolation. The forest class for the > 73% forest partition shows a large decline from 1993 through to 2006, beginning with a value of over 4100 and ending in 2006 with a value of 275. As would be expected, this increase in forest patch isolation results in a decrease in patch isolation of the mountain pine beetle-infested class, as indicated by the increase from less than 10 in 1993 to approximately 800 in 2006 for the <73 % partition and an increase to approximately 2500 in 2006 for the  $\geq 73\%$  partition. Similar to the previous class-level plots, the harvest class has relatively low values throughout the time-series and displays very little change.

The interspersion/juxtaposition index class-level plot in Figure 3.5F reflects changes in the degree of aggregation of patches for the forest, mountain pine beetle-infested, and harvest classes. The forest class shows a trend of declining values through the time-series, ranging from between a 300 and 800% decrease. Interspersion/juxtaposition index values for the mountain pine beetle-infested class decrease from 1993 through to 1998 but then rebound through to 2006 ending with similar values as the initial time step. Similarly, the harvest class trendlines initially increase but also return to similar values as at the initial time step.

### **3.4 Discussion**

Our purpose in analyzing these landscapes through time has been 1) to determine how mountain pine beetle infestation changes landscape spatial pattern, and 2) to assess to what degree mountain pine beetle and timber harvesting contribute to forest fragmentation and loss of connectivity. The results of all landscape pattern indices applied to the twenty-three image subsets suggest a trend toward a more fragmented landscape. This is consistent with what we would expect based on the considerable historic inventory of mature lodgepole pine in the study area, the presence of operational and salvage logging in the study area, and the severity of the current mountain pine beetle epidemic in the central interior of British Columbia.

In general, the results of this analysis confirm that the impacts of the mountain pine beetle on forest spatial pattern consist of:

1. an increase in the number of patches
2. an increase in forest patch shape complexity
3. a reduction in forest patch size
4. an increase in forest patch isolation
5. a decrease in interspersion

#### **3.4.1 How does the mountain pine beetle change landscape spatial pattern?**

At the landscape level, a large increase in number of patches and edge density and a large decrease in area-weighted mean patch area through the time-series suggest that the landscape has become

more fragmented. A reduction in total habitat area affects a variety of processes such as species viability, dispersal, and threat of invasion (Saunders et al. 1991, Olff and Ritchie 2002).

Furthermore, Saunders et al. (1991) observed that when areas of habitat patches are reduced, conditions of these remnant patches are increasingly vulnerable to external influences, which can have an adverse affect on species occupying those habitats. Another aspect of fragmentation is that the dominant factor dictating species persistence is the total amount of habitat (Fahrig 2002). Species or populations persist until a particular amount of reduced habitat is reached, at which a threshold effect results in a relatively rapid decline. Furthermore, according to Forman (1995) small patches are likely to contain mainly common edge species whereas larger patches tend to contain more specialist interior species. Based on our results, the landscape under study is clearly becoming more favourable for common edge species.

The differences in mean proximity index values for partitions 1 and 2 can be explained by the amount of forest available to be fragmented by the beetle. In the case of partition 1 consisting of those image subsets with less than 73% forest, the relatively stable trajectory reflects the presence of abundant harvest and non-forest mask polygons, thereby limiting the number of patches calculated by this pattern index. Alternatively, the relatively large increase in mean proximity values for partition 2 indicates the presence of contiguous forest patches that are subject to attack by the beetle.

The decrease in interspersion/juxtaposition index values reflects a trend in which patch types are becoming more disproportionally distributed or clumped. Contrary to what we expected, this trend represents a reduction in patch complexity. However, the stable period of the trajectories following

1998 suggests that while fragmentation continues to occur on the landscape, the relative distribution of classes remains constant.

The initial increase in Simpson's diversity index values followed by relative stability from 1998 to 2006 for both partitions also suggests that the landscape is being fragmented. The initial increase in Simpson's diversity index values reflects the increasing abundance of patches following the splitting and division of forest patches due to mountain pine beetle infestation. The stable period beginning in 1998, indicating a relatively even abundance of patches, suggests that while the beetle is still active on the landscape the diversity of patches do not change considerably. This trend for both partitions suggests that initially, the dominance of one or more land cover classes is decreasing through to 1998. Following this period, Simpson's diversity index values remain relatively constant indicating that the relative proportions of the land cover classes do not change.

### **3.4.2 What is the relative impact of mountain pine beetle infestation and timber harvesting on forest fragmentation and connectivity?**

The class-level plots provide detailed information related to the relative contribution that mountain pine beetle infestation and forest harvest makes to overall landscape fragmentation and patch connectivity. Based on our results, forest harvest plays a minor role when compared to the impacts of the mountain pine beetle. For instance, the class-level plots for number of patches and area-weighted mean patch area indicate that the landscape has become more fragmented through the time-series due to a decrease in forest patch size and an increase in the number of forest patches. This observation is further supported by the trends of the mountain pine beetle-infested class, which shows a similar trend in magnitude but results in an inverse trajectory when compared to the

forest class. After 1998, the number of mountain pine beetle-infested patches declines suggesting that patches of beetle-impacted forest are coalescing, resulting in a more contiguous distribution as the mountain pine beetle-infested class becomes the dominant matrix component. In contrast, the timber harvest class remains relatively stable both in terms of the number of patches and patch size.

Likewise, the class level plot for edge density shows a relatively low and stable trajectory for timber harvest when compared to the forest and mountain pine beetle-infested classes. The increase in edge for both the forest and mountain pine beetle-infested classes is consistent with the impacts of mountain pine beetle infestation on a pine forest; namely, mostly contiguous forest being fragmented by small isolated patches of beetle-impacted forest, which continue to multiply and spread across the landscape. Although the trajectories for the forest and mountain pine beetle classes follow an almost identical trend, a threshold is crossed at which point the beetle-impacted forest replaces the forest as the major landscape matrix component. This is represented as the levelling off, and is followed by the decline which suggests that these small patches of beetle-impacted forest are merging, resulting in patches with a greater core/edge ratio.

The trajectories for number of patches and edge density are similar to what we had predicted in a previous study (Gillanders et al. 2008), although we anticipated that timber harvest would display a considerable increase through the time-series for both landscape pattern indices. This discrepancy can in part be explained by how the classifier merges adjacent polygons, thereby exhibiting an increase in patch area but not an increase in number of patches. However, even with the use of a classifier that treated individual clearcuts as distinct objects, the trajectories for the timber harvest class would have remained relatively static compared to those of the forest and

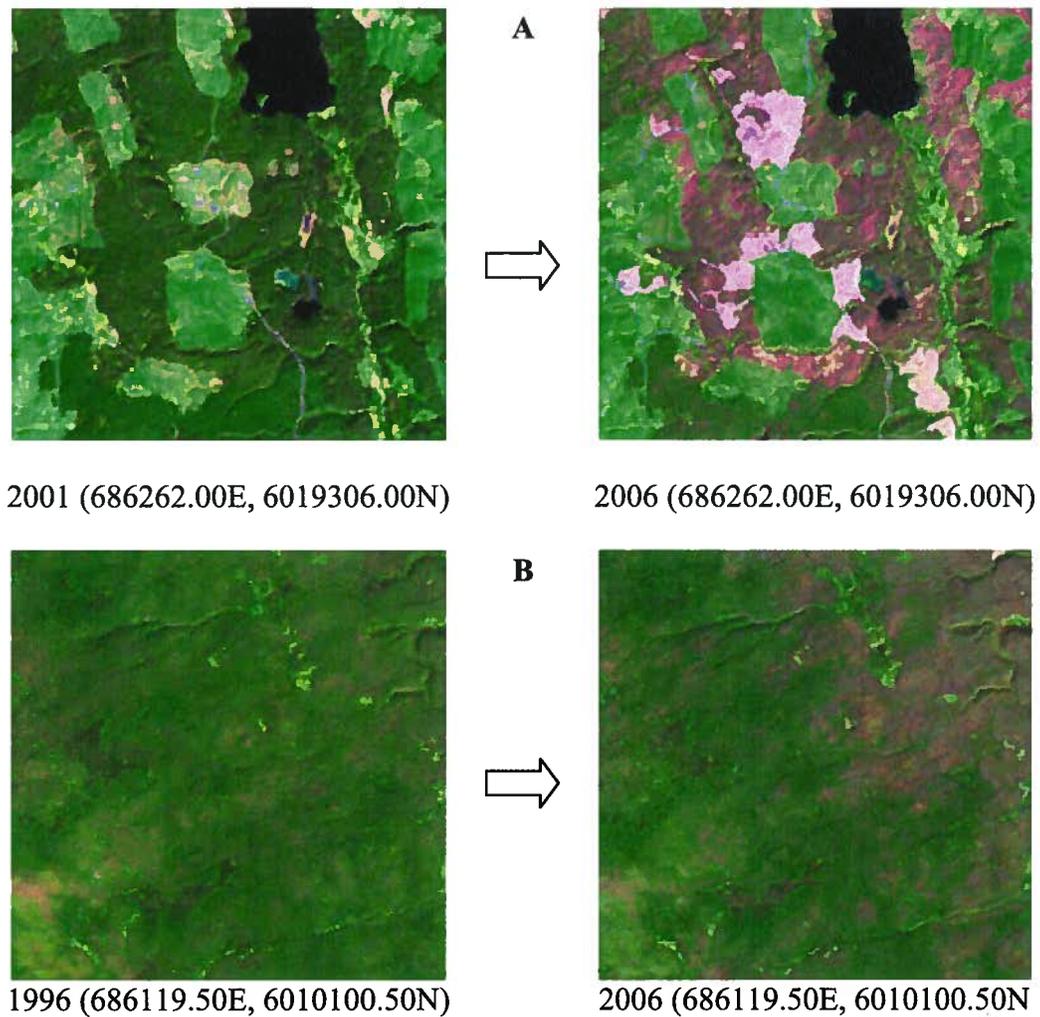
mountain pine beetle-infested classes. Of interest is that we did predict the threshold near the end of the time-series in number of patches in which beetle-impacted forest becomes the dominant matrix component.

The area-weighted mean fractal dimension plot also shows a relatively stable trajectory for the harvest class when compared to the more dynamic trajectories of both the forest and mountain pine beetle-infested classes. This indicates that shape complexity for the harvest class remains relatively stable, which is not surprising considering that clearcut harvesting tends to consist of simple linear shapes including rectangles and simple polygons.

Similarly, the harvest class in the mean proximity index plot is relatively stable when compared to the forest and mountain pine beetle-infested classes. This suggests that the progression of timber harvesting through the time-series is relatively minor when compared to the spread and subsequent impacts of the mountain pine beetle. Within a 100m buffer surrounding each patch, the changes to the landscape in terms of forest harvest are minor when compared to that of forest and the mountain pine beetle infestation classes.

Of interest is that each of the class level plots including the class area bar chart show a threshold between 2001 and 2003 at which the mountain pine beetle class trend line crosses the forest trend line. This represents the point at which the mountain pine beetle-infested class becomes the dominant matrix component within the image subset samples. While this phenomenon is an indicator of the severe impacts of mountain pine beetle infestation, the inverse trajectory could serve as an indicator of forest regeneration and recovery from disturbance.

Evidence of changes to the landscape resulting from mountain pine beetle infestation and timber harvesting can be observed by viewing regions of the imagery where these processes have clearly occurred. For example, Figure 3.6A shows a managed landscape in 2001, with forest patches intersected by roads linking harvest clearcuts, most of which are undergoing reforestation as indicated by the bright green reflectance. The adjacent image window shows the same landscape in 2006 with recent harvest activity as bright pink polygons as well as some new roads. Also clearly visible in the 2006 window is the replacement of much of the formerly dark green forest by reddish-brown pixels, which represent the red or grey-attack stage of tree mortality caused by mountain pine beetle.



**Figure 3.6 Landsat TM and ETM+ image subset windows (RGB bands 543) displaying mountain pine beetle infestation (reddish-brown) and timber harvest (bright green = regenerating clearcut; magenta = recent clearcut). a) land cover changes over a window representing a managed forest between 2001 and 2006; b) land cover changes over a window representing an unmanaged forest between 1996 and 2006.**

Likewise, Figure 3.6B shows an unmanaged landscape characterized by mostly contiguous forest in 1996. The 2006 image shows evidence of mountain pine beetle infestation, particularly in the northeast of the window, but also distributed as smaller patches amongst the green forest throughout other regions of the window.

By viewing the image subsets we can gain insight into how tree mortality resulting from mountain pine beetle infestation is manifested on the landscape. For example, Figure 3.6A shows a landscape fragmented by timber harvest activities. By 2006, this landscape has been further impacted by the mountain pine beetle in addition to recent harvest activity. We can observe the patchy distribution of beetle-impacted stands and can see that what began as forest and harvest being the dominant matrix components in 2001, has changed to beetle-impacted forest and timber harvest; intact contiguous forest is now a minor component of the matrix. Likewise, in Figure 3.6B we can observe a reduction in forest patch size, an increase in forest patch complexity, and an increase in the number of patches resulting from mountain pine beetle infestation.

While both timber harvesting and the impacts from mountain pine beetle infestation contribute to forest fragmentation and loss of connectivity, they represent different disturbance agents with vastly different impacts. Although the results of this study clearly indicate that the mountain pine beetle has a greater relative impact on forest fragmentation and loss of connectivity than timber harvest, beetle infestation represents a natural disturbance and a natural fragmentation event. Thus although the impacts of mountain pine beetle infestation to spatial pattern may be greater than timber harvesting in the study area, the implications to biotic and abiotic processes are markedly different.

Unlike other natural disturbances such as wildfire and windthrow, mountain pine beetle infestation results in a more irregular distribution of forest patches due to its discriminate selection of pine hosts. While timber harvesting is performed using a variety of methods, clearcut harvesting in British Columbia is the predominant method. This method of timber harvesting results in the removal of the majority of trees from a given harvest block. Clearcuts are often represented on the

landscape by a uniform, simple shape with linear edges. This is a truly stand-replacing disturbance in which an entire forest stand is removed. In the majority of cases, clearcut harvest blocks are connected by a road network.

### **3.4.3 Patch-level dynamics**

While the results of these analyses provide a general indication of changes to the ecological conditions of the landscape due to changes in spatial pattern, it is important to recognize the inherent limitations of the spatial resolution of a data source such as Landsat satellite imagery. The use of these data do not allow for an investigation of patch-level dynamics, which are expected to be very different for natural and anthropogenic disturbances. For instance, tree mortality caused by mountain pine beetle infestation leaves an abundance of snags and coarse woody debris, which represent valuable habitat for cavity nesters and a range of forest vertebrates (Chan-McLeod 2006), while timber harvesting does not. Furthermore, the complexity and differences in edge effects between a natural and anthropogenic disturbance event are generalized, preventing the observation of patch-level differences.

A landscape represents a network of patches connected by fluxes of air, water, energy, nutrients, and organisms (Jongman and Smith 2000). Interactions between patches are thus defined by the transition zones, or edges. The arrangement and geometry of patch edges influences species distribution and affects the quality of movement corridors (Jongman and Smith 2000). Many species are adapted to edge habitats created by natural disturbance regimes. When changes in forest spatial pattern occur, the resultant changes in habitat can adversely affect these species and can affect the competitive advantages among populations (Riitters et al. 2002). Forest

fragmentation results in an increase in forest edge, which is often adjacent to patches with a more open physical structure such as a timber harvest clearcut. Edge areas tend to receive more solar radiation, which can result in higher temperatures and drier conditions, as well as increased wind flow (Rutledge 2003). According to Murcia (1995), there are three types of edge effects resulting from forest fragmentation: 1) abiotic effects resulting in changes in environmental conditions due to proximity to a dissimilar patch, 2) direct biological effects involving changes in the abundance and distribution of species affected by physical conditions near the forest edge, and 3) indirect biological effects involving changes in species interactions such as predation, competition, and dispersal. Conversely, because edge areas have attributes of both adjacent patches they may actually support more species (Berry 2001).

Disturbances have a major influence on landscape heterogeneity in unmanaged landscapes (Radeloff et al. 2000). While natural disturbances such as wildfire directly affect landscape pattern (Chuvieco 1999, Goetz et al. 2006), anthropogenic disturbances often have an indirect influence by altering natural disturbance cycles such as wildfire suppression, and a direct influence by activities such as timber harvest. When multiple interacting disturbance processes occur in a forested landscape, the resultant changes to spatial pattern may differ from those caused by the disturbance processes acting independently (Radeloff et al. 2000). For instance, fuel loads may be increased following insect defoliation, leading to a greater likelihood and greater severity of wildfires.

#### **3.4.4 Biological legacies**

Unlike anthropogenic forest disturbances often characterized as a removal or modification of land cover to a different land use, natural disturbances in forests result in the retention of features from the original stand in the form of biological legacies. These legacies including organisms, organically-derived structures, and patterns from the pre-disturbance system (Franklin et al. 2000) represent a source from which disturbed ecosystems begin to recover. Furthermore, biological legacies also provide structural complexity and habitat for a range of organisms. These important differences between natural and anthropogenic disturbances have implications to both ecosystem recovery following disturbance and for the sustainable management of forested lands. For instance, knowledge and an understanding of ecological legacies can be used to help guide forest management practices in an effort to protect biodiversity and allow for the continued functioning of ecological processes (Lindenmayer and Franklin 2008).

While we do not differentiate operational timber harvest from salvage logging in this study, it is important to consider some of the impacts that result from salvage logging following a natural disturbance. For instance, natural disturbances are often associated with unusual environmental conditions, which result in significant stress to plants and animals. An example is prolonged drought preceding wildfire. Consequently, plants and animals may not have been able to recover from the dual impacts of environmental stress and the results of the natural disturbance before salvage logging takes place. In addition, salvage logging involves the removal of dead or dying trees which often results in a reduction in stand complexity. Logging practices for salvage operations also tend to be more intensive at the stand level and extensive at the landscape level than standard operational logging, resulting in larger clearcuts, the removal of younger or older

trees not otherwise allowed, and the further development of road networks (Lindenmayer and Franklin 2008).

Lindenmayer et al. (2008) classify the ecological impacts of salvage logging into two categories: impacts on organisms and habitats, and impacts on key ecosystem processes. In general, salvage logging removes some of the biological legacies generated by natural disturbances, thereby potentially reducing the efficacy of ecosystem recovery. For instance, natural disturbances provide pulses of biological legacies through the establishment of large-diameter standing dead trees and large pieces of coarse woody debris, which represent important habitat for cavity nesters and small mammals. In addition, post-disturbance plant recovery can be changed by salvage logging, leading to lower levels of recruitment and natural regeneration. Alterations to ecosystem processes resulting from salvage logging can include changes to hydrologic regimes, soil profile development, and nutrient cycling. Ultimately, the removal of biological legacies simplifies the structure of resultant forest stands, homogenizes landscape pattern, and reduces connectivity between undisturbed areas thereby diminishing or eliminating the ecological benefits generated by large-scale natural disturbances (Lindenmayer and Franklin 2008).

### **3.5 Conclusions**

This research represents a methodological approach to monitoring disturbance by applying landscape pattern indices to classified maps derived from multitemporal Landsat imagery. Landscape pattern indices quantify landscape structure and provide a means to infer ecological conditions. In this case, the use of multitemporal data provided a historical perspective and contributed to our understanding of how the mountain pine beetle interacted with the landscape of

the study area over a period of 13 years, beginning with low levels of infestation progressing to epidemic levels where mountain pine beetle-impacted forest had become the dominant matrix component.

The outcome of this research reveals that the study area has undergone significant land cover changes. The impacts of the mountain pine beetle on landscape spatial pattern are significant in terms of both the immediate impacts to biota and ecological processes in the region but also the legacy that these changes will have in the future. The implications of these structural changes to ecological processes are unclear, but changes in structural diversity would be expected to result in changes to both compositional and functional diversity (Mladenoff et al. 1993).

The potential for landscape pattern indices to be applied to a monitoring program to evaluate land cover dynamics for a range of natural and anthropogenic disturbances has been demonstrated.

These methods can easily be applied to monitor other landscape-scale forest disturbances such as wildfire, forest insects, and disease to allow for the characterization of the disturbance as well as to provide an indication of its ecological implications. As climate change is expected to contribute to an increased likelihood of forest insect infestations, the findings of this paper are relevant to not only the mountain pine beetle but other forest insects. While the use of Landsat data is appropriate for landscape-scale studies, these methods could be applied using other image data sources.

Another key component of this work has been the use of NDMI to detect and classify forest stands impacted by the mountain pine beetle. This research further supports the applicability of this vegetation index for studies associated with forest disturbance.

This utilization of multitemporal Landsat data to monitor disturbance dynamics via changes in spatial pattern further supports the wide-ranging applicability of the Landsat suite of sensors for monitoring the earth's surface. With the recent announcement by the USGS (United States Geological Service) of unrestricted global access to the entire Landsat data archive (Woodcock et al. 2008), it is expected that research utilizing multiple satellite images will continue to proliferate. In addition to the utility and availability of Landsat data, this research highlights the data-rich nature of satellite imagery in general; namely, the value of assessing spatial pattern rather than solely relying on spectral information. The assessment of the distribution and arrangement of patches on a given landscape provides opportunities to infer broad-scale ecological conditions, and when used in a multitemporal setting allows for the detection of changes which can affect a wide range of both biota and ecological processes.

In the mountain pine beetle-impacted forest, landscape homogeneity is likely to result in a broad scale regime shift to an alternate state. This would represent an inability of the ecosystem to effectively absorb the impacts and recover from the disturbance caused by mountain pine beetle. Traditional forest management tends to produce more homogenous forests than those forests disturbed naturally and increases the likelihood of shifts to alternate stable states (Drever et al. 2006). Landscape heterogeneity contributes to ecosystem resilience and reduces the possibility of a shift to an alternate stable state. In managed forest lands consistent with much of British Columbia's crown land, a landscape consisting of a mosaic of different age classes, tree sizes, stand densities, and species distributions would be less favourable for the mountain pine beetle and would represent an ecosystem with increased ecological resilience.

Landscape heterogeneity is believed to inhibit the spread of contagious disturbance so management initiatives that promote this diverse landscape structure would be a pertinent approach to aim for. In order to manage British Columbia's forests to promote resilience to large disturbance events such as the current mountain pine beetle epidemic, land managers should aim to emulate the complexities and characteristics of natural, unmanaged landscapes with active disturbance regimes. These management considerations should provide adequate ecosystem patch area and connectivity for both animal and material movement and species dispersal, and must allow for the recovery of ecosystem process in response to ecosystem disturbance and subsequent forest successional changes.

Further work is required to determine the degree to which our results are characteristic of other landscapes undergoing epidemic mountain pine beetle infestation. This would require applying these methods to other forested landscapes in the British Columbia interior undergoing beetle infestation in order to determine the natural variability inherent in both the landscape and the nature of the beetle infestation.

### **3.6      *References***

- Berry L. 2001. Edge effects on the distribution and abundance of birds in a southern Victorian forest. *Wildlife Research* **28**:239-245.
- British Columbia Ministry of Forests and Range. 2008. Beetle facts. URL: [http://www.for.gov.bc.ca/hfp/mountain\\_pine\\_beetle/facts.htm](http://www.for.gov.bc.ca/hfp/mountain_pine_beetle/facts.htm). Date accessed 9 February 2009.
- Canty M. J., A. A. Nielsen, and M. Schmidt. 2004. Automatic radiometric normalization of multitemporal satellite imagery. *Remote Sensing of Environment* **91**:441-451.
- Carroll A. L., L. Safranyik. 2004. The bionomics of the mountain pine beetle in lodgepole pine forests: Establishing a context. Pages 21-32 *In* T.L. Shore, J.E. Brooks, and J.E. Stone, editors. *Mountain Pine Beetle Symposium: Challenges and Solutions*. October 30-31, 2003, Kelowna, British Columbia. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Information Report BC-X-399, Victoria, BC. 298.
- Chan-McLeod, A.C.A. 2006. A review and synthesis of the effects of unsalvaged mountain-pine-beetle-attacked stands on wildlife and implications for forest management. *BC Journal of Ecosystems and Management* **7**:119-132.
- Chavez P. S. 1996. Image-based atmospheric corrections - Revisited and Improved. *Photogrammetric Engineering and Remote Sensing* **62**:1025-1036.
- Chuvieco E. 1999. Measuring changes in landscape pattern from satellite images: short-term effects of fire on spatial diversity. *International Journal of Remote Sensing* **20**:2331-2346.
- Connell J. H. 1978. Diversity in Tropical Rain Forests and Coral Reefs. *Science* **199**:1302-1310.
- Coops N. C., M. A. Wulder, and J. C. White. 2006. Identifying and Describing Forest Disturbance and Spatial Pattern: Data Selection Issues and Methodological Implications. Pages 31-62 *In* S. E. Franklin and M. A. Wulder, editors. *Understanding Forest Disturbance and Spatial Pattern: Remote Sensing and GIS Approaches*, Taylor and Francis, Boca Raton, Florida, USA. 246.
- Drever C. R., G. Peterson, C. Messier, Y. Bergeron, and M. Flannigan. 2006. Can forest management based on natural disturbances maintain ecological resilience? *Canadian Journal*

of Forest Research **36**:2285-2299.

Fahrig L. 2002. Effect of Habitat Fragmentation on the Extinction Threshold: A Synthesis. *Ecological Applications* **12**:346-353.

Forman R. 1995. *Land Mosaics: The Ecology of Landscapes and Regions*. Cambridge University Press, New York, N.Y. USA. 650.

Franklin J. F., D. B. Lindenmayer, J. A. MacMahon, A. McKee, J. Magnusson, D. A. Perry, R. Waide, and D. R. Foster. 2000. Threads of continuity: ecosystem disturbances, biological legacies and ecosystem recovery. *Conservation Biology in Practice* **1**:8-16.

Franklin S. E., M. A. Wulder, R. S. Skakun, and A. L. Carroll. 2003. Mountain Pine Beetle Red-Attack Forest Damage Classification Using Stratified Landsat TM Data in British Columbia, Canada. *Photogrammetric Engineering & Remote Sensing* **69**:283–288.

Gillanders S. N., N. C. Coops, M. A. Wulder, S. E. Gergel, T. Nelson. 2008. Multitemporal remote sensing of landscape dynamics and pattern change: Describing natural and anthropogenic trends. *Progress in Physical Geography* **32**: 503-528.

Goetz S. J., G. J. Fiske, and A. G. Bunn. 2006. Using satellite time-series data sets to analyze fire disturbance and forest recovery across Canada.. *Remote Sensing of Environment* **101**:352-365.

Goodwin N. R., N. C. Coops, M. A. Wulder, S. Gillanders, T. A. Schroeder, and T. Nelson. 2008. Estimation of insect infestation dynamics using a temporal sequence of Landsat data. *Remote Sensing of Environment* **112**:3680-3689.

Gustafson E. J., G. R. Parker. 1994. Using an index of habitat patch proximity for landscape design. *Landscape and Urban Planning* **29**:117-130.

Han T., M. A. Wulder, J. C. White, N. C. Coops, M. F. Alvarez, and C. Butson. 2007. An efficient protocol to process Landsat images for change detection with tasselled cap transformation. *IEEE Geoscience and Remote Sensing Letters* **4**:147-151.

Hansen A. J., R. P. Neilson, V. H. Dale, C. H. Flather, L. R. Iverson, D. J. Currie, S. Shafer, R. Cook, and P. Bartlein. 2001. *Global Change in Forests: Responses of Species, Communities,*

and Biomes. *Bioscience* **51**:765-779.

Hargis C. D., J. A. Bissonette, and J. L. David. 1998. The behavior of landscape metrics commonly used in the study of habitat fragmentation. *Landscape Ecology* **13**:167-186.

Hudak A. T., P. Morgan, M. Bobbitt, and L. Lentile. 2007. Characterizing stand-replacing harvest and fire disturbance patches in a forested landscape: a case study from Cooney Ridge, Montana. Pages 209-231 *In* M. A. Wulder and S. E. Franklin, editors. *Understanding Forest Disturbance and Spatial Pattern: Remote Sensing and GIS Approaches*, CRC Press (Taylor and Francis), Boca Raton, FL. 246.

Hughes J, A. Fall, L. Safranyik, and K. Lertzman. 2006. Modeling the effect of landscape pattern on mountain pine beetles. Victoria, BC: Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre; 2006. Report nr BC-X-407. 53.

Jentsch A. 2007. The challenge to restore processes in face of nonlinear dynamics - On the crucial role of disturbance regimes. *Restoration Ecology* **15**:334-339.

Jongman R. H. G., D. Smith. 2000. The European experience: From site protection to ecological networks. Pages 157-182 *In* J. Sanderson and L. D. Harris, editors. *Landscape ecology: A top-down approach*, Lewis Publishers, Boca Raton, FL.

Li X., H. S. He, R. Bu, Q. Wen, Y. Chang, Y. Hu, and Y. Li. 2005. The adequacy of different landscape metrics for various landscape patterns. *Pattern Recognition* **38**:2626-2638.

Lindenmayer D. B., J. F. Franklin. 2008. *Salvage logging and its ecological consequences*. Island Press, Washington DC, USA. 227.

McGarigal K., B. J. Marks. 1995. FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure. Portland, OR: U.S. Department of Agriculture, Forest Service. Pacific Northwest Research Station; 1995. Report nr Gen. Tech. Rep. PNW-GTR-351. 122.

Mladenoff D. J., M. A. White, J. Pastor, and T. R. Crow. 1993. Comparing Spatial Pattern in Unaltered Old-Growth and Disturbed Forest Landscapes. *Ecological Applications* **3**:294-306.

- Murcia C. 1995. Edge effects in fragmented forests: implications for conservation. *Trends in Ecology & Evolution* **10**:58-62.
- Nelson T., B. Boots, K. J. White, and a. A. C. Smith. 2006. The impact of treatment on mountain pine beetle infestation rates. *BC Journal of Ecosystems and Management* **7**:20-36.
- Noss R. F., D. B. Lindenmayer. 2006. Special Section: The ecological effects of salvage logging after natural disturbance. *Conservation Biology* **20**:946-948.
- Olf H., M. E. Ritchie. 2002. Fragmented nature: consequences for biodiversity. *Landscape and Urban Planning* **58**:83-92.
- Perry G. L. W. 2002. Landscapes, space and equilibrium: shifting viewpoints. *Progress in Physical Geography* **26**:339-359.
- Pickett S. T., P. S. White. 1985. *The ecology of natural disturbance and patch dynamics*. Academic Press, New York, NY, USA. 472.
- Radeloff V. C., D. J. Mladenoff, and M. S. Boyce. 2000. Effects of interacting disturbances on landscape patterns: Budworm defoliation and salvage logging. **10**:233-247.
- Riitters K. H., J. D. Wickham, R. V. O'Neill, K. B. Jones, E. R. Smith, J. W. Coulston, T. G. Wade, and J. H. Smith. 2002. Fragmentation of Continental United States Forests. *Ecosystems* **5**:0815-0822.
- Rutledge D. 2003. *Landscape indices as measures of the effects of fragmentation: Can pattern reflect process?* Wellington, New Zealand: New Zealand Department of Conservation; 2003. Report nr DOC Science Internal Series 98. 27.
- Saunders D. A., R. J. Hobbs, and C. R. Margules. 1991. Biological Consequences of Ecosystem Fragmentation: A Review. *Conservation Biology* **5**:18-32.
- Schroeder T. A., W. B. Cohen, C. Song, M. J. Canty, and Z. Yang. 2006. Radiometric correction of multi-temporal Landsat data for characterization of early successional forest patterns in western Oregon. *Remote Sensing of Environment* **103**:16-26.

Skakun R. S., M. A. Wulder, and S. E. Franklin. 2003. Sensitivity of the thematic mapper enhanced wetness difference index to detect mountain pine beetle red-attack damage. *Remote Sensing of Environment* **86**:433-443.

Taylor S. W., A. L. Carroll 2004. Disturbance, Forest Age, and Mountain Pine Beetle Outbreak Dynamics in BC: A Historical Perspective. Pages 41-51 *In* T.L. Shore, J.E. Brooks, and J.E. Stone, editors. *Mountain Pine Beetle Symposium: Challenges and Solutions*. October 30-31, 2003, Kelowna, British Columbia.. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Information Report BC-X-399, Victoria, BC. 298.

Tellería J. L., E. Virgós, R. Carbonell, J. Pérez-Tris, and T. Santos. 2001. Behavioural responses to changing landscapes: flock structure and anti-predator strategies of tits wintering in fragmented forests. *Oikos* **95**:253-264.

Tesera Systems Inc. 2006. Morice TSA timber supply analysis report for the current status, decision & mitigation scenarios. Chocrane, Alberta: Morice and Lakes timber supply area innovative forest practices agreement. 216.

Tinker D. B., C. A. C. Resor, G. P. Beauvais, K. F. Kipfmüller, C. I. Fernandes, and W. L. Baker. 1998. Watershed analysis of forest fragmentation by clearcuts and roads in a Wyoming forest. *Landscape Ecology* **13**:149-165.

Turner M. G., R. V. O'Neill, R. H. Gardner, and B. T. Milne. 1989. Effects of changing spatial scale on the analysis of landscape pattern. *Landscape Ecology* **3**:153-162.

Turner M. G., S. L. Collins, A. L. Lugo, J. J. Magnuson, T. S. Rupp, and F. J. Swanson. 2003. Disturbance dynamics and ecological response: The contribution of long-term ecological research. *Bioscience* **53**:46-56.

Wickham J., K. Riitters, T. Wade, and C. Homer. 2008. Temporal change in fragmentation of continental US forests. *Landscape Ecology* **23**:891-898.

Wilcove D. S., C. H. McLellan, and A. P. Dobson. 1986. Habitat fragmentation in the temperate zone. Pages 237-256 *In* M. Soulé, editor. *Conservation Biology: Science of Scarcity and Diversity*, Sinauer Associates, Sunderland, MA.

Wilson B. 2004. An Overview of the Mountain Pine Beetle Initiative. Pages 3-9 *In* T.L. Shore, J.E. Brooks, and J.E. Stone, editors. *Mountain Pine Beetle Symposium: Challenges and Solutions*. October 30-31, 2003, Kelowna, British Columbia.. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Information Report BC-X-399, Victoria, BC. 298.

Woodcock C. E., R. Allen, M. Anderson, A. Belward, R. Bindschadler, W. Cohen, F. Gao, S. N. Goward, D. Helder, E. Helmer, R. Nemani, L. Oreopoulos, J. Schott, P. S. Thenkabail, E. F. Vermote, J. Vogelmann, M. A. Wulder, and R. Wynne. 2008. Free Access to Landsat Imagery. *Science* 320:1011-1011.

Wulder M.A., J. C. White, N. C. Coops, T. Han, M. F. Alvarez. 2005a. A protocol for detecting and mapping mountain pine beetle damage from a time-series of Landsat TM or ETM+ data. Victoria, British Columbia: Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre; Report nr Version 1.0. 70.

Wulder M. A., C. C. Dymond, J. C. White, D. G. Leckie, and A. L. Carroll. 2005b. Surveying mountain pine beetle damage of forests: A review of remote sensing opportunities. *Forest Ecology and Management* 221:27-41.

Wulder M. A., R. S. Skakun, S. E. Franklin, and J. C. White. 2005c. Enhancing forest inventories with mountain pine beetle infestation information. *The Forestry Chronicle* 81:149-159.

Wulder M. A., J. C. White, B. J. Bentz, and T. Ebata. 2006a. Augmenting the existing survey hierarchy for mountain pine beetle red-attack damage with satellite remotely sensed data. *The Forestry Chronicle* 82:187-202.

Wulder M. A., J. C. White, B. Bentz, M. F. Alvarez, and N. C. Coops. 2006b. Estimating the probability of mountain pine beetle red-attack damage. *Remote Sensing of Environment* 101:150-16

## 4 CONCLUSION

As a result of the relationship between spatial pattern and ecological process, monitoring changes in landscape pattern allows for the interpretation of changes in ecological conditions. Chapter 2 described a summary of a selection of research articles that involved the use of multitemporal data to perform landscape pattern analysis. The information gained from this literature review was used to provide a context for our analysis approach and to inform the methods used for the analyses presented in this manuscript. Furthermore, we identified some of the caveats and limitations of landscape pattern analysis and developed hypotheses for expected results using two landscape pattern indices.

While the application of landscape pattern indices to one or two classified image dates is a routine approach, the use of a more dense time-series to analyze changes in spatial pattern is less common. In Chapter 3 we applied a set of landscape pattern indices to a time-series consisting of six classified Landsat image dates in order to gain an understanding of how mountain pine beetle infestation changes forest spatial pattern, and also to what degree beetle infestation and timber harvesting contribute to forest fragmentation and loss of connectivity. Our results suggest a trend toward a more fragmented landscape, primarily as a consequence of broad-scale lodgepole pine defoliation and mortality resulting from mountain pine beetle infestation. For instance, during the 13-year study period the mean number of landscape-level patches increased from approximately 400 to greater than 1100. Likewise, landscape-level edge density

values increased by as much as 600% during the same period. Area-weighted mean patch area values showed a considerable decline through the time-series, reflecting the severe impacts of mountain pine beetle infestation in the study area. Furthermore, the mean forest area within the 3,249 ha subsets declined by approximately 300%, primarily as a result of mountain pine beetle infestation. The hypothetical number of patches and edge density trajectories we predicted in Chapter 2 were largely confirmed for the mountain pine beetle-infested class; however, the trajectory for the timber harvest class was over-estimated, both in terms of magnitude and the general increasing trend for these pattern indices. Likewise, the number of patches and edge density trajectories for the forest class was predicted to be less dynamic than what was observed in the results.

The implications of these changes to both landscape and forest structure are expected to be significant to both biotic and abiotic processes in the central interior of British Columbia, as well as the socio-economic impacts for resource-dependent communities. A major concern of these ecologically significant changes to the landscape in the study area is the retention of biological legacies allowing for recovery following the multiple disturbances of mountain pine beetle infestation and operational and salvage logging. In an intensively managed landscape such as the Morice Timber Supply Area where salvage logging is regularly practiced, this represents a significant concern with far-reaching implications. For instance, based on the severity of the beetle infestation in the study area and the pressures associated with timber harvesting in nearby resource-dependent communities, trajectories of forest succession could be altered resulting in the regeneration of a forest which is not only highly susceptible to future insect outbreaks but

lacks the heterogeneity required to support a diversity of species, communities, and populations.

Monitoring forest disturbance using methods based on multitemporal landscape pattern analysis represents a challenging yet informative approach. By monitoring changes in landscape pattern through a time-series, both the direction and magnitude of trends can be derived and interpreted in an ecological context. This information is becoming increasingly important for resource managers in order to inform forest policy and management decisions. For example, legislation was passed in Ontario, Canada, mandating that Crown forests be managed in an attempt to keep landscape patterns consistent with long-term norms (Perera et al. 2000). While a landscape pattern monitoring approach will not replace the fine-scale information provided by field-based studies, we believe that this approach provides unique and indispensable information that complements traditional methods of forest management.

#### **4.1 *Future research***

In order to address the challenges of sustainable resource management, managers could benefit from emerging disciplines such as landscape ecology. By providing a spatial systems perspective, landscape ecology is particularly relevant to natural resource management. Furthermore, management activities are often associated with disturbances that affect landscape structure and function, drive landscape change, and alter landscape integrity (Liu and Taylor 2002). Thus a broad-scale perspective incorporating spatial relationships should be considered a critical part of resource management planning.

Of benefit to British Columbia would be the adoption of forest management initiatives to monitor changes in forest spatial pattern and to gain an understanding of these changes in terms of natural variability and the influence that broad-scale disturbances such as the current mountain pine beetle epidemic have on existing landscape pattern. This information could be used to better inform policy makers and resource managers, thereby providing information related to ecological processes. An appropriate data choice for this initiative would be Landsat imagery with a data archive of over 30 years and a spatial resolution pertinent for landscape-scale studies. In particular, a classified data product such as Earth Observation for Sustainable Developments of Forests (EOSD), which conforms to a standardized and repeatable classification procedure (Wulder et al. 2008), would be well suited for this purpose. These data provide a snapshot of land cover attributes circa 2000, but additional temporal coverage is anticipated in order to conduct analysis related to forest cover change over time.

In addition to monitoring changes in spatial pattern, the practice of adaptive management as a means to approach environmental problems is also recommended for the sustainable management of British Columbia's forests. By proposing and implementing management initiatives to address critical environmental issues, and then re-evaluating these prescriptions based on ecosystem response, managers could work toward maintaining forest resources in a 'desired state'. However, this management approach would likely require forest management goals driven by a more ecologically-based approach than an industrial approach.

Further investigations are required to determine what proportion of forested area in a given landscape is required to sustain critical ecological processes and species. While we have the ability to quantify the amount of disturbed forest resulting from natural and anthropogenic events, we lack a reference to gauge the implications of these land cover modifications. For example, threshold effects associated with species persistence and amount of habitat are a common theme in ecological literature (With and Crist 1995, With and King 1999, Fahrig 2002, Homan et al. 2004, Groffman et al. 2006), but applying these principles to a variety of species and processes in a biologically and topographically diverse forested landscape such as that in the British Columbia interior presents a considerable challenge.

This research represents an under-investigated method to characterize and monitor forest cover dynamics using landscape pattern indices, providing information to infer broad-scale ecological conditions. In particular, this work contributes to a greater understanding of both the challenges and the value of implementing multitemporal analysis using remotely-sensed data. Further, it demonstrates the utility and benefits of the application of a multitemporal approach to land cover monitoring for forest resource management.

## **4.2      *References***

- Fahrig L. 2002. Effect of habitat fragmentation on the extinction threshold: A synthesis. *Ecological Applications* **12**:346-353.
- Groffman P. M., J. S. Baron, T. Blett, A. J. Gold, I. Goodman, L. H. Gunderson, B. M. Levinson, M. A. Palmer, H. W. Paerl, G. D. Peterson, L. N. Poff, D. W. Rejeski, J. F. Reynolds, M. G. Turner, K. C. Weathers, and J. Wiens. 2006. Ecological thresholds: The key to successful environmental management or an important concept with no practical application? *Ecosystems* **9**:1-13.
- Homan R. N., B. S. Windmiller, and J. M. Reed. 2004. Critical thresholds associated with habitat loss for two vernal pool-breeding amphibians. *Ecological Applications* **14**:1547-1553.
- Liu J., W. W. Taylor. 2002. Integrating landscape ecology into natural resource management. Cambridge University Press, Cambridge, U.K. 480.
- Perera A. H., D. L. Euler, and I. D. Thompson. 2000. Ecology of a Managed Terrestrial Landscape: Patterns and Processes of Forest Landscapes in Ontario. UBC Press, Vancouver, B.C., Canada 336.
- With K. A., A. W. King. 1999. Extinction Thresholds for Species in Fractal Landscapes. *Conservation Biology* **13**:314-326.
- With K. A., T. O. Crist. 1995. Critical Thresholds in Species' Responses to Landscape Structure. *Ecology* **76**:2446-2459.
- Wulder M. A., J. C. White, T. Han, N. C. Coops, J. A. Cardille, T. Holland, D. Grills. 2008. Monitoring Canada's forests. Part 2: National forest fragmentation and pattern. *Canadian Journal of Remote Sensing* **34**: 563-584.

## 5 APPENDIX A

### 5.1 *Glossary*

Biological legacy: the organisms, organic materials, and organically generated patterns that persist through a disturbance and are incorporated into the recovering ecosystem (Franklin et al. 2000).

Contagious disturbance: a disturbance that once initiated at one location, has the ability to self-propagate to neighbouring locations.

Disturbance: A disturbance is any relatively discrete event in time that disrupts ecosystem, community, or population structure and changes resources, substrate availability, or the physical environment (White and Pickett 1985).

Disturbance regime: the spatial and temporal characteristics of disturbances affecting a particular landscape over a particular time (Anke 2007)

Ecological integrity: the dimension of health that reflects the capacity to maintain organization. Ecological integrity incorporates the idea of resilience, vigor, and homeostasis (Karr 1992). Other definitions include the notion of the evolution of an ecosystem without human disturbance (Nielsen 1999).

**Ecological resilience:** the capacity of a system to absorb disturbance and reorganize while undergoing change so as to retain essentially the same function, structure, identity, and feedbacks (Walker et al. 2004).

**Ecological services:** services which humans derive from ecological functions such as photosynthesis, oxygen production, and water purification.

**Ecological threshold:** the point at which there is an abrupt change in a quality, property, or phenomenon or where small changes in a driver (i.e. pollutant input, landscape fragmentation) may produce large responses in the ecosystem (Groffman et al. 2006).

**Ecosystem function:** the services performed by the organisms in an ecological system such as energy flow, nutrient cycling, filtering and buffering of contaminants, and regulation of populations.

**Ecotone:** the transitional area connecting different ecological communities (ecosystems). It may appear as a gradual blending of the two communities across a broad area, or it may manifest itself as a sharp boundary line.

**Fragmentation:** a process by which landscape units (i.e. habitat patches) are increasingly subdivided into smaller units, resulting in their increased insularity as well as losses of total habitat area.

Landscape structure: the spatial relationships between distinctive ecosystems. Structure specifically refers to the distribution of energy, materials, and species in relation to the sizes, shapes, numbers, kinds and configurations of components (Turner 1989).

## **5.2 References**

- Anke, J. 2007. The challenge to restore processes in face of nonlinear dynamics: On the crucial role of disturbance regimes. *Restoration Ecology* 15: 334-339.
- Franklin, J. F., D. Lindenmeyer, J. A. MacMahon, A. McKee, J. Magnuson, D. A. Perry, R. Waide, D. Foster. 2000. Threads of continuity: Ecosystem disturbance, recovery, and the theory of biological legacies. *Conservation Biology in Practice* 1: 8-16.
- Groffman, P. M., J. S. Baron, T. Blett, A. J. Gold, I. Goodman, L. H. Gunderson, B. M. Levinson, M. A. Palmer, H. W. Paerl, G. D. Peterson, L. N. Poff, D. W. Rejeski, J. F. Reynolds, M. G. Turner, K. C. Weathers, J. Wiens. 2006. Ecological thresholds: The key to successful environmental management or an important concept with no practical application? *Ecosystems* 9: 1-13.
- Karr, J. R. 1992. Ecological integrity: Protecting earth's life support systems. Pages 223-238 In R. Costanza, B. G. Norton, and B. D. Haskell, editors. *Ecosystem Health*. Island Press, Washington, D.C., pp. 223-238.
- Nielsen, N. O. 1999. The meaning of health. *Ecosystem Health* 5: 65-66.
- Turner, M. G. 1989. Landscape ecology: The effect of pattern on process. *Annual Review of Ecology and Systematics* 20: 171-197.
- White, P. S. and Pickett, S. T. 1985. *The ecology of natural disturbance and patch dynamics*. Academic Press, New York, N.Y. 472.
- Walker, B. H. and Meyers, J. A. 2004. Thresholds in ecological and social-ecological systems: A developing database. *Ecology and Society* 9: 3.