Multitemporal remote sensing of landscape dynamics and changing patterns: describing natural and anthropogenic trends

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Abstract

Science and reporting information needs for monitoring dynamics in land cover over time have prompted research, and made operational, a wide-variety of change detection methods utilizing multiple dates of remotely-sensed data. Change detection procedures based upon spectral values are common; however, landscape pattern analysis approaches which utilise spatial information inherent within imagery present opportunities for the generation of unique and ecologically important information. While the use of two images provides the means to identify trend, the use of multitemporal imagery for long-term monitoring affords the ability to identify a greater range of processes of landscape change. The main objective of this review is to investigate and summarize the methods and applications of land cover spatial pattern analysis using three or more image dates. The potential and the limitations of landscape pattern indices are identified and discussed to inform application recommendations. The second objective of this review is to make recommendations, including appropriate landscape pattern indices, for the application of landscape pattern analysis of a long time-series of remotely-sensed data to a case study involving the mountain pine beetle in British Columbia, Canada. The review concludes with recommendations for future research.

Key words: Landscape pattern, change, dynamics, Landsat, monitoring, spatial, insect, disturbance

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 et al., 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 et al., 2003). Balancing the human need for these ecological services (i.e., timber harvesting) 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 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 et al., 2003). For many studies, it represents the only data source available for measuring habitat characteristics and for detecting and monitoring environmental change (Kerr et al., 2003; Turner et al., 2003; Wulder et al., 2004). The use of satellite-based remote sensing 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 Thematic Mapper (TM) sensors allows for land cover characterization and change detection consistent with the grain of land management (Cohen et al., 2004). Furthermore, the orbital revisit period of 16 – 18 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 (Lunetta et al., 2006; Yen et al., 2005), recognizing that the terrestrial ecosystem is 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 result in 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 of 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. 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., 2004), 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 et al., 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 et al., 1996; Lu et al., 2004; Skole et al., 1997; Treitz et al., 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 (Liu et al., 2004; Singh, 1989). 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 Spectrometer (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 eliminating the issue related to 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, thereby restricting the types of land cover objects 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 (Systeme Pour l'Observation de la Terre). 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[1]. 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). 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 et al., 2005).

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[1] http://landsat.usgs.gov/images/squares/USGS_Landsat_Imagery_Release.pdf

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 et al., 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.

3. Landscape ecology and spatial pattern

Landscape patterns result from complex biotic and abiotic interactions operating at various spatial and temporal scales (Bolliger et al., 2007; Turner, 2005). 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 (Irish et al., 2006; Johnson et al., 1992). 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 ecosystem and region.

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 et al., 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 et al., 2002) and represent two commonly used indices to quantify fragmentation (McGarigal et al., 2002; McGarigal, 2002).

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).

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 (Gergel, 2007; Turner et al., 2001). 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 (Cushman et al., 2008; Riitters et al., 1995), 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 (Gergel, 2007; Gustafson, 1998; Li et al., 2004; Turner et al., 2001). 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 et al., 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 et al., 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 et al., 2004).

Another consideration 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 (Fahrig, 2002; Folke et al., 2004; Peterson, 2002; With et al., 1995). Thus, without a thorough understanding of the ecological system and the historical variability of landscape pattern determining significant change can be challenging.

5. Multitemporal spatial pattern analyses

There are many examples of change detection applications using spatial pattern based on two dates of imagery (Franklin et al., 2003; Sachs et al., 1998; Stueve et al., 2007; Wang et al., 2005; Yang et al., 2005). 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 (Fortin et al., 2005; Henebry et al., 2002; Lausch et al., 2002; Wagner et al., 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 1: please see end of document). The majority of these studies are concerned with 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^2 to over 7,600 km^2. 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.

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^2 agricultural landscape in southwest Finland. Using ARC/INFO GIS software, were rectified and then digitized according to an existing classification scheme. In addition to the percentage of the total area occupied by each of the classes 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 timesteps 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^2, 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 landcover 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^2 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 timesteps (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 (Hargis et al., 1998; Riitters et al., 2000; Trani et al., 1999; Wickham et al., 2007; Wilcox et al., 1985; With et al., 1995; With et al., 1999). 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. 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 et al., 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. The most commonly used landscape pattern indices in the reviewed literature.

Landscape pattern index (LPI)	**Number of times used**
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

6. Case study

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 (Hoekstra et al., 2005; Laurance, 1999; Simberloff, 2000). 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 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 is characterized by the loss of needles which occurs in most trees after a three-year period following attack (Wulder et al., 2006). 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., 2005).

Monitoring the magnitude and tracking the leading edge of MPB infestation is critical to forest resource managers. Due to the broad scale of the current epidemic, monitoring strategies utilizing remotely-sensed data have been developed and successfully applied (Coops et al., 2006; Wulder et al., 2005; Wulder et al., 2006a; Wulder et al., 2006). The Landsat TM and ETM+ sensors have proven to be useful for several MPB red-attack mapping applications (Franklin et al., 2003; Skakun et al., 2003; Wulder et al., 2005). 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 MPB-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

(Aukema et al., 2006; Goodwin et al., (In Press); Nelson et al., 2003; Skakun et al., 2003). A developing approach for the mapping and characterization of MPB red-attack is landscape spatial pattern analysis. Since the impacts of MPB 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.

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 et al., 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 3). The pattern indices in Table 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 (Harrison et al., 1999; Olff et al., 2002; Saunders et al., 1991). 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 3. Landscape pattern indices selected to measure aspects of habitat fragmentation for the case study.

Name	Symbol	Description	Interpretation	Reference(s)
Number of patches	*NP*	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	*AWMPS*	Measures patch area multiplied by proportional abundance of the patch (or patch type)	Lower values indicate more fragmentation	(McGarigal et al., 2002)
Fractal dimension	*FD*	Measures patch shape complexity	Higher values indicate an increase in shape complexity	(McGarigal et al., 2002)
Edge density	*ED*	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	*PRD*	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	*MPI*	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	*IJI*	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 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).

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 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.

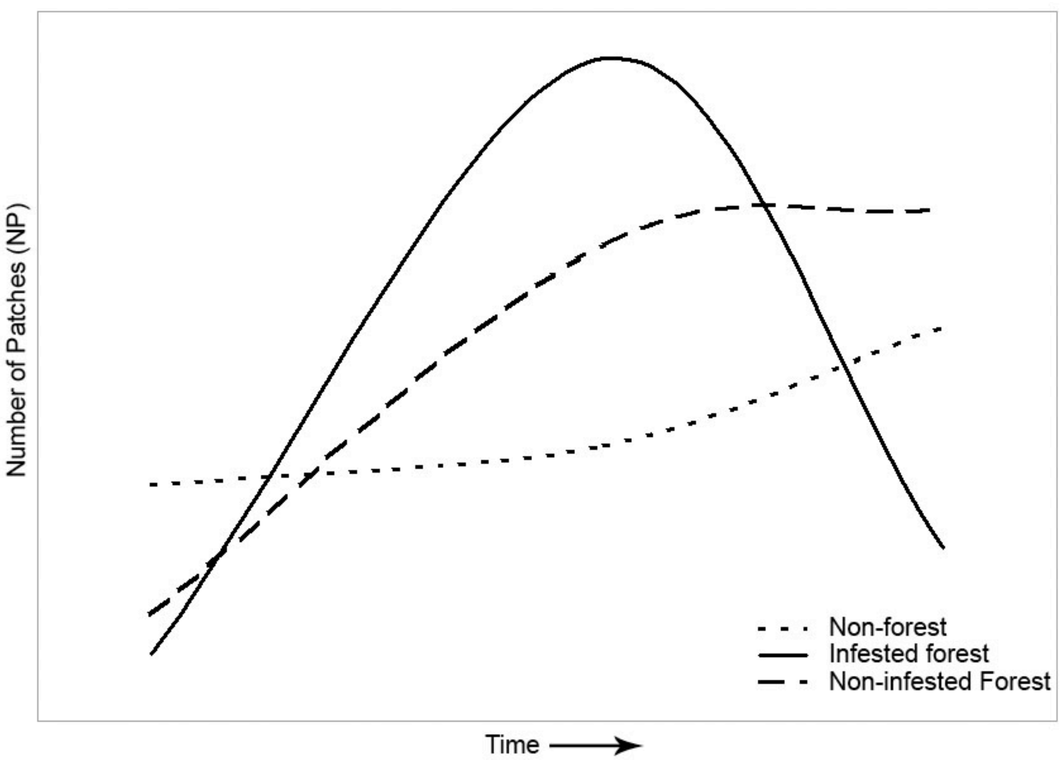

Figure 1. Expected results for number of patches (NP) landscape trajectory of non-forest, infested forest, and non-infested forest classes.

Figure 2 shows a hypothesised 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.

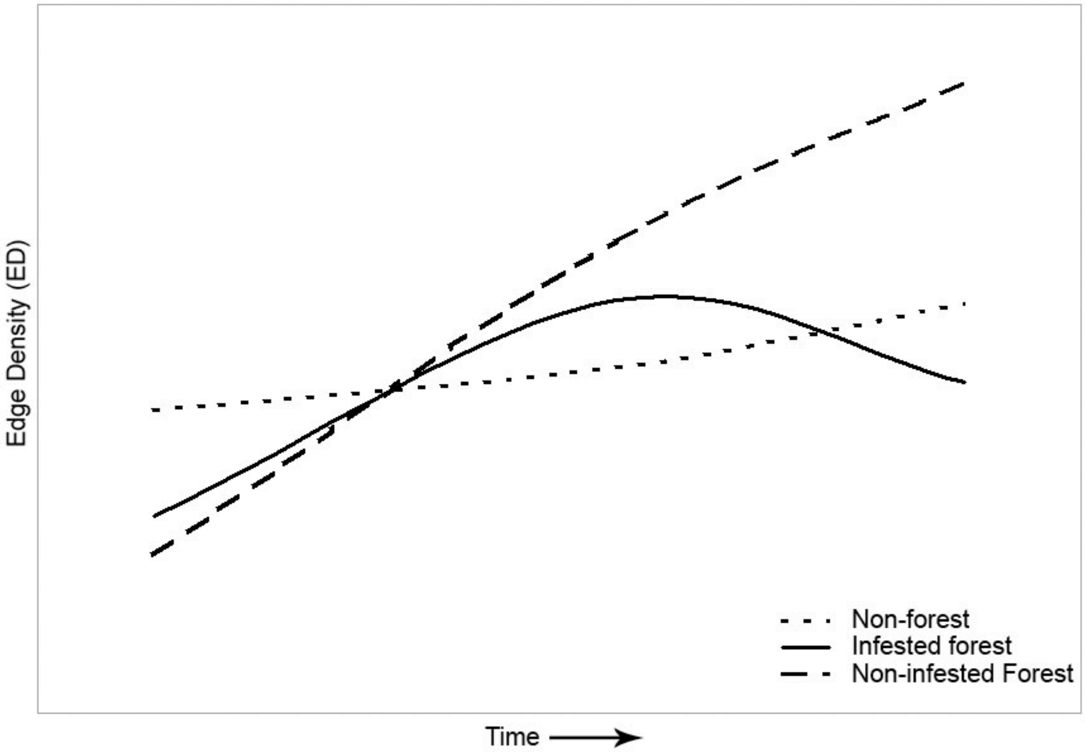

Figure 2. Expected results for edge density (ED) landscape trajectory of non-forest, infested forest, and non-infested forest classes.

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 & 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.

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