ABSTRACT

Human disturbances are the source of much contemporary landscape change, and constitute a major driver of wildlife population declines throughout the world and subsequent calls for enhanced monitoring schemes. The intensely used Alberta forest landscape, where the iconic grizzly bear (*Ursus arctos*) has recently been designated as threatened, is no exception to this trend. Monitoring of such large areas is typically conducted via multi-temporal land-cover maps derived from remote-sensing imagery, but automated and efficient change-analysis procedures that are both reliable and flexible for modern applications have yet to be fully developed. This thesis addresses these needs through the development of an innovative, semi-automated multi-temporal mapping framework that produces spatially consistent, temporally and categorically dynamic vegetation and land-cover maps. This framework is operationally relevant, and constitutes an effective foundation for contemporary landscape monitoring. The underlying conceptual model combines object-based classification and change-detection strategies with feature boundary-conditioning routines designed to maximize the spatial and thematic integrity of the resulting maps, without the need for manual editing. The model is capable of handling the basic landscape dynamics, including feature appearance, disappearance, succession, expansion, and shrinkage. The effectiveness of this framework, together with the formulation of transparent and efficient data-handling methods, is demonstrated through its application across a 40,000-km² forested study area in west-central Alberta. A multi-temporal database was used to track human-induced disturbances annually from 1998 to 2005, allowing a first-time, landscape-scale analysis of the impact of rates and directions of environmental change on grizzly bears.
PREFACE

This is a paper-based PhD thesis. Chapters 2, 3, and 4 have been published in peer-reviewed journals over the course of my studies. Chapter 5 will soon be submitted to an applied-ecology journal. I am intellectually responsible for all of these works. I was the primary person identifying the research questions, designing the research, undertaking the analysis, creating the graphical and tabular results, and writing the manuscripts.


ACKNOWLEDGEMENTS

During the course of this thesis, I was surrounded by a great team of supervisors, mentors and colleagues. Above all, I want to thank my supervisor, Dr. Greg McDermid, who instilled in me the confidence to take on and lead this research which soon proved to be a big undertaking, and helped me throughout these five years with sound and practical advice at all times, when the tasks seemed overwhelming and never-ending. The research environment he provided was always supportive and empowering. Also, I want to thank my mentor Dr. Steven Franklin, who, after one phone call in Winter 2004/2005, immediately encouraged me to continue my graduate schooling and to start a PhD in Calgary no later than May 2005. Dr. Franklin has guided my academic career since 1999 and since that time, I am grateful to have always been able to count on his advice and support whenever I needed it. With patience and great advice, Dr. Mryka Hall-Beyer supported me to develop my own research program at the pace that I needed, in order to become productive. Many thanks go to Dr. Hall-Beyer for all her help. I want to thank Dr. Marie-Josee Fortin who shared highly valued advice regarding habitat analysis and modelling. I feel very fortunate to have had the honour of working together with such an exceptional team over the course of this thesis. I am also very thankful to the external members of my PhD Defense committee, Dr. Allessandro Massolo and Dr. Paul Treitz for their constructive criticism during the defense and their positive feedback afterwards.

Much of the large amount of data processing would not have been possible without the many hours spent by Adam McLane, David Laskin, and Alysha Pape in our Foothills Facility for Remote Sensing and GISscience, and Jerome Cranston with the Foothills Research Institute Grizzly Bear Research Program. I thank you all for your
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I am also thankful for the close friendships I returned to after my two year absence. Families Seward and McDermid both helped to make us feel at home again in Calgary. The good times we shared together will always stay on my mind. And last but definitely not least, I thank my loving husband Guillermo and our dear children, Sophia and Rosa. Without you, I would have neither had the will nor the strength for taking and completing this journey.

Finally, I want to acknowledge that this research was carried out as part of the Foothills Research Institute Grizzly Bear Research Program, which was funded by an NSERC Collaborative Research and Development Grant, and many other project sponsors. I am also grateful for all the financial support I received from a National Science and Engineering Research Council (NSERC) PGS-B scholarship, a Canadian Forest Service Graduate Supplement (2005-2007), an Alberta Ingenuity Award and Research Grant (2006-2010), an ERDAS award for the Best Scientific Paper in Remote Sensing (third place in 2010), the ESRI Canada Scholarship Award (2008), Graduate Student Association Travel Award (2007), and the teaching assistantships and sessional-instructor appointments administered through the Department of Geography.
DEDICATION

I dedicate this thesis to the women of my family: my Mother, Eva Linke-Welte, my Grandmother, Anneliese Krah, my sister, Kathrin Welte, and my daughters, Sophia Anna and Rosa Lia.
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<tr>
<th>Abbreviation</th>
<th>Complete Name</th>
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<tbody>
<tr>
<td>AF</td>
<td>Area of Forest</td>
</tr>
<tr>
<td>AIC</td>
<td>Akaike Information Criterion</td>
</tr>
<tr>
<td>BD</td>
<td>Density of Natural Burns</td>
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<tr>
<td>CC</td>
<td>Crown Closure Map</td>
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<td>Cutblock Density</td>
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<td>CDP</td>
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<td>DD98/04</td>
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<td>DDN04</td>
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<tr>
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</tr>
<tr>
<td>ETM+</td>
<td>Enhanced Thematic Mapper Plus</td>
</tr>
<tr>
<td>EWDI</td>
<td>Enhanced Wetness Difference Index</td>
</tr>
<tr>
<td>FRIGBRP</td>
<td>Foothills Research Institute Grizzly Bear Research Program</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>--------------</td>
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</tr>
<tr>
<td>GBMOM</td>
<td>Grizzly Bear Map-O-Matic</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information System</td>
</tr>
<tr>
<td>LC</td>
<td>Land-cover Map</td>
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<tr>
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CHAPTER 1: INTRODUCTION

Human activities and disturbances have become the source of much contemporary landscape change, in part by altering the amount, spatial pattern, and character of global vegetation communities (Houghton 1994, Meyer and Turner 1994, Riitters et al. 2002). These human-induced land-cover changes have been identified as major causes of biodiversity decline and species endangerment (Hansen et al. 2001), highlighting the critical necessity to monitor habitats and populations through time (Balmford et al. 2003).

The public lands that comprise much of Alberta’s Rocky Mountain foothills are an example of a fast-changing forested landscape, and support intensive use by a variety of resource-extraction industries, including forestry, coal mining, and petroleum (Schneider 2002, Linke et al. 2005). This raises the questions of where and when disturbances have actually been occurring in this area, and how these may in turn be affecting Alberta’s native wildlife, such as the iconic grizzly bear (Ursus arctos): recently designated as a threatened species in the province (ASRD/ACA 2010).

For research questions like these, remote sensing has long been considered an essential tool for gathering data across large spatial extents and at relatively high temporal frequencies (Kerr and Ostrovsky 2003, Gillanders et al. 2008). However, many remote-sensing products can be criticized for presenting an overly-simplistic depiction of the natural landscape, due primarily to the ubiquitous use of single, catch-all maps consisting of broad land-use/land-cover categories. An alternative approach (McDermid et al. 2005) focuses instead on the characterization of continuous attributes of vegetation structure that can be combined with categorical land-cover maps in a GIS environment to
produce composite maps with many possible legends, which in the end allows for greater flexibility and support for a variety of applications (McDermid 2005).

With the growing availability of free, multi-temporal satellite imagery (e.g. Woodcock et al. 2008) and the critical need for landscape monitoring, we require research aimed at developing reliable change-analysis strategies (Gillander et al. 2008). Conventional change-detection relies primarily on post-classification analysis, whereby changes are detected using independently classified map products, derived normally from remote sensing. This procedure can lead to considerable amounts of spurious change arising from differential classification errors in the individual maps (e.g. Brown et al. 2000). As an alternative approach, McDermid et al. (2008) described a simple, bi-temporal object-based updating approach whereby change features, detected between time $T_1$ and time $T_2$, could be overlaid onto an existing classified map depicting conditions at $T_1$ to create a new updated map at $T_2$. However, small spurious objects (i.e. slivers), created along the boundaries of the change features, are a common by-product of this approach. Even if slivers are inconspicuous at normal visualization scales, they create spatial inconsistencies between the different map dates, creating a potential source of bias in landscape monitoring.

These and other problems related to automated change-detection procedures have forced most operational projects to resort to manual digitization and integration techniques (e.g. Loveland et al. 2002, Feranec et al. 2007). While skilled photo-interpretation can yield very precise and accurate products (Sohl et al. 2004), it is an exceptionally labour-intensive process, and is inefficient for monitoring projects covering large areas. Automated processing strategies that reduce labor costs while maintaining
accuracy and consistency remain “the Holy Grail of change detection” (Loveland et al. 2002 p. 1098).

We require remote sensing-based analytical techniques that are capable of creating spatially consistent and temporally dynamic time series of information in an efficient and automated fashion, without the need for manual editing. These techniques should be integrated into a larger framework that is suitable for representing both discrete and continuous phenomena at a variety of measurement scales, in order to accommodate the large variety of vegetation and land-cover attributes that are of interest to contemporary monitoring programs. This doctoral thesis research addresses these problems in both a theoretical and applied context.

1.1 Research Objectives

The overall research goal of this thesis was to develop a flexible and reliable multi-temporal monitoring framework that could be implemented in a longitudinal study aimed at documenting changes in the human footprint across the foothills of west-central Alberta, for the purpose of assessing their impact on the abundance of grizzly bears in the area. In order to pursue this overall goal, five specific research objectives were formulated:

1) To assess the impacts of slivers generated during the backdating and updating of raster-based land-cover maps on the types of quantitative metrics commonly used in landscape-monitoring programs;

2) To develop a conceptual model that outlines an automated map backdating- and updating-approach capable of creating a spatially consistent time series;
3) To develop and implement an overarching framework for performing flexible and reliable landscape monitoring using remote sensing;

4) To quantify the status and trends of recent disturbances in the west-central Alberta foothills; and

5) To assess how human-induced disturbance processes explain the spatial distribution and relative abundance of the region’s threatened grizzly bear population.

1.2 Organization of Thesis

This first chapter briefly introduces the role of multi-temporal remote sensing imagery for landscape monitoring, and highlights the pressing research needs. It also gives an overview of the specific research objectives to be addressed within this thesis, including the development of a sound conceptual and methodological monitoring framework that can be directed towards the multi-use Rocky Mountain Foothills landscape of Alberta, and its inhabitants, including grizzly bears. The pursuit of these objectives is presented in four self-contained research articles that together fit into one unified body of research. Chapter 2 investigates the necessity for maintaining spatial consistency across a multi-temporal land-cover trajectory in order to perform reliable change analysis (Objective 1). Using a case-study approach, this research explains and documents the impacts of generally overlooked slivers, located along the boundaries of individual change features, on landscape pattern analysis. Chapter 3 introduces the over-arching conceptual model that was developed for generating a time series of spatially consistent land-cover maps in an object-based environment (Objective 2). It provides the theoretical strategy for suppressing slivers and other spatial inconsistencies, and outlines the conceptual
framework for representing the basic landscape processes including feature appearance, disappearance, succession, expansion, and shrinkage, without the need for manual editing. These are illustrated here using simple theoretical examples. Chapter 4 develops the full theoretical and practical framework for producing spatially consistent, temporally and categorically dynamic land-cover maps for flexible and reliable landscape monitoring (Objective 3). Extensive detail is directed towards exemplifying the practical application of the conceptual framework, including its demonstration and implementation in the Rocky Mountain foothills of west-central Alberta between 1998 and 2005. Chapter 5 uses the results created in Chapter 4 to quantify and monitor the spatio-temporal development of disturbance features across the study area, and investigates the impact of these disturbances on the distribution and relative abundance of grizzly bears (Objectives 4 and 5). Chapter 6 summarizes the conclusions of this work, outlines the main contributions, and suggests potential directions for future research.
CHAPTER 2: THE INFLUENCE OF PATCH-DENEALATION MISMATCHES ON MULTI-TEMPORAL LANDSCAPE PATTERN ANALYSIS

2.1 ABSTRACT

Investigations of land-cover change often employ metrics designed to quantify changes in landscape structure through time, using analyses of land-cover maps derived from the classification of remote sensing images from two or more time periods. Unfortunately, the validity of these landscape pattern analyses (LPA) can be compromised by the presence of spurious change, i.e., differences between map products caused by classification error rather than real changes on the ground. To reduce this problem, multi-temporal time series of land-cover maps can be constructed by updating (projecting forward in time) and backdating (projecting backward in time) an existing reference map, wherein regions of change are delineated through bi-temporal change analysis and overlaid on to the reference map. However, this procedure itself creates challenges, because sliver patches can occur in cases where the boundaries of the change regions do not exactly match the land-cover patches in the reference map. In this paper, we describe how sliver patches can inadvertently be created through the backdating and updating of land-cover maps, and document their impact on the magnitude and trajectory of four popular landscape metrics: number of patches (NP), edge density (ED), mean patch size (MPS), and mean shape index (MSI). In our findings, sliver patches led to significant distortions in both the value and temporal behaviour of metrics. In backdated maps, these distortions caused metric trajectories to appear more conservative, suggesting lower rates.

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of change for ED and inverse trajectories for NP, MPS and MSI. In updated maps, slivers caused metric trajectories to appear more extreme and exaggerated, suggesting higher rates of change for all four metrics. Our research underscores the need to eliminate sliver patches from any study dealing with multi-temporal LPA.

2.2 INTRODUCTION

A key research topic in landscape ecology (LE) surrounds understanding the causes, processes, and consequences of land-use and land-cover change (Hobbs and Wu 2007). In addressing these issues, landscape pattern analysis (LPA) has emerged as an important tool for quantifying, tracking, and projecting the changes in a given landscape through time (Li and Wu 2007). Particular emphasis on the subject has been directed towards forests, where the aim is often to understand the effects of human disturbance on such issues as carbon cycling (Houghton et al. 2001), biodiversity (Hansen et al. 2001) and wildlife habitat (Pearson et al. 1999). Researchers in these areas have come to rely on multi-temporal satellite imagery – particularly the 35+ year archive from the Landsat mission (Woodcock et al. 2008) – as the foundation for detecting forest change (e.g. Coppin and Bauer 1996, Cohen and Goward 2004) and conducting subsequent LPA (e.g. Skole and Tucker 1993, Turner et al. 2003, Trani and Giles 1999, Huang et al. 2006).

Setting aside the question of the adequacy of the metrics themselves as landscape descriptors (e.g. Tischendorf 2001, Remmel and Csillag 2003, Fortin et al. 2003, Li and Wu 2004), one issue that can seriously constrain the validity of LPA in multi-temporal raster data sets is the presence of spurious change, i.e., differences between maps caused by classification and spatial errors rather than real changes on the ground.
The most common method for generating a multi-temporal series of maps for use in LPA studies involves the independent classification of remote sensing images from two or more different dates (e.g. Cayuela et al. 2006, Lung and Schaab 2006, Ward et al. 2006, Boentje and Blinnikov 2007, Kozak et al. 2007). This technique entails the exhaustive labeling of each pixel in an image into map categories – usually of land-cover or land-use type – for every date of interest in the time series. While the strategy appears theoretically sound, it is often troubled in practice by significant map integration challenges, wherein classification errors from independently-generated map products tend to compound themselves in the finished product. Time-sensitive variations in atmosphere, illumination conditions, vegetation phenology, soil moisture, satellite sensor configuration, and image-to-ground registration quality all contribute to the problem (Yuan and Elvidge 1998), and even slight spatial misalignments between the multi-temporal maps can cause spurious change-detection errors that may seriously distort representations of change (Carmel et al. 2001, Mas 2005). To date, only a few studies have investigated the propagation of map classification errors to errors in LPA (Wickham et al. 1997, Brown et al. 2000, Shao et al. 2001, Langford et al. 2006), and their prime focus has been directed on single-date analyses. As a result, the conclusions of these studies have been largely mixed and of limited value for extending inferences (Gergel 2006). However, concern surrounding the issue is beginning to mount. A recent study by Langford et al. (2006) concluded that there is potential for large metric errors in nearly every LPA study ever published, and Gergel (2006) emphasized the potentially serious consequences arising from our current inability to assess the direction and magnitude of metric inaccuracies arising from classification errors in base maps. In recognition of
these “hidden map errors”, guidelines regarding consistency in spatial resolution, data processing, accuracy levels, seasonality, and minimum mapping unit of independently-classified, remote-sensing derived maps, have recently been proposed (Shao and Wu 2008).

An alternative strategy for reducing the problem of compounding errors in independently-generated map products involves updating (projecting forwards in time) or backdating (projecting backwards in time) a base map through change analysis. In general terms, an existing base map (Map T₀) can be updated or backdated to represent ground conditions at a second point in time (Map Tₙ) through the overlay of change features acquired through bi-temporal change detection (Change Tₙ-T₀), and can be expressed in the general form

\[
\text{Map } Tₙ = \text{Map } T₀ + \text{Change } Tₙ-T₀ \quad \text{(Equation 2.1)}
\]

The strategy is attractive since it greatly reduces the number of pixels that require classification in Map Tₙ to only those that have undergone change (McDermid et al. 2008). No change areas that were determined to have remained constant between the two image dates – normally the vast majority of pixels in the area of interest – require no additional processing. While classification errors in the original base map (Map T₀) will carry through to the finished product, the introduction (and subsequent compounding) of new errors from independent classifications is vastly reduced (Feranec et al. 2007). The strategy can be extended across multiple time periods to create a spatially-consistent, temporally-dynamic time series, wherein the base map is treated as a stable reference for
newly-derived backdated and/or updated map products. However, the accurate detection, characterization, and seamless integration of change areas into the reference map are key factors governing the success of this approach (McDermid et al. 2008).

The detection and labeling of change areas between two unclassified remote sensing images can take on a variety of forms (Lu et al. 2004, Radke et al. 2005). However, one approach that is particularly suited to homogenous landscape units is object-based change detection (Blaschke et al. 2005, Desclée et al. 2006, Kennedy et al. 2007). In this strategy, change objects – groups of contiguous pixels delineated through automated segmentation routines – become the units for analysis. The term object in this context is synonymous with patch in LPA, and we will use both terms interchangeably.

McDermid et al. (2008) outlined the issues and challenges associated with change analysis and thematic map backdating and updating in an object-based environment, highlighting the need for high standards of spatial and thematic fidelity. A particular problem is posed by spatial errors caused by boundary delineation mismatches in objects that appear in both the change and reference map layers. Sliver objects are spurious polygons generated within the overlap zone of slightly different delineations of the same entity, and are a common byproduct of polygon overlay operations (Goodchild 1978, Chrisman 1989). While the issue is well-known in the GIS literature (e.g. Chrisman 1989, Edwards and Lowell 1996, João1998, Zhang and Goodchild 2002, Mas 2005), it has remained largely unreported elsewhere (but see Blaschke 2005, McDermid et al. 2008).

The LE community has yet to assess the impacts of spatial delineation errors generated during the backdating and updating of raster land-cover maps – referred to
hereafter as *slivers* or *sliver patches* – on LPA. This paper attempts to fill that gap, and seeks to determine the extent to which sliver patches distort the quantification of landscape pattern and change. We address this issue by (i) explaining how sliver patches can be easily and inadvertently created in the backdating and updating of land-cover maps, and (ii) documenting the relative impact of slivers on the magnitude and temporal trajectory of four commonly-used landscape metrics: number of patches (NP), mean patch size (MPS), edge density (ED), and mean shape index (MSI). We trace these four metrics over a seven-year time period across three case study areas in west central Alberta, Canada: a multi-use forested landscape undergoing high rates of change.

### 2.2.1 Backdating and Updating of Existing Land-cover Maps and the Creation of Slivers

An existing reference land-cover map (T₀) can be backdated or updated to reflect the land-cover conditions at a specific time period (T₋₁ or T₊₁) through the integration of classified change patches in the manner outlined in Equation 1. In the case of backdating, bi-temporal change detection between T₀ and T₋₁ is used to identify the land-cover patches which did not previously exist, or perhaps existed in an earlier successional stage. By assigning these change patches with the appropriate land-cover label and overlaying them onto the reference map, a *backdated map* (T₋₁) can be created (Figure 2.1A). The updating case operates in a similar manner, wherein change detection between T₀ and T₊₁ is used to identify newly-appearing land-cover patches, or perhaps existing patches that have undergone change. By assigning these change patches an appropriate land-cover labels and overlaying them on the reference map, an *updated map* (T₊₁) can be created (Figure 2.1A).
Figure 2.1: Backdating and updating of an existing reference land-cover map in a sample area of about 1 km². Change patches between consecutive image dates are identified and overlaid on the reference map with the appropriate land cover label: in the case of backdating, change patches I and II are classified as ‘upland tree’, and ‘barren’ respectively, to remove the barren patch I, and to reflect an earlier successional stage of herbaceous patch II; for updating, change patches I, II, and III are classified as ‘upland herb’, ‘shrub’, and ‘barren’ respectively, to introduce the new barren patch III, and to reflect the successional changes of existing land-cover patches I and II. Change patches that do not spatially match their counterparts in the reference map have the potential to generate maps with slivers (B) when compared to the spatially consistent maps (A).

The issue of sliver patches arises as follows: if the delineation of the change patches matches the delineation of the land-cover patches in the existing reference map, then no slivers will be created (Figure 2.1A). However, sliver patches will appear if the change patches delineated through change detection do not precisely match the relevant boundaries that exist in the reference map (Figure 2.1B). Boundary delineation mismatches can arise from spatial misalignments between data from different dates, but the overarching challenge stems from the depiction of hard boundary lines in areas that
may in reality represent more gradual, fuzzy transitions. Just as two photointerpreters will not produce the exact same delineations of forest stands – even when using the same imagery – automated segmentation algorithms working with two different input images are not likely to produce the exact same results.

In the case of backdating, if the change patches are slightly smaller than the corresponding land-cover patches in the reference map, then the area of omission will generate one or more artificial sliver patches. For example, the clearcut patch in the reference map at $T_0$ (barren patch, Figure 2.1B), may be identified as a change patch between $T_0$ and $T_1$, indicating that it was harvested within this time frame. The change patch, classified as ‘forest’, is now to be integrated in the reference map through GIS overlay, thereby erasing the barren clearcut patch in the backdated map ($T_1$). However, since the delineation of the change patch is slightly different than the delineation of the original barren clearcut patch (a difference depicted by red and black outlines in Figure 2.1B), slivers corresponding to the area of mismatch (blue outlines of change patch I in Figure 2.1B) will result. Similarly, slivers in the update direction are created by corresponding delineation mismatches between reference objects and change patches derived from future images (Figure 2.1 B). In the presence of slivers, LPA based on multiple map dates may inadvertently generate erroneous metrics that lead to false conclusions about the magnitude and direction of change. Of particular relevance to this study is not the removal of these sliver patch errors, but rather how they manifest themselves during the backdating and updating of landscape maps, and their subsequent impact on multi-temporal LPA.
2.3 Methods

2.3.1 Multi-temporal Map Production

The study area for this research was located in the west-central portion of Alberta, Canada (Figure 2.2), where the Foothills Research Institute Grizzly Bear Research Program (FRIGBRP) monitors land-use and land-cover conditions as part of its ongoing research on grizzly bear habitat selection, health, and genetics (Stenhouse and Graham 2007). The main agents of land-cover change on this landscape are human activities related to forestry, petroleum development, mining, and road construction; though natural disturbances such as fire and insect defoliation also occur.

Figure 2.2: Location of three 13 x 13 km case study areas representing three levels of forest change between 1998 and 2005.
In monitoring human activities in the region, FRIGBRP personnel have used change-detection strategies to transform an existing ten-class land-cover reference map depicting 2003 conditions (McDermid 2005) into a multi-temporal time series of land cover maps covering the period 1998 to 2005 (McDermid et al. 2008). In pursuing this work, object-based change-detection procedures were used to generate backdated (1998-2002) and updated (2003-2005) land-cover maps that contained change patches created by forestry, mining, and petroleum activities. Change analysis was performed on an annual series of summer Landsat Thematic Mapper and Enhanced Thematic Mapper Plus images (path 45, row 23), using the enhanced wetness difference index (EWDI) method of Franklin et al. (2001). The image pixels of each annual difference layer were segmented into homogenous objects on the basis of similar spectral values using Definiens Professional 5.0 (Definiens 2006). Afterwards, these objects were manually thresholded into change and no change objects on the basis of visual inspection of the respective image pairs. The change objects of all annual difference layers were merged, exported to ArcMap 9.2 (Esri 2005), and labeled with land-cover categories using temporal decision rules to create annual change maps for integration with the original reference map. Despite a nominal 100% change-detection accuracy (Kappa = 1.0), the resulting annual land-cover maps contained sliver patches generated by boundary delineation mismatches between change patches and land-cover patches in the 2003 reference map (McDermid et al. 2008).

2.3.2 Sliver Corrections to Backdated and Updated Maps

In order to investigate the influence of sliver patches on multi-temporal LPA, we chose three 13x13 km case study areas (Figure 2.2) for detailed analysis. The size of the areas
was selected as a compromise balancing the effort necessary to generate sliver-corrected maps with the need to work with representative areas of forest. The level of change in the three areas varied from low (area 1) to high (area 3). The mean number of annual change patches ranged from 3 to 21, and mean area of annual change patches varied from 58 ha to 368 ha. In total, the change patches corresponded to 1.4%, 11.9%, and 15.2% of the total case study extents for areas 1, 2, and 3, respectively (Table 2.1). While approximately two sliver patches were associated with each change patch across the three study areas on average, the areal coverage of slivers associated with the total area of change patches varied (McDermid et al. 2008). The largest coverage of sliver patches occurred in area 1, with a mean area of 0.12 ha per ha of change; the lowest occurred in area 2, with a mean area of 0.3 ha (Table 2.1).

In order to create validation layers representing a geometrically-accurate time series across each case study area, we removed the sliver patches from the annual land-cover maps. We accomplished this using an algorithm that identified and classified

<table>
<thead>
<tr>
<th>Case Study Area</th>
<th>Amount of Forest Change Patches</th>
<th>Associated Slivers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Annual Area</td>
<td>Total Area</td>
</tr>
<tr>
<td></td>
<td>Mean (ha)</td>
<td>Absolute (ha)</td>
</tr>
<tr>
<td></td>
<td>St. Dev.</td>
<td>Relative (%)</td>
</tr>
<tr>
<td>1 – Low Change</td>
<td>57.8</td>
<td>231</td>
</tr>
<tr>
<td>2 – Moderate Change</td>
<td>288.5</td>
<td>2019</td>
</tr>
<tr>
<td>3 – High Change</td>
<td>368.3</td>
<td>2576</td>
</tr>
</tbody>
</table>
mismatch areas (i.e. small polygons enclosed by misaligned boundaries: the blue outlines in Figure 2.1B), from an intermediate vector data layer created by intersecting the boundaries of the total change layer with those of the 2003 reference map. Among the population of mismatch areas, we identified sliver polygons (polygons which would create sliver patches upon change integration) on the basis of size, shape, and context to change patches. Only small (maximum 10 pixels), or elongated (minimum perimeter-area ratio of 20) polygons that were fully contained within a 4-pixel (120m) buffer outside the boundaries in the change data layer were selected. We then appended these sliver polygons to the change data layer, and subsequently merged each sliver polygon with the closest adjacent change polygon, in order to produce aligned change boundaries that were consistent with the reference land-cover map. An ArcObjects script executing this algorithm is freely available from the authors upon request. Using the revised change data layers as the basis for change integration, we backdated and updated the 2003 reference map to create a spatially-consistent time series that was free of sliver artifacts.

2.3.3 Landscape Pattern Analysis and Sliver Impact Characterization

We used Fragstats 3.3 build 5 (McGarigal et al. 2002), to calculate NP, ED, MPS, and MSI at the landscape level across each case study area from 1998 to 2005, for both the original and corrected map series. The computations were performed using the 8-cell (Queen’s case) patch neighborhood rule, with the study area boundaries excluded. Since the landscape area and classification schemes were constant across each case study area (1690 km²) throughout the eight years, there were no deviations in spatial scale or thematic resolution to interfere with metric computations. In order to characterize sliver
impacts on multi-temporal LPA, the metric values of the uncorrected time series (i.e. maps with slivers) were compared to the ones derived from the corrected time series (i.e. maps without slivers). Since the only difference between the two time series was the presence or absence of slivers, any deviation in metric values was assumed to be attributed to this factor. The corrected map series was therefore treated as truth, and formed the basis for subsequent evaluation. While recognizing that land-cover composition (i.e. proportion of landscape occupied by a given land-cover or change class) influences the characterization of landscape pattern and associated metrics (e.g. Gardner et al. 1987, Neel et al. 2004), we assumed that the land cover area differences between the two map series were small enough (on average less than 0.1% of the total landscape area) to be disregarded in this analysis.

In order to quantify the impact of sliver patches on the direction and magnitude of metrics, we calculated the absolute percent metric error ($E_a$) as

$$E_a = \frac{\chi_s - \chi_c}{\chi_c} \times 100\%$$

(Equation 2.2)

where $\chi_s$ is the metric value from map with slivers and $\chi_c$ is the metric value from the sliver-corrected map. In addition, we also calculated the relative percent metric error ($E_r$) designed to normalized for the amount of change in each landscape as

$$E_r = \left( \frac{\chi_s - \chi_c}{\chi_c} \times 100\% \right) / A \times 100ha$$

(Equation 2.3)

where $A$ is the total area of change in hectares. To facilitate interpretation, we multiplied the entire calculation by 100 ha to reduce the number of decimals, thereby changing the error estimate to present relative percent metric error *per 100 ha of change*. The purpose
of $E_r$ was to allow for direct metric error comparisons among the three case study areas. Summary statistics of these annual error calculations were computed for each area.

In order to measure the impact of slivers on the temporal trajectory of landscape metrics, we compared the divergence of annual trends derived from the two different map series. Instead of showing the raw metric values over time, we calculated and plotted cumulative percent metric changes for each map series in each area, treating the first year (1998) of the series as the baseline. The cumulative percent metric change between the first year in the time series and any other year in the time series ($\Delta_{T1-Ty}$) was calculated as

$$\Delta_{T1-Ty} = \frac{X_{T1} - X_{Ty}}{X_{Ty}} \times 100$$

(Equation 2.4)

where $X_{T1}$ is the metric value for the first year in the time series and $X_{Ty}$ is the metric value for any other year in the time series. Differences in the direction and the rate of changes in metric trajectories between the maps with slivers and the correct maps could henceforth be directly compared in context to the amount of annual forest loss within and among case study areas.

Loss of forested area was driven by the detected annual forest change – the process whereby forested land-cover is converted to barren ground – and presented in the form of annual percent forest area coverage relative to the total landscape area. The actual estimate was calculated from the sliver-corrected maps only, since the deviation of these estimates in the map with slivers were below any discernable magnitude (on average less than 0.1 units) in a graph.
2.4 RESULTS

In all case study areas, the presence of slivers led to substantial quantitative metric discrepancies when compared to the estimates derived from the sliver-corrected maps. We observed consistent underestimations of MPS and MSI and overestimations of NP and ED (Table 2.2). The magnitude of the absolute mean percent metric error increased with increasing forest change, with the largest absolute errors observed in case study area 3 (high change) for all four metrics. Within each case study, the standard deviations of these mean metric errors indicated large annual variations (Table 2.2), ranging to equivalent maximum variations of between 30% and 60% of the mean. However, when normalizing the percent metric error for total area of forest conversion, the largest relative errors in all four metrics were found in area 1 (Table 2.2), where the highest areal coverage of slivers had been observed (Table 2.1). The smallest relative errors were found in area 3 (Table 2.2), where the lowest areal sliver coverage occurred (Table 2.1). Across all areas, NP and MPS exhibited consistently larger absolute and relative errors than ED and MSI (Table 2.2).

Table 2.2: Mean and standard deviations of absolute and relative annual percent errors of selected metrics, number of patches (NP), edge density (ED), mean patch size (MPS), and mean shape index (MSI), in uncorrected maps containing sliver patches across the three case study areas. Relative metric errors were normalized for total area of change on the basis of 100 ha.

<table>
<thead>
<tr>
<th>Case Study Area</th>
<th>Absolute % Error (Mean, St. Dev.)</th>
<th>Relative % Error/100 ha of Change (Mean, St. Dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NP</td>
<td>ED</td>
</tr>
<tr>
<td>1 - Low Change</td>
<td>7.9, 1.8</td>
<td>1.6, 0.8</td>
</tr>
<tr>
<td>2 - Moderate Change</td>
<td>30.6, 13.6</td>
<td>4.3, 2.7</td>
</tr>
<tr>
<td>3 - High Change</td>
<td>42.5, 6.1</td>
<td>6.1, 3.3</td>
</tr>
</tbody>
</table>
The metric trajectories for the corrected time series, relative to the year 1998, paralleled the trends portrayed by the loss of forest area across all case study areas between 1998 and 2005 (Figure 2.3). Conforming to general expectations, NP and ED increased while MPS and MSI decreased with increasing forest loss, and remained static between years where no change in forest loss was displayed (i.e. between years 2000-2001 and 2003-2005 in case study 1, Figure 2.3). The one exception to this observation occurred in case study 3 between the years 2002 and 2003 (Figure 2.3, B-3, D-3, E-3). Despite the increase in forest loss, NP and MSI decreased slightly while MPS increased slightly, due to the aggregation of several adjacent change patches.

In regards to the observed metric trajectories of change over time, the presence of slivers led to divergences in the direction of change and/or in distortions of the rate of change for all four metrics (Figure 2.3). The trajectory of ED showed only a distortion in the rate of change, while the direction of change was the same as that observed in the sliver-corrected time series (Figure 2.3, C). Notwithstanding, ED increased at a slightly lower inter-annual rate in the backdated maps (between 1998 and 2003) and at a slightly higher inter-annual rate in the updated maps (between 2003 and 2005) (Figure 2.3, C). It is important to note that we could only make observations related to changes in the update direction in case study areas 2 and 3, since no forest change was observed in case study area 1 between 2003 and 2005.

NP, MPS and MSI demonstrated highly variable inter-annual trends, and even inverse directions of change compared to the sliver-corrected time series over the backdated time frame (Figure 2.3, B, C, E). For example, in the first years of the backdated time series, MPS and MSI were observed to decrease in response to loss of
Figure 2.3: Trajectory of A) loss in percent forest area, and percent change in B) number of patches (NP), C) edge density (ED), D) mean patch size (MPS), and E) mean shape index (MSI) over time (1998 and 2005) relative to the values in 1998 in areas of low (case 1), moderate (case 2), and high (case 3) annual mean forest change.
forested area, with rates of change either similar (Figure 2.3, D-1, E-1) or lower than the ones displayed by the sliver-corrected map trajectories (Figure 2.3, D-2&3, E-2&3). Following these initial decreases however, MPS and MSI displayed altered directions of change and increased to either similar (Figure 2.3, D-1, E-1) or considerably higher levels to those observed in 1998 (Figure 2.3, D-2&3, E-2&3), despite continued forest loss. A similar divergence in the direction of change was also observed in the trajectory of NP, where NP decreased regardless of the growing forest loss over some of the years in the backdated time frame (Figure 2.3, B). Only in the updated time frame (between 2003 and 2005) did the direction of change for NP, MPS and MSI follow the expected trend associated with continuous forest loss (Figure 2.3, A,B,D,E). However, the presence of slivers appeared to slightly inflate the inter-annual rates of metric change compared to those observed in the sliver-corrected maps.

2.5 DISCUSSION

The underlying motivation of this research was to determine the extent to which sliver patches, created through the backdating and updating of a reference land-cover map with change analysis, distorted the quantification of (i) landscape pattern and (ii) changes in landscape pattern through time. Regarding the first issue, substantial overestimations in NP and ED and underestimations in MPS and MSI were observed in each of the annual maps that contained slivers. Since slivers were associated with change areas, it makes sense that larger absolute metric errors occurred in areas with higher amounts of change. However, the magnitude of these errors may not depend solely on the amount of forest change, since the areal coverage of slivers may also be related to the particular
configuration of the landscape mosaic and the spatial distribution of change patches. The largest boundary delineation mismatches, resulting in the highest areal coverage of slivers, were displayed in the area containing the lowest amount of initial forest area in the year 1998 (case study 1), which was also the area where highest relative metric errors were observed. Ranking the other two case study areas by areal sliver coverage and initial forested area also revealed an overall inverse relationship between original landscape fragmentation (i.e. forested area) and sliver areal coverage, resulting in corresponding relative metric errors.

Fragmented landscapes contain more edges between land-cover classes, and this pattern has been shown to lead to increased classification errors related to the assignment of mixed pixels (Hlavka and Livingston 1997). Uncertainty in boundary delineation may be related to the fragmented structure of landscapes, yielding for example higher errors in the estimates of areal proportions of the given land-cover classes in more fragmented landscapes (Roesch et al. 1995, Jeanjean and Archard 1997). Considering that proportional areal measures strongly impact pattern quantification and behaviour of landscape metrics (e.g. Gardner et al. 1987, Neel et al. 2004), Gergel (2006) described a “chicken-and-egg problem”, wherein the original landscape structure may impact the resulting areal proportion measures derived from a classified image. In our study, metric error was quantified based on deviations from the corrected map, under the assumption that the presence and absence of slivers was their dominant driver, and differences in the areal proportion estimates were sufficiently small to be neglected. Since the average number of slivers produced per change patch was consistent across the three case study areas, inferences about the direction of metric errors based on this assumption are valid.
However, the difference in magnitudes of the relative metric errors across study areas is expected to be slightly inflated by the differences in metric values, as caused by the minuscule differences in proportional areal measures. The quantification of the impact of such deviations on pattern metrics was beyond the scope of this study, but, as already outlined by Gergel (2006), is a topic deserving of further attention.

A related concern regarding our approach for sliver correction involves the potential removal of real change patches, particularly small changes that could be mistaken for slivers. For example, a windthrow along the boundary of a cut block could appear as an elongated, narrow change patch that fit the size, shape, and context criteria for slivers. A filtering strategy designed to suppress slivers might inadvertently remove these real changes along with targeted spurious ones. However, our technique restricts sliver identification to areas appearing in the mismatch layer (i.e., the GIS intersect of the change layer and reference layer). As such, small patches appearing exclusively in the change layer remain untouched.

Comparisons of the relative sensitivities to the presence of slivers among the four different metrics showed errors to be consistently largest in NP and MPS, moderate in MSI, and lowest in ED. This observation was expected, since each individual patch has equal weight in the computation of NP, MPS and MSI. As a result, the presence of numerous individual sliver patches (by definition small) on a map will cause a strong increase in NP and a strong decrease in MPS. Since sliver patches contained some variability in shape, the impact on MSI was slightly lower on metric error than in NP and MPS; however, on average their complexity was lower than the integrated change patches, thereby decreasing the overall shape complexity of the mosaic. The computation
of edge density, in contrast, did not include the individual patches per se, but was rather a function of total edge length. Therefore, the amount of additional edge being created by small sliver patches led to a comparatively small impact on edge density. These differences in metric error magnitude have previously been documented by studies investigating the impact of classification differences and errors. For example, Brown et al. (2000) compared metric values obtained from classifications of different images of the same area at the same time, and showed that NP and MPS displayed higher relative deviations than ED. Similarly the systematic simulation study by Langford et al. (2006) showed that the magnitude of metric errors were generally larger for MPS and NP than for MSI.

Regarding the analysis of landscape patterns over time, the trajectories of the four metrics in the sliver-corrected map series generally reflected the trajectories of forest loss that would be expected. The associated increases in ED and NP, and decreases in MPS and MSI over time have been well-documented as part of the fragmentation syndrome wherein increasing forest losses are mirrored by associated changes in these metrics (Tinker et al. 1998, Staus et al. 2002). However, depending on the particular spatial distribution of the disturbances, the responses of individual metrics may vary (Wickham et al. 2007). We observed this in case study 3 between the years 2002-2003, where change patches were generally more numerous, smaller and in closer proximity to each other than in the other two case study areas. The presence of slivers in the uncorrected maps, however, caused substantially different landscape change patterns for all four metrics, misrepresenting the consequences of forest area conversion and rendering such analysis unreliable.
We limited our analysis to four metrics, despite the wealth of other metrics describing other aspects of landscape structure, such as patch isolation, proximity, landscape contagion etc. (e.g. O’Neill et al. 1988, Gustafson et al. 1998, Hargis et al. 1998, McGarigal et al. 2002). While the sliver sensitivity of other metrics could be speculated here, the subject is outside the scope of the present study. Once again, our purpose was to (i) investigate the impact of slivers on widely understood aspects of structure and (ii) demonstrate the critical need for suppressing slivers in multi-temporal LPA. Leitão et al. (2006) recommended the use of area-weighted metrics as a means of reducing the influence of very small patches, which in this context could be interpreted as a potential sliver fix. However, this strategy greatly restricts the number of available metrics, and ignores the potentially-important contributions of small patches to the landscape mosaic.

On a similar note, it is anticipated that thematic resolution and spatial scale could also affect the sensitivity of the investigated metrics to the presence of slivers. It has been demonstrated previously that changing numbers of land-cover categories may significantly affect landscape metrics and their ability to detect landscape changes (Buyantuyev and Wu 2007). A landscape with higher thematic resolution may on average contain more numerous and smaller land-cover patches. In such a case, sliver patches would be expected to impact the quantification of pattern to a lesser degree than in a landscape with a lower thematic resolution, since the difference in overall number of patches attributable to sliver patches would be proportionally lower. Distortions in the direction of pattern change over time would be expected to follow similar trends, although with reduced distortions in the rates of change.
With the recent release of the Landsat archive (Woodcock et al. 2008), it is anticipated that the issue of patch-delineation errors surrounding the backdating and updating of medium-resolution satellite imagery will become an increasingly-important factor in multi-temporal LPA studies based on this imagery. However, even in the advent of new high-spatial-resolution imagery, it can be argued that the issue of patch-delineation mismatches and associated sliver patches remains relevant. While changing spatial scale (in grain and extent) has a significant effect on landscape metrics *per se* (Wu 2004), we believe that the occurrence of slivers and their impact on metrics will remain. Due to the fractal nature of landscapes, boundary length and complexity increase indefinitely with increasing spatial resolution (Castilla et al. 2008), along with the potential for multi-temporal patch-delineation mismatches. As a consequence, it is expected that while sliver patches generated by high-resolution sensors may be proportionally smaller, their number and impact on metrics will be undiminished.

### 2.6 Conclusions

In summary, updating and backdating an existing, classified reference map through change analysis constitutes an effective alternative to the independent classification of multi-temporal remote sensing images, thereby limiting the occurrence of spurious changes. However, the overlay operation of change patches can inadvertently generate slivers in the finished map products, due to slight patch-delineation mismatches between the change and reference images. In this study, we have demonstrated that these slivers can induce large biases in patch-based metrics such as NP, ED, MPS, and MSI, and thereby distort the quantification of changes in land use and land cover inferred from landscape pattern analyses. In the case of backdated maps, this phenomenon may cause
metric trajectories to appear more conservative, suggesting lower rates of change in the case of ED, and even inverse rates of change in the case of NP, MPS and MSI. In updated maps, this bias makes metric trajectories appear more extreme and exaggerated, suggesting slightly higher rates of change for all four metrics. While area-weighted metrics have been proposed as strategies for avoiding the omission and addition of very small patches from compromising LPA, their sole application may constrain the aspects of landscape structure that can be measured. Our findings support those of Goodchild (1980) in suggesting that slivers create serious problems in spatial datasets, and need to be suppressed. With the growing awareness of misclassification errors and their impacts on landscape metrics, and with object-based approaches to change monitoring becoming more common, attention needs to be paid to the avoidance of spurious change introduced by patch-delineation mismatches.

2.7 Acknowledgements

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CHAPTER 3: A CONCEPTUAL MODEL FOR MULTI-TEMPORAL LANDSCAPE MONITORING IN AN OBJECT-BASED ENVIRONMENT

3.1 ABSTRACT

Remote sensing plays a critical role in contemporary monitoring programs, but our strategies for processing these data using automated procedures are not always reliable. In particular, the task of separating real from spurious changes remains problematic, especially in an object-based environment where differential errors in classification quality, spatial registration, scene illumination, resolution, and object delineation have forced some operators to adopt labor-intensive visual-interpretation strategies, or employ manual interaction on an object-by-object basis. In this paper, we present an updated summary of our new disturbance-inventory approach to land-cover monitoring that combines object-based classification and change-detection strategies with boundary-conditioning routines designed to maximize the spatial and thematic integrity of the finished products. With this approach, the final maps are only altered in regions of confirmed change, and spurious gaps, slivers, stretches, and encroachments are avoided. The approach constitutes an innovative, efficient, and transparent framework that can handle all the basic landscape dynamics, including feature appearance, disappearance, succession, expansion, and shrinkage, without the need for manual editing.

3.2 INTRODUCTION

Remote sensing plays a key role in contemporary monitoring programs designed to track changes in land use and land cover through time, and in this manner supports a large number of regional (Yan et al. 2007, Jones et al. 2009, Wang et al. 2009), national (Homer et al. 2007, Wulder et al. 2008, Zhang and Zhang 2007), and international (DeFries and Townshend 1994, Potapov et al. 2008, Pekkarinen et al. 2009) efforts aimed at assessing the impacts of human activities and environmental change. In particular, object-based strategies for classification (Burnett and Blaschke 2003) and change detection (Desclée et al. 2003, Jensen and Tullis 2008, Blaschke 2005) comprise a promising set of analytical techniques designed to generate geographic information system (GIS)-ready information layers that integrate easily with existing data sets (Benz et al. 2004). However, previous studies have highlighted issues related to the influence of spatial (Townshend et al. 1992, Sundaresan et al. 2007) and thematic (Brown et al. 2000, Shao and Wu 2008) inconsistencies on multi-temporal change analysis, particularly when performed in an object-based environment (McDermid et al. 2008, Linke et al. 2009a). As a result, many operational monitoring programs have opted for more reliable but labor-intensive manual interpretation strategies (Sohl et al. 2004, Loveland et al. 2002, Feranec et al. 2007) which are designed to maximize consistency, though often at the expense of spatial or temporal coverage. There is a strong need for the development and articulation of automated or semi-automated change-detection procedures that reduce labor costs while maintaining the required spatial and thematic integrity.

Landscape monitoring entails the analysis of landscape conditions across two or more time periods in an effort to reveal changes occurring on the surface of the Earth.
These changes are generally summarized through landscape pattern analyses (LPAs), wherein various metrics are used to calculate transitions in the structural composition (e.g. area of given cover types, diversity of cover types) and configuration (e.g. edge density, interspersion) of land cover through time. The actual measurements are commonly extracted from classified land-cover data, derived from remotely sensed images and stored in a GIS; with – unfortunately – little attention directed towards the effects of map misclassifications (Hess 1994, Shao and Wu 2008). Classification errors in such products may stem from various sources, including radiometric and geometric calibrations, data handling, and analysis procedures (Lunetta et al. 1991, Yuan and Elvidge 1998, Roy 2000). However, the distribution of errors is not random. Many errors are spatially autocorrelated around the boundaries of map entities, and are largely attributable to data misregistration and/or mixed pixels (Congalton 1988). It is precisely in fragmented landscapes, with many edges existing between cover classes, where interest in conducting a LPA is highest, therefore causing pronounced concern about the associated errors in these studies (Gergel 2007).

Early research on the impact of uncertainty on LPA, performed on single-date classifications with varying simulated classification errors, demonstrated that landscape metric errors were no greater than the misclassifications themselves, and therefore metrics did not appear to amplify the uncertainty inherent in the underlying base maps (Wickham et al. 1997). When viewed from a monitoring perspective, however, more recent investigations have shown that the comparison of multi-date land cover maps tends to compound any errors present in the initial classifications, and can therefore yield large amounts of spurious change (Singh 1989) (Figure 3.1). For example, Linke et al.
(2009a) documented the impact of spurious changes in a LPA of a fragmented landscape in west-central Alberta, Canada undergoing rapid forest conversion from industrial development. In that study, spatial inconsistencies led to serious distortions in the observed trajectory of edge density, mean patch size, number of patches, and mean shape index through time; a result that supported Langford et al.’s (2006) assertion that undocumented map errors could undermine the findings of nearly every LPA ever published.

![figure 3.1](image)

**Figure 3.1:** A hypothetical example of geometric inconsistencies observed between two independent delineations of the same object at two different times. The object at time $T_{+1}$ appears to have increased in edge length and shape complexity in relation to that at time $T_0$, raising the question as to whether this change is real or due to differences in classification, segmentation, or image registration.

To summarize, effective landscape monitoring requires the use of land-cover maps with high standards of thematic and geometric consistency, so that differences between map dates accurately reflect real changes occurring on the ground. With little doubt, this goal is best achieved through the use of manual procedures performed by skilled photo-interpreters, since the human eye is well-equipped to detect the relatively rare, localized, and spectrally ambiguous events that typically characterize change events.
(Sohl et al. 2004). For example, the United States Geological Survey’s Land Cover Trends project used manual interpretation strategies to derive “back and forward classifications” from an edited version of the 1992 North American Landscape Characterization for five-year intervals between 1973 and 2000 (Loveland et al. 1999, 2002). However, the labor-intensive nature of such procedures places practical limitations on the scope of the underlying monitoring effort – the Land Cover Trends project was limited to 20-by-20 km sample blocks, for instance – and automated or semi-automated approaches to monitoring that reduce labor costs while maintaining accuracy and consistency remain “the Holy Grail of change detection” (Loveland et al. 2002).

While a great deal of progress has been made in object-based classification and change-detection procedures (e.g. Walter 2004, Desclée et al. 2003, Blaschke 2005), the task of separating real from spurious changes in operational monitoring programs using automated strategies geared towards wall-to-wall mapping remains problematic. For example, Feranec et al. (2007) used computer-aided visual interpretation of Landsat imagery to delineate change objects manually across 29 European countries (4.5 million square kilometers) between 1990 and 2000 as part of the IMAGE and CORINE Land Cover 2000 project. The methods were deemed necessary because of the challenges associated with identifying real changes consistently using automated techniques. Faced with similar issues, Gamanya et al. (2009) relied on manual interaction by skilled operators to deal with spatial inconsistencies in a post-classification analysis of object-based maps used to document changes in the city of Harare, Zimbabwe between 1989 and 2002.
Our research (McDermid et al. 2008, Linke et al. 2009a, 2009b) has focused on the development of an automated approach to landscape monitoring that involves creating time series of reliable, spatially consistent land-cover maps using object-based processing strategies. Applied correctly, our methods permit the application of LPA and change analysis techniques in a manner that avoids the labor-intensive, manual intervention methods documented above. This approach revolves around the identification, boundary conditioning, and integration of thematically classified change objects stored in a GIS vector database: a so-called disturbance inventory (Linke et al. 2009b). In its basic form, the disturbance-inventory framework to multi-temporal landscape monitoring consists of (i) identifying dynamic features that occur over the extent of the monitoring horizon (i.e. objects that appear, disappear, and/or change thematically), and (ii) overlaying these features onto a previously classified reference map in a manner that represents changes occurring on the ground. The framework can handle all the basic landscape dynamics as represented by the vector (object-based) data model, including feature appearance, feature disappearance, feature shrinkage, feature expansion, feature persistence, and feature succession. Spatial consistency across the time series is achieved by maintaining the constant delineation of static features (i.e. objects that do not change over the monitoring horizon), and performing boundary-conditioning routines on dynamic features to ensure their proper integration into the reference map.

The objective of this short paper is to provide an updated summary of the disturbance-inventory framework to landscape monitoring, and describe its use of object-based classification and change-detection techniques for creating a spatially consistent
time series. Our presentation here is largely conceptual; readers interested in a more technical description of the framework and its successful sample application to a 40,000 km² study area in west-central Alberta over an eight-year time frame are directed to Linke et al. (2009b – Chapter 4 of this PhD Thesis).

3.3 THE DISTURBANCE-INVENTORY APPROACH TO BACKDATING AND UPDATING LAND-COVER MAPS

The disturbance-inventory approach to landscape monitoring involves identifying and then modifying an existing object-based reference map of land cover. By modifying the reference map in areas of documented change, additional maps that represent time steps over the specified monitoring horizon are thereby constructed (Figure 3.2). A prerequisite for this approach is that the existing map at the reference year T₀ must foremost meet acceptable spatial and thematic quality standards.

In order to facilitate change detection, a multi-temporal image stack covering the desired time span is prepared, and forms the basis for identifying land cover-conversion disturbances, which are to appear, disappear, and/or change attributes with respect to the reference map (Step 1, Figure 3.2). Standard bi-temporal change-detection techniques (e.g. semi-automated image differencing and thresholding strategies) between consecutive images (e.g. T₁–T₀ in Step 2, Figure 3.2) are used to create a binary change/no change layer, which is then segmented to create discrete entities. These change entities are hereafter referred to as dynamic objects. Each dynamic object is stored as a unique record in a spatial database with the following attributes: (i) unique identifier (ID), (ii) time of origin (i.e. disturbance year), and (iii) disturbance type (Figure 3.2). The time of origin corresponds to the date of the image where the dynamic object
Figure 3.2: A flow chart summarizing the conceptual framework for the disturbance-inventory approach to generating spatially consistent maps through the updating and backdating of a categorical land cover map (treated as the reference map) at time $T_0$ over a given monitoring horizon (given here as $T_{-1}$ to $T_{+1}$).

first appears, and is important for tracking its age and appearance (i.e., land cover attribute) over time. The disturbance type may be derived from a combination of spectral, spatial, and contextual information using a decision-tree classification approach (Linke et
al. 2009b), though other methods are certainly applicable. This attribute is used to infer the land-cover class that the particular disturbance type can assume over time (e.g. a clearcut is initially barren, and will eventually become forest after a few decades), and may also imply the spatial overlay order of appearance in areas of overlap (e.g. a new road built on top of a previously burned area). After each dynamic object has been classified as a unique entity in this manner, all these vector records are appended to one all-inclusive vector database which constitutes the multi-temporal disturbance inventory (Step 4, Figure 3.2). The objects in the disturbance inventory are stored in temporally ascending order (e.g. T₀, T₁, ...), according to their time of origin and spatial overlay order. This ensures that dynamic objects, overlapping each other in space and time, can behave in a logically consistent manner. Finally, each dynamic object is assigned a land-cover class for each time step in the series, consistent with the cover class used in the reference map. For example, a cutblock that originated in the reference year and hence also existed in the reference map (T₀), would need to be backdated to a forest class for the previous year (T₁), and could transition to a herbaceous category in the year following (T₂) (object 1 in Step 4, Figure 3.2). Any disturbance objects that originate after the reference year require dynamic land-cover labels in the update direction only (object 3 in Step 4, Figure 3.2). Ideally, these labels should be derived through multi-spectral classification of the images from the respective year, in correspondence with GIS rules that prevent successional illogical sequences (e.g. classification errors that suggest a dynamic object progresses from barren to forest, then back to herbaceous in three subsequent years). Using the land-cover attributes in the disturbance inventory as legend categories, a backdated or updated map can easily be generated by overlaying the
relevant dynamic objects on to the reference map in a GIS (Steps 5 and 6, Figure 3.2). Performed properly, the strategy helps maintain the spatial and thematic consistency of the new map (relative to the reference map) by altering only those areas that have undergone change. All other areas of the map (i.e. static objects) remain unchanged. In addition, since the dynamic objects are only delineated once, their spatial positioning is maintained consistently across the monitoring horizon. In this manner, dynamic changes in the final map series can arise only through the alteration of land-cover attributes, thereby ensuring spatial consistency throughout.

3.3.1 Boundary Conditioning to Ensure the Seamless Integration of Dynamic Objects

While the basic framework outlined above ensures the spatial consistency of all static and dynamic entities over the course of the monitoring horizon, the final time series is not inherently free of spurious changes. The quality of the final map series depends naturally on the accuracy of the detected dynamic features, since both errors of omission and commission will affect the representation of change within the time series. In addition, spatial consistency requires that the boundary delineation of the dynamic features respects those of objects already existing in the reference map (McDermid et al. 2008, Linke et al. 2009a, 2009b). This is a key point that largely determines the spatial integrity of the overall map series. It is practically impossible to delineate objects consistently in images from two or more time periods, even if the corresponding feature has remained perfectly stable on the ground. Subtle differences in illumination conditions, sensor geometry, registration, and segmentation routines conspire to frustrate any attempt to overlay image objects delineated from one scene (e.g. the dynamic objects from one of the binary change/no change layers) onto objects in an existing layer (e.g. the
reference map) without creating spatial inconsistencies. The issue arises when the boundaries of dynamic objects undershoot or overshoot those of objects in the reference map – hereafter referred to as a *reference object* (Figure 3.3). During the integration of the dynamic objects into the reference map, these boundary mismatches create *intersect objects* that manifest themselves as slivers, spurious gaps, stretches, or encroachments (Linke *et al.* 2009b). These map-overlay byproducts are known to cause serious problems in spatial datasets and ought to be suppressed (Goodchild 1979).

**Figure 3.3:** Boundary-delineation mismatches between the independently derived dynamic objects and the objects in the reference map ($T_0$) can introduce spurious changes and hence spatial inconsistencies in the final time series. For example, if the dynamic-object boundary falls short (i.e. boundary undershoot) of a coinciding (such as object 1) or an adjacent (such as object 3) reference-object, spurious slivers or gaps will appear. If the dynamic-object boundary extends slightly beyond an existing object in the reference map (i.e. boundary overshoot), the object will appear stretched in size compared to the reference map (object 2). (Please note that an overshoot can also create a stretch in the backdate direction if the attribute contrasts with the ones of the adjacent, or surrounding objects.)

In order to ensure the seamless integration of dynamic object features, our approach employs the following boundary-conditioning rules:

1. Object boundaries in the reference map are assumed to be correct and
must be adhered to (McDermid et al. 2008), and

2. All intersect objects that are narrower than the minimum mapping width (MMW) will be assumed to originate from boundary mismatches and deemed as spurious.

The MMW refers to the minimum width that dynamic objects must achieve in order to be included in the disturbance inventory. The size of the MMW can be determined through visual inspection of a randomly stratified sample of dynamic objects in relation to spatially coincident reference objects and the underlying imagery. Specifically, the analyst overlays the outline of a randomly sampled collection of dynamic objects onto their spatially coincident reference objects (e.g. objects 1 and 2 in Figure 3.3). The potential boundary mismatches can be visually evaluated with respect to the two relevant remote-sensing images: one from the time of origin of the dynamic object, and the other from the reference year. If, in the judgment of the analyst, the feature of interest remained unaltered between the two image dates – i.e., no change occurred – then the boundary mismatch in question would constitute spurious change in the final time series. However, if the feature in question has in fact expanded or shrunk between the two time steps, then this boundary mismatch would be indicative of real changes on the ground. By inspecting a number of dynamic objects sampled throughout the monitoring horizon, it is anticipated that the analyst will arrive at a MMW threshold that balances the omission of small disturbance features (larger MMW) against the commission of spurious change slivers (smaller MMW), based on the specific conditions encountered. Once the MMW is set, the spurious boundary mismatches can be corrected in an automated manner by intersecting the dynamic objects with the reference objects in
a GIS, and subsequently trimming or expanding the dynamic objects by the spurious intersect objects using proximity and respective width constraints (Linke et al. 2009a, 2009b).

While these boundary-conditioning rules ensure the production of a spatially and temporally consistent time series of land cover maps, they – by definition - also preclude the inclusion of dynamic objects narrower than the MMW. However, if registration errors are kept to a minimum, the MMW should remain within an acceptable range. In an operational application using 30m-resolution Landsat Thematic Mapper imagery, the MMW is anticipated to not exceed two to four pixels (Linke et al. 2009b), which is comparable to other published photo-interpretation guidelines (Loveland et al. 2002).

It should be emphasized that the time series of maps generated by the disturbance-inventory approach to landscape monitoring is still subject to any spatial or thematic errors that were present in the initial reference map. As a result, it is important to apply this framework to suitable (i.e. accurate) reference maps. If the reference map is of sub-standard quality, it may be necessary to manually correct the thematic and spatial attributes of those reference objects underlying the regions of change, as outlined by the disturbance inventory, before any boundary-conditioning rules are applied. Any errors in the reference map that exist outside the regions of change will not seriously affect the change analysis performed on the generated time series, since they will remain unaltered throughout the framework application. These static errors may lead to a systematic under- or over-estimation of certain land-cover classes or patterns, but should not become compounded across the monitoring horizon. Linke et al. (2009a) explored the
propagation of map errors on multi-temporal LPA; interested readers are referred to that work for more information on this important topic.

Since our approach to landscape monitoring assumes that the original base map is correct, any retroactive improvements to that map – the acquisition of new high-spatial-resolution imagery designed to improve the original boundary delineations, for example – would require the creation of a new base map and the subsequent re-construction of the entire time series. In all cases, we encourage the use and reporting of standard accuracy-assessment strategies and statistics (Foody 2002).

3.3.2 Landscape Dynamics in the Backdated and Updated Map Series

A full range of landscape dynamics can be represented using the disturbance-inventory approach outlined above, including (i) feature appearance (object 3 at T+1, Figure 3.2), (ii) feature disappearance (objects 1 and 2 at T-1, Figure 3.2), (iii) feature persistence (an object which does not change thematically over a time step), and (iv) feature succession (objects 1 and 2 at T+1, Figure 3.2). In each of these cases, the same dynamic objects (boundary-conditioned) have been used throughout the time series; only the object’s land-cover attribute has been allowed to change. However, there are disturbances or succession events that can affect the location and shape of a feature. For example, the boundary of a clearcut-harvested area can be expanded if an adjacent strip of trees falls down during a windstorm. Alternatively, the very same area could shrink in size if the area was partially planted with trees. Human activities related to crop production, urban development, and forest harvesting have been documented to simplify the shape of land cover patches, by smoothing and flattening their boundaries (Krummel et al. 1987), and to fragment the forest landscape, causing increases in edge density and decreases in patch
size and shape complexity (Tinker et al. 1998). It could be mistakenly assumed that the boundary-conditioning rules used by the disturbance-inventory approach could preclude the detection of such subtle landscape changes. However, these two additional categories of landscape dynamics – (v) feature shrinkage and (vi) feature expansion – are accommodated indirectly through the overlay of new dynamic features on top of or adjacent to existing ones (Figure 3.4). As a result, any landscape dynamic involving the thematic transition from one land cover class to another can be represented in the final map series, so long as they exceed the MMW.

Figure 3.4: Subtle landscape dynamics such as feature expansions and shrinkages over the monitoring time horizon are achieved by overlaying thematically classified dynamic objects either on top of or adjacent to objects delineated in the reference map.
3.4 CONCLUSIONS

A framework for generating temporally and categorically dynamic forest land-cover maps has been presented. The work constitutes an innovative approach designed to enable the seamless updating and backdating of existing map products based on a combination of different types of disturbance features, delineated by manual or automatic methods, stored in a disturbance-inventory database and conditioned with boundary-matching procedures and overlay orders. By implementing the framework over an eight-year time interval across a large, multi-use study area in western Alberta, we demonstrated that the resulting products are reliable, and free of artifacts generated through the mismatched integration of change features. Furthermore, by accommodating both categorical and continuous-variable maps, the approach allows for flexible monitoring at any categorical scale of interest: an important consideration for specific wildlife and environmental applications. While our framework does not eliminate pre-existing errors in the reference maps, it successfully enables the production of reliable, spatially consistent representations of landscape dynamics through time by suppressing the introduction of new errors.

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3.6 REFERENCES


CHAPTER 4: A DISTURBANCE-INVENTORY FRAMEWORK FOR FLEXIBLE AND RELIABLE LANDSCAPE MONITORING: DEVELOPMENT AND IMPLEMENTATION IN THE ALBERTA FOOTHILLS

4.1 ABSTRACT

Remote sensing plays a key role in landscape monitoring, but our handling of these data in a multi-temporal time series is not yet fully developed. Of particular concern is the presence of spatial and thematic errors in independently created maps that distort measures of landscape pattern and constrain the reliability of change analysis. In addition, there is a need to incorporate continuous attributes of cover gradients for flexible map representations that support a variety of applications. In this paper, we present a framework for generating temporally and categorically dynamic land-cover maps that provide such a reliable and adaptable foundation. The centerpiece is a spatio-temporal disturbance-inventory database, created through semi-automated change detection and conditioned with boundary-matching procedures, which can be used to backdate and update both continuous and categorical reference maps. We demonstrate our approach using multi-annual Landsat imagery from a forested region in west-central Alberta, Canada, between the years 1998 and 2005.

4.2 INTRODUCTION

Over the past three decades, landscape monitoring has emerged as a major focus for geospatial research, particularly in forest ecosystems (Coppin and Bauer 1996, Franklin 2001, Rogan and Chen 2004), where human activities are the source of much
contemporary change (Houghton 1994, Riitters et al. 2002). In this regard, the multi-
temporal analysis of remote sensing imagery has been used to assess the impact of
landscape change on carbon cycling (Houghton et al. 2001, Conard et al. 2002, Song et
al. 2007), the conservation of protected areas (Vester et al. 2007, Huang et al. 2007,
Forrest et al. 2008), biodiversity (Hansen et al. 2001, Boentje and Blinnikov 2007, Sader
and Legaard 2008), and wildlife habitat (Pearson et al. 1999, Reyes et al. 2000, Berland
et al. 2008). While many approaches to change detection and analysis exist (Lu et al.
2004, Radke et al. 2005), post-classification analysis is the most commonly applied in
this context. The strategy involves the analysis of changes based on a series of two or
more independently classified maps, where each map reflects the investigated landscape
at a different instance in time (e.g. Skole and Tucker 1993, Kozak et al. 2007, Gamanya
et al. 2009).

A serious concern in post-classification analysis is the presence of spurious
change arising from classification errors and spatial inconsistencies in independently
generated map products (Shao and Wu 2008, Linke et al. 2009). These problems have
been shown to cause significant errors, particularly in the quantification of land-cover
pattern (e.g. Brown et al. 2000, Langford et al. 2006). In response to these issues,
researchers have suggested several remediation techniques designed to improve the
reliability of remote sensing-based map products for landscape monitoring, such as (i)
guidelines regarding spatial resolution, data processing, accuracy levels, seasonality, and
minimum mapping unit (Shao and Wu 2008); and (ii) Bayesian-based statistical
corrections to post-classification change-area estimates (Van Oort 2005). However,
while these strategies may serve to reduce the occurrence of spurious changes due to classification differences, they will not eliminate them.

An alternative approach to multi-temporal mapping that can reduce the issue of spurious change is to avoid the independent classification of images from different time periods, and focus instead on updating (projecting forward in time) and backdating (projecting backward in time) an existing map product through bi-temporal change detection (Coppin et al. 2004). A major benefit of this approach is that by limiting the scope of re-classification to include only those areas where change has been detected, one can drastically reduce the introduction of new errors. This is akin to the visual interpretation approach to updating an existing land-cover map through manual editing of a vector-based map. After editing, the updated and original vector layers can be compared, and the associated changes stored in a spatio-temporal database. Feranec et al. (2000, 2007) used this approach to update and backdate baseline maps, allowing features to appear, disappear, change thematically, or increase/decrease in size. However, these manual approaches are extremely labor-intensive, and the separation of technical inconsistencies from real change on the ground is challenging (Jansen et al. 2008, Jansen et al. 2006, Käyhkö and Skånes 2006). It would be highly desirable to incorporate automated approaches to change detection and multi-temporal land-cover mapping strategies within the structured framework of a spatio-temporal database.

Despite significant methodological advancements in the automatic detection of change features with remote sensing (e.g. Desclée et al. 2006, Blaschke 2005), little emphasis has been placed on the integration of these features into existing map products. The operation is problematic, due to potential variation in spatial resolution, registration
errors, illumination conditions, and object segmentation results between the two time periods (Yuan and Elvidge 1998, McDermid et al. 2008). Issues arise when the boundaries of disturbance features delineated via change analysis do not precisely match with shared boundaries in the existing reference map. Under these conditions, overlay operations applied in the updating or backdating procedure will generate small artifacts of spurious change, which can limit the quality of the finished product, and cause serious problems with subsequent interpretation (McDermid et al. 2008, Linke et al. 2009). These spatial errors are well known in the GIS literature as slivers, and constitute one of the biggest challenges associated with spatial overlay operations (e.g. Goodchild 1978, Chrisman 1989, Mas 2005), though they have received scant attention in the remote sensing community.

Additional concerns surrounding landscape monitoring revolve around our understanding of how to best represent land cover and vegetation in a forested environment. Unfortunately, many remote sensing products can be criticized for presenting an overly-simplistic depiction of the natural landscape; a situation based at least in part on historical limitations of satellite data and the ubiquitous use of classification as an information-extraction technique (McDermid et al. 2005). However, forested ecosystems are comprised of a complex interplay of continuous gradients of variation (Betts et al. 2007, McGarigal and Cushman 2005, Wiens, 1994) and are not well characterized by a single catch-all map product; particularly a categorical one produced exclusively by classification. Recent discussions on the limitations of classification in multi-disciplinary work (McDermid et al. 2005) have pointed out the problems with low-level (nominal or ordinal) information layers, and the difficulty in
adjusting thematic class boundaries in the finished maps. These practical challenges can hamper our efforts to understand forest dynamics, and likely contribute to the criticism of remote sensing that appears occasionally in the literature (e.g. Plummer 2000, Thogmartin et al. 2004, Gottschalk and Huettmann 2006). McDermid et al. (2005) argued for the use of multi-layer information databases over single catch-all map products, and an increased emphasis on continuous, ratio-level end products that retain their flexibility. The strategy has been recently employed in the creation of single-date maps of spatially continuous representations of percent forest species composition and crown closure in layers that can be merged with basic land-cover information in a GIS to produce composite maps with many possible legends (McDermid 2005). We believe that these emerging approaches have important role to play in reliable and adaptable landscape monitoring.

The recent release of the Landsat archive (Woodcock et al. 2008) represents a tremendous opportunity to pursue research programs that monitor the long-term temporal dynamics of land cover using this exceptional data set (e.g. Homer et al. 2007, Huang et al. 2007, Kuemmerle et al. 2007). However, in order to undertake such studies effectively, we require better strategies for creating reliable, spatially consistent time series of map products, that are free of spurious changes and, ideally, well-suited for supporting multiple applications. The goal of the research reported in this paper was to develop a framework for performing flexible and reliable landscape monitoring with remote sensing, using a semi-automated backdating and updating approach designed to generate temporally and categorically dynamic land-cover maps. In this manuscript, we provide a detailed description of the proposed methodological approach for creating time
series of both discrete and continuous land-cover maps, presented within the context of
the overall conceptual framework. We then demonstrate the effectiveness of the
approach through a practical eight-year monitoring application over a large, multi-use
study area in west-central Alberta, Canada, using Landsat imagery.

4.3 PROPOSED METHODOLOGICAL APPROACH: SPATIALLY CONSISTENT BACKDATING
AND UPDATING WITH A DISTURBANCE INVENTORY

Under ideal conditions, an existing thematic map product can be backdated and updated
to produce a spatially consistent time series, representing the basic succession of ground
features over time (Figure 4.1). The existing map at time $T_0$ constitutes the reference for
all dynamic features that are to appear, disappear, and/or change over the observed time
frame. Two types of dynamic features exist: (i) those that originate during the overall
time interval monitored ($T_n - T_{-n}$) (e.g. the small cutblock in the northern part of Figure
4.1 that originates between $T_0$ and $T_{+1}$), and (ii) those that pre-date the beginning of the
time series ($T_{-n}$), but change thematically over the course of the monitoring period (e.g.
the cutblock in the south-eastern part of Figure 4.1 that changes from shrub land cover in
$T_{-2}$ to forest in $T_{+2}$). The remaining features, which do not change over the observed time
frame, constitute static features of the reference map (e.g. the road section in the eastern
part of Figure 4.1 that does not change between $T_{-2}$ and $T_{+2}$).

Backdating of dynamic features can follow one of four possible scenarios: (i)
feature insertion, in which an entity is inserted into the reference map to reveal a feature
that was present at the backdated stage but has disappeared from the reference map by
blending into its surroundings (e.g. the cutblock inserted into the south-central portion of
Figure 4.1 with shrub land cover in years $T_{-1}$ and $T_{-2}$); (ii) feature regression, in which an
Figure 4.1: An ideal representation of a spatially consistent time series created by backdating and updating an existing thematic land cover map, wherein features persist, are removed, or inserted, and display their thematic attribute according to their successional stage of development.
entity in the reference map changes to a previous successional stage in the backdated map (e.g. the central cutblock in Figure 4.1 that regresses from a herbaceous land cover in the reference map to a barren land cover in year T₁); (iii) *feature persistence*, in which an entity in the reference map persists and undergoes no thematic change in the backdated map (e.g. the south-eastern cutblock in Figure 4.1 that persists unchanged from the reference condition in the years T₁ and T₂); or (iv) *feature removal*, in which an entity from the reference map is removed in the backdated map to reveal an earlier feature (e.g. the southern wellsite in Figure 4.1 with barren land cover in T₀ which is removed in T₂ to reveal a partially forest and partially shrub land-cover area). Similarly, updated dynamic features can follow four possible scenarios: (i) *feature insertion*, in which an entity is detected in an updated map that did not appear in the reference year (e.g. the northern cutblock in Figure 4.1 with barren land cover in T₁ in an area that appears forested in T₀); (ii) *feature succession*, in which an entity existing in, or inserted into the reference map, changes to a later successional stage (e.g. the northern cutblock in Figure 4.1 with barren land cover in T₁ and herbaceous land cover in year T₂); (iii) *feature persistence*, in which an entity in the reference map persists and undergoes no thematic change in the updated map (e.g. the road and wellsite in Figure 4.1 with barren land cover in years T₀ through T₂); and (iv) *feature removal*, in which an entity in the reference map blends into its surroundings in the updated map (e.g. the south-eastern cutblock in Figure 4.1 with shrub cover in T₀ developing to forest in T₂).

Guided by the concepts described above, a methodological approach for generating spatially consistent backdated and updated map products can be proposed. Changes in the time series described can be achieved through the identification of
dynamic features as *spatially segregated entities* and their integration into the reference map with temporally relevant land-cover labels, using an *overlay order* that corresponds logically to the sequence of their appearance on the ground. The best way to implement this strategy is through the creation of a database that stores spatially referenced dynamic entities and their corresponding thematic attributes. Using the previous time series displayed in Figure 4.1 as an example, we refer to the dynamic entities as *disturbance features*, since the actual agents of change are disturbance based. The database of disturbance features is referred to as the *disturbance inventory* (Figure 4.2). *Backdated* map products can be created from existing reference maps using a disturbance inventory (e.g., the backdated land-cover map labeled T-2 in Figure 4.2) by overlaying the existing reference map with a *backdate layer* that is comprised of the relevant features from the disturbance inventory assigned with the correct thematic labels. Similarly, *updated* map products can be created from an existing reference map (e.g., the updated land-cover map at T+2 in Figure 4.2) by overlaying an *update layer* consisting of all the relevant features from the disturbance inventory labeled with their corresponding land-cover attributes.

Before the disturbance-inventory approach to backdating and updating can be applied effectively, it is crucial to consider the quality assurance criteria that must be employed. The quality of map products generated by updating/backdating strategies is a function of two basic factors: (i) the accuracy at which change features can be detected and classified, and (ii) the suitability of these features for integration into the original reference map (McDermid *et al.* 2008). Regarding the first factor, if disturbance features are *not detected* and excluded from the disturbance inventory (i.e. error of omission), or if some static features are *erroneously detected* and included in the disturbance features are
Figure 4.2: The proposed methodological approach for generating a spatially consistent time series of thematic land cover through the use of a disturbance inventory. Dynamic features over the time series period are detected as spatially segregated objects, classified according to the disturbance type and year of origin (i.e., disturbance year), and assigned land cover (LC) attributes for each year of the time series. Disturbance features are organized into a database, which is subsequently used for creating backdating and updating layers to be overlaid on the original reference map to create backdated and updated land cover maps. Please note that features IDs 2 and 8 are examples of feature insertion. For insertions during backdating, no land-cover label is assigned after the reference year (n/a for ID2 in LC$_{T>0}$). For insertions during updating, no land-cover label is assigned before the reference year (n/a for ID8 in LC$_{T<0}$).
erroneously classified (e.g., a small cutblock confused with a large wellsite), the multi-temporal map sequence may exhibit thematic errors. Adherence to efficient change-detection protocols (e.g. Han et al. 2007), robust algorithms (Sundaresan et al. 2007, Walter et al. 2004), and the specification of the minimum size for disturbance features can largely fulfill the needs surrounding the need for accurate change detection.

The second factor, surrounding the seamless integration of detected disturbance features into the reference map, constitutes a methodological challenge that has rarely been described in the remote sensing literature. Unfortunately, it is virtually impossible to delineate the boundaries of disturbance features in a manner that coincides precisely with existing entities in the reference map (McDermid et al., 2008, Linke et al., 2009) under operational conditions. Two basic forms of spurious delineation mismatches can occur: (i) an overshoot, wherein the boundary of the disturbance feature extends slightly past the boundary of either a coinciding feature (Figure 4.3a), or an adjacent feature (Figure 4.3b) appearing in either the reference map or the disturbance inventory; and (ii) an undershoot, wherein the boundary of the disturbance feature falls slightly short of either a coinciding feature (Figure 4.3a), or an adjacent feature (Figure 4.3b) existing in the reference map, or disturbance inventory. It is important to note that the specification of overshoots and undershoots in operational terms requires the definition of a minimum mapping width: the maximum allowable deviance below which mismatches are deemed spurious. Mismatches equal to or larger than the minimum mapping width are assumed to represent real changes on the ground.

Of special concern are artifacts in the backdated and updated maps that arise from boundary undershoots in the disturbance feature. These errors manifest themselves in
Figure 4.3: A demonstration of spurious boundary-delineation mismatches and associated artifacts in an example map update created by the overlay of mismatched disturbance features into the reference map. The boundaries of disturbance features slightly overshoot and undershoot the boundaries of a) coinciding features in the reference map and b) adjacent features in either the reference map or other disturbance features, leading to the creation of slivers, spurious gaps, spurious feature expansions, and encroachments. The form of sliver objects (Figure 4.3a), or spurious gaps (Figure 4.3b) when the disturbance feature is overlaid onto the reference map. These slivers and gaps impact the visual appearance of the finished product, and can seriously distort interpretations about the direction and magnitude of multi-temporal changes in landscape pattern (Linke et al. 2008). The spurious overlaps arising from boundary overshoots create less-conspicuous artifacts, but still contribute to inconsistent changes related to the size and shape of mapped features over the course of the monitoring horizon. A feature may appear stretched when a reference-map feature is overlaid with a coinciding disturbance feature with overshot boundaries (Figure 4.3a). A feature may also appear encroached when an adjacent disturbance feature with overshot boundaries is overlaid (Figure 4.3b). In order to suppress any of these spatial errors, disturbance features processing must adhere the following three boundary-matching principles: (i) the boundaries of the original reference map features should be treated as correct and must be adhered to (McDermid et al. 2008), (ii) the precedence among disturbance features must be established so that the order of
overlay operations can be determined, and (iii) a minimum mapping width must be set to
delimit spurious delineation mismatches. If these principles are implemented, then
precisely aligned disturbance boundaries can be generated through processing algorithms
that merge spurious gaps and slivers to the adjacent disturbance feature (Linke et al.
2009), and trim spurious boundary overshoots.

The disturbance-inventory approach we propose relies on two criteria: (i)
disturbance features must be accurately detected, delineated, and classified into a
disturbance inventory as spatially segregated disturbance features; and (ii) these
disturbance features must be integrated seamlessly into the reference map through the use
of boundary-matching conditions and strict spatial-overlay order. It is important to note
that the general application of this backdating and updating approach is not limited to the
generation of categorical land-cover maps. Continuous maps of land-cover attributes,
such as those representing forest crown closure (e.g. percent of canopy cover) or tree-
species composition (e.g. percent relative abundance), can be handled by using the
disturbance inventory as a means of identifying the areas over which the continuous
reference map must be backdated or updated with new continuous-attribute values, which
can be derived from the temporally relevant imagery. The strategy for accomplishing the
backdating of a continuous reference map (e.g. the percent crown-closure layer
represented in Figure 4.4) relies on the selection of all features in the disturbance
inventory that originate prior to the reference year (T<0), over which area a continuous
mask can be created and integrated into the reference map. The resulting backdated mask
erases any disturbance features that were originally visible in the reference map at year
T0, thereby simulating the conditions occurring earlier in the time series (T<0). For each
Figure 4.4: An example application of the principle of backdating and updating a continuous map of forest-cover attributes (percent crown closure, in this case) with a disturbance-inventory. Zero values are in white. Disturbed areas in the reference year ($T_0$) are identified by the disturbance inventory, and are replaced with crown closure values derived from imagery at the beginning of the time series ($T_{-n}$) in backdated maps. In this case, the disturbed areas originating after the reference year are inserted with values of zero for crown closure, since this area is no longer considered forested.
successive year, masked areas are lifted, exposing the disturbance features in their proper sequence. Updating a continuous map may be accomplished in the same manner, by replacing the values of the continuous reference map according to the timing of any post-reference year disturbance feature (Figure 4.4).

4.3 A Disturbance-Inventory Framework for Generating Temporally and Categorically Dynamic Land-Cover Maps

A diagram explaining the conceptual framework for generating temporally and categorically dynamic land-cover maps through the backdating and updating of discrete and continuous reference maps is shown in Figure 4.5. The centerpiece of the framework is a spatio-temporal disturbance inventory, which contains the disturbance features and their associated attributes. In our approach, the disturbance inventory can be created using either automated or manual methods of change detection using remote sensing imagery covering the time interval \( n \). Once accurately detected and classified, these features must be conditioned with boundary-matching procedures and labeled with land-cover attributes appropriate to the individual application. The disturbance inventory is employed in the generation of a spatially consistent time series of map products, derived from reference maps characterizing conditions at time \( T_0 \). The results can be described as temporally dynamic across the time period of interest \( (T_n - T_{-n}) \). The framework handles either high-level (interval, ratio) or low-level (nominal, ordinal) attributes in discrete (vector) or continuous (raster) environments, depending on available data and the needs of the analyst. In the sample application below, we present a blended approach which handles map products of both types, thereby enabling the creation of categorically
dynamic output maps whose number and types of land-cover categories are flexible, and can be generated easily through integrative post-processing routines.

An existing reference land-cover map (T₀) can be backdated or updated to reflect the land-cover conditions at a specific time period (T₋₁ or T₊₁) through the integration of classified change patches in the manner outlined in Equation 1. In the case of backdating, bi-temporal change detection between T₀ and T₋₁ is used to identify the land-cover patches which did not previously exist, or perhaps existed in an earlier successional stage. By assigning these change patches with the appropriate land-cover label and overlaying them onto the reference map, a backdated map (T₋₁) can be created (Figure 4.2.1A). The updating case operates in a similar manner, wherein change detection between T₀ and T₊₁ is used to identify newly-appearing land-cover patches, or perhaps existing patches that have undergone change. By assigning these change patches an appropriate land-cover label and overlaying them on the reference map, an updated map (T₊₁) can be created (Figure 4.2.1A).
Figure 4.5: The proposed conceptual flowchart for generating temporally and categorically dynamic land-cover maps with flexible number of forest land-cover categories. Inputs are a time series of basic land-cover (LC) maps and a series of continuous forest-cover attributes (CC: crown closure, SC: species composition) created by backdating and updating existing reference maps (REF) at time 0 (T0) with a remote sensing imagery-based disturbance inventory.
4.4 METHODS

4.4.1 Study Area and Existing Map Layers

The study area for this research was located in the west-central portion of Alberta, Canada, along the eastern slope of the Rocky Mountains (Figure 4.6). The 40,000–km$^2$ area encompasses a diverse forested landscape, and includes portions of Jasper National Park and adjacent multi-use public lands. The region is subject to a wide variety of human and natural disturbance processes, including forestry, oil and gas development, mining, road construction, forest fires, and insect defoliation: a fast-changing environment that challenges our capacity to characterize spatial change.

![ Study Area for Generating Temporally and Categorically Dynamic Land Cover Maps

Figure 4.6: Location of the study area for generating temporally and categorically dynamic forest land-cover maps, where reference maps of discrete thematic land cover, and of continuous forest-cover attributes (species composition and crown closure) exist. ]
The study area is part of the Foothills Research Institute Grizzly Bear Research Program’s (FRIGBRP’s) region of interest, and the work reported here represents a key element of the landscape mapping and monitoring activities taking place within that project. The FRIGBRP is a collaborative, multi-agency initiative whose main goal is the development of knowledge and planning tools designed to ensure the long-term conservation of grizzly bears in Alberta, and has been conducting work in the area since 1998 (Stenhouse and Graham 2007). Part of these activities include the mapping and monitoring of vegetation and land cover in support research on grizzly bear habitat selection, population, and health (Nielsen et al. 2002, Nielsen et al. 2004, Linke et al. 2005). McDermid (2005) described the development of a three-part base map designed to provide a categorically dynamic representation of land cover and forest structure. Existing map layers in the area include an object-based land-cover map (ten classes; 91.8% accuracy), and continuous-variable representations of crown closure (accuracies in the 90% range for a two-class configuration; 50% for four classes) and tree species composition (90% accuracy in a two-class configuration; 73% for four classes) (Figure 4.6). The layers were derived primarily from Landsat imagery, and represent 2003 ground conditions.

4.4.2 Data Sources

The study area is covered by Landsat paths/row 44/23 and 45/23, and we acquired annual summer imagery from each scene from 1998 to 2005 to aid in our characterization of changing forest conditions across this time interval (Table 4.1). The images were a blend of Landsat-5 Thematic Mapper (TM) and Landsat-7 Enhanced Thematic Mapper Plus (ETM+), and included a single ETM+ SLC-off scene (gap-filled) from 2004.
Table 4.1: Remote sensing imagery used for the detection of disturbance features with time assignments in reference to the methodological framework for generating the disturbance inventory

<table>
<thead>
<tr>
<th>Landsat Path/Row</th>
<th>Image Acquisition Date</th>
<th>Sensor</th>
<th>Time Assignment acc. to Disturbance Inventory Framework</th>
</tr>
</thead>
<tbody>
<tr>
<td>45/23</td>
<td>September 5, 1998</td>
<td>Landsat 5 TM</td>
<td>T-5</td>
</tr>
<tr>
<td></td>
<td>September 8, 1999</td>
<td>Landsat 5 TM</td>
<td>T-4</td>
</tr>
<tr>
<td></td>
<td>August 17, 2000</td>
<td>Landsat 7 ETM+</td>
<td>T-3</td>
</tr>
<tr>
<td></td>
<td>September 14, 2001</td>
<td>Landsat 7 ETM+</td>
<td>T-2</td>
</tr>
<tr>
<td></td>
<td>August 23, 2002</td>
<td>Landsat 7 ETM+</td>
<td>T-1</td>
</tr>
<tr>
<td></td>
<td>September 3, 2003</td>
<td>Landsat 5 TM</td>
<td>T-0</td>
</tr>
<tr>
<td></td>
<td>August 12, 2004</td>
<td>Landsat 7 SLC-Off</td>
<td>T-1</td>
</tr>
<tr>
<td></td>
<td>July 22, 2005*</td>
<td>Landsat 5 TM</td>
<td>T-2</td>
</tr>
</tbody>
</table>

| 44/23            | August 29, 1998        | Landsat 7 ETM+  | T-5                                                    |
|                  | August 24, 1999*       | Landsat 7 ETM+  | T-4                                                    |
|                  | September 27, 2000*    | Landsat 7 ETM+  | T-3                                                    |
|                  | September 14, 2001     | Landsat 7 ETM+  | T-2                                                    |
|                  | June 13, 2002          | Landsat 7 ETM+  | T-1                                                    |
|                  | July 10, 2003*         | Landsat 5 TM    | T-0                                                    |
|                  | August 13, 2004        | Landsat 5 TM    | T-1                                                    |
|                  | September 13, 2005     | Landsat 5 TM    | T-2                                                    |

* indicates >10% Cloud

In addition to satellite data, we also acquired a variety of supplementary GIS data sets to aid in image processing and disturbance classification procedures. The Alberta government’s 30-metre digital elevation model was used for orthorectification, and to derived additional slope and aspect layers used in the categorization of change. We also had access to the provincial road layer and a forest fire database, as well as agriculture and settlement masks developed by Collingwood (2007). The masks were used to exclude changes occurring within these two land-use zones, which occur primarily along the study area’s eastern boundary. Pre-existing disturbances ($T_{\leq-5}$) for cutblocks were available from industrial forest landholders as digitized feature polygons. We also acquired as much orthophotography as possible, in order to facilitate the independent validation of change features. However, the availability of spatially coincident, consecutive, cloud-free ortho-photography was limited to the years 2000 and 2001.
Image processing procedures were performed in PCI Geomatica 9.1, while segmentation and object-based classifications were performed using Definiens Professional 5.0. All vector and raster database management took place in ArcGIS 9.2.

4.4.3 Implementation of the Framework

4.4.3.1 Generating the Disturbance Inventory

In characterizing changes on the landscape, we focused our efforts on the six types of forest-replacing disturbances that dominate the study area: (i) burns from forest fires, (ii) cutblocks from forest clearcutting, (iii) mines from surface extraction for coal and gravel, (iv) wellsites from petroleum extraction, (v) pipelines from oil and gas transportation, and (vi) roads from mechanized human access (Table 4.2). Because of the scale at which mapping activities took place, we treated burns, cutblocks and mines as areal features, wellsites as point features, and roads and pipelines as linear features. These feature classes will be adhered to throughout this framework implementation, though applications in other landscapes (or using other remote sensing data sets) might assign features differently. In following the nomenclature introduced in the manuscript previously, we will refer to the 2003 reference year as T₀, while 1998 is T₋₅, and 2005 is T₊₂.

An overview of the entire methodological flowchart used to generate the inventory of disturbance features outlined above is summarized in Figure 4.7. The procedure is comprised of 19 steps, organized into three major components: (A) annual disturbance mapping, (B) pre-existing disturbance mapping, and (C) disturbance inventory conditioning. Each part is described briefly below, with the steps corresponding to those listed in Figure 4.7.
Table 4.2: Feature type, disturbance type, spatial overlay order (increasing numbering corresponds to bottom-up direction), and land-cover transition rules for disturbance features mapped in the study area (T<sub>D</sub> refers to the points in time prior to the origination of the disturbance feature, T_D refers to the point in time when the disturbance originated, and T<sub>D+n</sub> refers to the point in time after a disturbance feature originated as specified by the time interval n, in this case years)

<table>
<thead>
<tr>
<th>Disturbance Features</th>
<th>Land-cover (LC) Transition Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre-disturbance LC label for backdating</td>
</tr>
<tr>
<td>Feature Type</td>
<td>T&lt;sub&gt;D&lt;/sub&gt;</td>
</tr>
<tr>
<td>Area Burn</td>
<td>Forest</td>
</tr>
<tr>
<td>Area Cutblock</td>
<td>Forest</td>
</tr>
<tr>
<td>Area Mine</td>
<td>Forest</td>
</tr>
<tr>
<td>Linear Pipeline</td>
<td>no data</td>
</tr>
<tr>
<td>Linear Road</td>
<td>no data</td>
</tr>
<tr>
<td>Point Wellsite</td>
<td>context determined</td>
</tr>
</tbody>
</table>

4.4.3.1.1 Annual Disturbance Mapping (Part A)

All TM and ETM+ images were converted to at-satellite reflectance following the methods of Chander and Markham (2003) to improve the radiometric consistency between scenes and sensor types. Each image was then orthorectified to a root mean square error tolerance of 0.5 pixels, and re-sampled via nearest-neighbour to 30-metre pixels in UTM Zone 11 NAD83, based on the GR80 ellipsoid. The result of this pre-processing was a spatially accurate, radiometrically consistent time series of Landsat images representing T<sub>-5</sub> to T<sub>+2</sub> ground conditions (Figure 4.7, step 1). We used the enhanced wetness difference index (EWDI) method of Franklin <i>et al.</i> (2001) to generate difference layers designed to characterize the changes observed along each step in the temporal time sequence (Figure 4.7, step 2). EWDI has been shown to be an effective strategy for forest disturbances, and the technique has been successfully employed under a variety of conditions in previous studies (e.g. Franklin <i>et al.</i> 2002, Skakun <i>et al.</i> 2003).

The annual difference layers were segmented in Definiens 5.0, using parameters of 10 for scale, 0.1 for shape, and 0.7 for compactness. The resulting vector layers were manually
Figure 4.7: A flowchart illustrating the steps used to generate the disturbance inventory at time intervals previous (T-1, T-0) and after (T+1, T+n) the reference year (T0).
thresholded using the mean EWDI value into change and no change objects using visual inspection of the respective image pairs (Figure 4.7, step 3). The change objects became the basis for all subsequent disturbance mapping for areal features.

With a decision tree approach, change objects were classified into areal disturbance categories (cutblocks, mines, and burns), using attributes related to the object’s spectral characteristics, size, shape, and context (Figure 4.7, step 4). In order to minimize errors in the annual disturbance mapping, the results of the areal disturbance classification were visually inspected and corrected where necessary. Linear and point features, although visually detectable from the imagery, could not be reliably mapped using automated detection and classification methods, since the resolution of the imagery was not sufficient to yield consistent and discrete object delineations for these features. As a result, change objects related to these feature types were discarded.

We used manual digitizing to delineate point and linear disturbance features associated with wellsites, roads, and pipelines with reference to the available imagery (Figure 4.7, steps 5-6). Wellsites were characterized with 3x3 pixel squares centered around each new wellsite location, with the boundaries snapped to the grid of the reference land-cover map (LC T₀). The centerlines of linear features were digitized as polylines and converted to polygon features using a total buffer width of 60 meters (i.e. 2 pixels). Linear features were visually classified into roads and pipeline on the basis of surface vegetation characteristics. Once again, the resulting features were rasterized and snapped to the T₀ reference map in order to create consistent boundary delineations, in preparation for seamless integration with other disturbance features and map products. Next, all the annual disturbance features (areal, linear, and point) were merged into an
annual disturbance database, including attribute information that specified disturbance
type and year of origin (Figure 4.7, step 7).

4.4.3.1.2 Pre-existing Disturbance Mapping (Part B)

In order to incorporate areal disturbance features existing on the landscape prior to 1998
(Tₐ₋₅) into the disturbance inventory, we selected digitized polygons representing
cutblocks, mines, and burns from ancillary GIS sources on the basis of attributes. In
order to ensure seamless integration of these entities with the other map products, we
used overlay procedures to extract the corresponding polygons of pre-existing features as
depicted in the T₀ reference map (Figure 4.7, step 8). This spatial overlay operation
yielded a multitude of potential pre-disturbance features, which needed to be attributed
according to land-cover characteristics.

The pool of potential pre-disturbance features included entities which had already
transitioned to mature forest at the beginning of our time series (Tₐ₋₅), and therefore no
longer constituted dynamic features capable of displaying successional change over the
investigated time frame. These features had to be removed. Since no land-cover or
temporal attribute information existed in the ancillary disturbance database, we
performed a supervised classification using 1998 Landsat imagery to identify pre-existing
land-cover values. Each entity was classified as either barren, herbaceous, shrub, or other
(unclassified) (Figure 4.7, step 9). We then removed all the unclassified disturbance
features from the disturbance inventory so that the resulting set of pre-disturbance
features corresponded only to dynamic features (Figure 4.7, step 10). All the point and
linear features that were visually discernable on the multi-spectral imagery at the
beginning of the time series (Tₐ₋₅) were manually digitized and converted using the same
procedures as described in steps 5 and 6 (Figure 4.7, steps 11 and 12). We then merged all the pre-existing disturbance features into a database, including attributes for date, year, and disturbance type (Figure 4.7, step 13).

4.4.3.1.3 Disturbance-Inventory Conditioning (Part C)

The databases for annual and pre-existing disturbance features were merged to create a single disturbance inventory database containing all dynamic features on the landscape over the time frame of this study (T−5 to T+2) (Figure 4.7, step 14). Despite our efforts to limit image registration errors, the disturbance features exhibited spurious overshoots and undershoots with the boundaries of coinciding and adjacent reference features, as well as with other adjacent disturbance features (this issue was described previously, and illustrated in Figure 4.4). We used visual comparison of the relative positioning of mapped features with the respective Landsat images to determine the minimum mapping width (MMW) requirement for real changes manifesting themselves in updated and backdated maps. The observed maximum deviation for spurious mismatches was just below 120 m for coinciding features and 60 m for adjacent features, corresponding to MMW’s of four and two pixels respectively. In order to eliminate spurious change caused by misregistration, all areal disturbance that fell below the respective MMW’s were discarded, hereby treating the features originating before 2003 (i.e. the disturbance year T<0) as ‘coinciding features’ and all others as ‘adjacent features’. Point and linear features were excluded from this rule, since they were manually digitized and verified.

The remaining steps in Part C relate to the processing and management of the final disturbance inventory, in order to conform to the principles necessary for seamlessly integrating the disturbance features into the reference map. First, the trimming of
spurious overshoots was handled (Figure 4.7, step 15), beginning with adjacent disturbance features. Since it was feasible for point and linear features in the disturbance inventory (e.g. wellsites, roads, and pipelines) to overlap other disturbance features on the ground over time, no boundary trimming procedures were applied to these features. However, in order to account for spurious overshoots between adjacent areal features of the same disturbance type (cutblocks, mines, and burns could overlap other features on the ground, but not with features of their own type), we employed a bottom-up temporal approach to erasing overlaps. Features originating in later years were trimmed or erased using the boundaries of disturbance features originating in earlier years. Spurious overshoots with boundaries of coinciding features in the reference map were corrected by creating an intersection between all disturbance features originating before 2003 (i.e. disturbance year T<0) and all reference-map features (LC Map T0 in Figure 4.7), and erasing the intersect portions that were contained within the MMW buffer around the boundaries of the selected disturbance features. We also applied a boundary-matching procedure to correct spurious boundary undershoots (Figure 4.7, Step 16), by identifying the mismatch areas between these undershoots, and then merging them with the nearest disturbance feature. In essence, we expanded the disturbance features to match the relevant reference boundaries (Figure 4.7, step 16; see Linke et al. 2009 for details).

Upon completion of the boundary-matching processing, the trimmed and expanded disturbance features were assigned land-cover labels for each of the backdated and updated years (Figure 4.7, step 17), using simple decision rules (Table 4.2). Cutblocks and burns features were assigned to the ‘barren’ class for the year in which they originated (T_D), ‘herbaceous’ in the year following disturbance (T_D+1), and ‘shrub’ in
years two and beyond \((T_{D+2})\). We did not allow disturbance features to progress beyond
the shrub class, since the time frame of the study was considered shorter than the time
horizon necessary for a mature forest stand to regenerate. Road and mine features were
labeled as ‘barren’ for all years, and pipelines were labeled ‘herbaceous’. The land-cover
labels for the years prior to the disturbance \((T_{<D})\) was assigned as ‘forest’ for all areal
disturbance features, under the assumption that all such disturbances were stand-
replacing. The respective label for roads and pipelines was ‘no data’ (an act that simply
prevented their insertion in previous years), since they were not mapped in the 2003
reference land-cover map. All features that originated after the reference year \((T_{>0})\) were
assigned ‘no data’ labels for their pre-disturbance years.

The classification of post-disturbance land cover for point features (Figure 4.7,
step 18) followed the same decision rules as those outlined above, but we used contextual
information to assign pre-disturbance \((T_{\leq 0})\) land-cover labels (Table 4.2). While point
features originating after the reference year \((T_{>0})\) were assigned ‘no data’ labels for pre-
disturbance years, many of the point features originating prior to \(T_{0}\) were already mapped
in the reference products, and therefore required the assignment of proper pre-disturbance
land-cover categories. Unfortunately, we could not simply assume that all wellsites were
cut from forests (like cutblocks), since they were commonly observed to occur on a
variety of land-cover types. We therefore assigned pre-disturbance land-cover attributes
for these features on the basis of context. Two separate situations were identified when
extracting context for a wellsites: (i) the feature could be fully contained within a
reference or disturbance feature, or (ii) the feature could straddle two or more reference
or disturbance features. In both cases, we used a 60-meter buffer (two Landsat pixel
widths) to establish context. Wellsites occurring in the first situation were retained as whole entities, and assigned the land-cover class of the surrounding feature. Wellsites occurring in the second situation were split, with each entity receiving different land-cover classes (for an example of this, see ID 4a & 4b in Figure 4.2).

In the final step of disturbance-inventory conditioning, the database was sorted according to spatial overlay order and disturbance year (Figure 4.7, step 19; Table 4.2). Burns were arranged as the bottom layer, since cutblocks (order 2) – if spatially co-existing – could potentially overlap these features. Mines in our study area normally appeared on forested land, but nevertheless had the potential of overlapping with a cutblock or burn, and therefore were assigned the overlay order 3. Pipelines and roads could cross any disturbance feature, and were therefore assigned overlay orders 4 and 5, respectively. Wellsites occupied the top order, since these features were smaller than any other disturbance type and remained persistent throughout the time period.

4.4.3.2 Accuracy Assessment of the Disturbance Inventory

The disturbance inventory was tested for thematic accuracy across three phases of compilation: (i) change detectability, or the ability of the algorithm to discern change areas from no change; (ii) disturbance type classification, or the ability to discriminate between cutblocks, wellsites, mines, burns, roads and pipelines; and (iii) land-cover classification, or the accuracy of land-cover labels assigned to the disturbance features. The size of the assessment samples varied, depending on the accuracy assessment being performed. The sample size for change detectability was obtained using methodology described by Husch et al. (2004), with the number of samples calculated as a function of the coefficient of variation in the pixel values and a 10% allowable error. As a result, we
distributed 178 random samples proportionally between the change and no-change features: 5 and 173 samples respectively. Since the classification of disturbance type produced nominal classes with no measurable variance, we calculated sample size for the second assessment using the method outlined in McCoy (2005) to arrive at a number of 256 with an allowable error of 20%. Those samples were randomly distributed proportionally to the area covered by each disturbance type. The same number of samples (256) was randomly distributed for the nominal disturbance land-cover classification; again with size-proportional representation. User’s, producer’s, overall accuracies, and the kappa coefficient (Congalton and Green 1999) were calculated for each of the three assessments.

4.4.3.3 Backdating and Updating of Reference Maps

Using the framework proposed in this paper, the discrete land-cover map of the study area (LC Map T0 in Figure 4.6) was backdated and updated through the systematic overlay of features from the conditioned disturbance inventory (Figures 4.2 and 4.5). The continuous reference maps (CC and SC Maps T0 in Figure 4.6) were backdated through the overlay of crown closure and species composition models created with spectral variables derived from Landsat images from the first year of the time series (T-5) using a mask area delineated by the conditioned disturbance features originating before T0 (Figures 4.4 and 4.5). We used regression modeling to estimate crown closure and species composition from the reference maps (T0) to spectral and topographic explanatory variables at T-5. Sample data was collected randomly from the imagery in forested areas that were never disturbed throughout the entire time series. The approach is analogous to the model extension technique described by McDermid (2005), though
the application here is temporal rather than spatial. In order to account for misregistration errors between the disturbance features and the continuous reference maps, the mask was buffered by two pixels. In the updating direction, areas corresponding to new disturbance features \((T_D>0)\) were replaced with values of ‘0’ for crown closure, and were assigned ‘no data’ for species composition, since these areas were no longer considered forested.

### 4.4.3.4 Generating Temporally and Categorically Dynamic Land-Cover Maps

The Grizzly Bear Map-O-Matic (GBMOM) is an ArcObjects program created in ArcGIS 9.2, and is designed to generate a series of multi-temporal land-cover maps for any configuration of land cover, species composition, and canopy closure through integrative post-processing. The program adds an important dynamic element to discrete land-cover products by allowing for user-specifed class breaks, or categories, within the forest class. For demonstration purposes, we used the GBMOM to generate a series of categorically refined sample composite maps across the full 8-year time series. Upland forested areas were divided into five discrete land-cover categories: (i) Open Conifer (species composition: 80-100% coniferous, crown closure: 0-50%), (ii) Moderate Conifer (species composition: 80-100% coniferous; crown closure: 51-70%), (iii) Closed Conifer (species composition: 80-100% coniferous; crown closure: 71-100%), (iv) Mixed Forest (species composition: 21-80% coniferous; crown closure 0-100%), and (v) Broadleaf Forest (species composition: 0-20% coniferous; crown closure 0-100%).
4.5 Results and Discussion

As previously described, the successful implementation of the proposed mapping framework depends on (i) the accurate detection and classification of disturbance features, and (ii) the seamless integration of disturbance features into the existing reference maps. We have organized this section around each of these two components, followed by comments and observations related to the categorically refined nature of the resulting composite time series, and considerations about the general applicability of the framework.

4.5.1 Accurate Detection of Disturbance Features

We assessed the detection and classification of the disturbance inventory on the basis of three elements: (i) detection of change features, (ii) classification of disturbance types, and (iii) classification of land cover. The results of all three assessments are summarized in Table 4.3.

The detection of change features produced excellent results, with an overall accuracy of 100% and a Kappa coefficient of 1.0. The EWDI change-detection procedure performed very well, and provided an effective tool for identifying change features in the study area. The classification of disturbance type had an overall accuracy of 98% and a ‘very good’ Kappa agreement of 0.97. There was some minor confusion between disturbances features that appeared similar in the imagery. For example, some large wellsites and small burns were committed to the cutblock class. Among the manually digitized features, classification was perfect (Table 4.3).

The classification of land cover for the disturbance features had an overall accuracy of 80% and a ‘good’ Kappa agreement of 0.64. The decision rules used to
assign land-cover labels to disturbance features in this implementation of the proposed framework was simplistic, relying only on idealized succession sequences (time from disturbance) and other basic rules. While the transition rules succeeded in avoiding temporal inconsistencies, the actual rates of land-cover transition change varied from feature to feature, according to other influencing factors such as solar radiation, moisture, and soil type, which alter the rate of succession. The process could be refined through the use of spectral information from the imagery.

Table 4.3: Summary Statistics of Confusion-matrices for classification of 1) change and no change, 2) disturbance type, and 3) land cover.

<table>
<thead>
<tr>
<th></th>
<th>Producer’s Accuracy</th>
<th>User’s Accuracy</th>
<th>Overall Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1) Change Detection</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change/No Change</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>1.0</td>
</tr>
<tr>
<td>No Change</td>
<td>100%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>2) Disturbance Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cutblock</td>
<td>100%</td>
<td>98%</td>
<td>98%</td>
<td>0.969</td>
</tr>
<tr>
<td>Wellsite</td>
<td>92%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burn</td>
<td>85%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mine</td>
<td>100%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Road</td>
<td>100%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pipeline</td>
<td>100%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>3) Land-cover Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barren</td>
<td>56%</td>
<td>82%</td>
<td>80%</td>
<td>0.640</td>
</tr>
<tr>
<td>Herb</td>
<td>74%</td>
<td>50%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrub</td>
<td>93%</td>
<td>89%</td>
<td></td>
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</tr>
</tbody>
</table>

4.5.2 Seamless Integration of Disturbance Features

The trimming and expansion of spurious boundary-delineation mismatches, and the consistent application of spatial overlay order for features in the disturbance inventory were the factors most strongly influencing the seamless integration of disturbance features. Through careful implementation of the disturbance-inventory framework
presented in this paper, we were successful in our attempts to produce spatially consistent maps of land cover, crown closure, and species composition (Figure 4.8). We observed no spurious changes in the land-cover maps. For example, within a 5.4 x 5.4 km sample area, several disturbances occurred in the form of new cutblocks (years 2000-2003, 2005), new roads (years 2000, 2005), and a wellsit (2000) (Figure 4.8). For the disturbance features that originated in 2003 or earlier, mismatched boundaries between the disturbance features and other adjacent features would have manifested themselves as small sliver objects or spurious gaps, especially conspicuous in the years before the disturbance appeared, had they not been suppressed (McDermid et al. 2008). The absence of these errors emphasizes the importance of boundary matching, and the success of the methods implemented here. Furthermore, as demonstrated in this sample, the spatial overlay order ensured that linear features remained visible when they occurred in conjunction with an areal feature. When several cutblocks transitioned to herbaceous and shrub cover types in 2004 and 2005, road features traversing these areas remained visible.

In the continuous maps of crown closure and species composition, the integration of the regression model – applied to the Landsat TM imagery at year T.5 (1998) within the buffered area of the disturbance inventory – yielded seamless map products without spurious values. In Figure 4.8, we can see areas corresponding to cutblocks originating between 2000 and 2003 that blend seamlessly in the years prior to their appearance.

4.5.3 Temporally and Categorically Dynamic Map Composite

By successfully creating a spatially consistent time series that blends categorical characterization of basic land cover with continuous-variable representations of crown closure and species composition, the disturbance-inventory framework implemented here
Figure 4.8: A sample area (5.4 x 5.4 km) displaying the derived annual backdated and updated maps of basic land cover (LC), crown closure (CC), and species composition (SC) over the time period 1998 and 2005. Additional rows contain example composite maps with five discrete forest cover categories, and false-colour Landsat TM/ETM+ imagery.
enables the production of temporally and categorically dynamic forest land-cover maps (Figure 4.5). The composite map generated in this implementation with the GBMOM exemplifies one such possible case, and reveals the value of the proposed approach (Figure 4.8).

4.5.4 Considerations Regarding the General Applicability of the Framework

For the first time, a framework has been described that enables the generation of land-cover maps, which are dynamic in their categorical definition and therefore capable of adapting to support a variety of applications. Since these maps are also updated by automated remote-sensing methods to yield products that are spatially consistent across time, we consider them an appropriate basis for conducting efficient and reliable landscape monitoring. The disturbance inventory is open to features delineated by different processing methods (manual digitizing, automatic segmentation) from different image sources (Landsat in this case), as long as the boundary-matching conditions can still be adhered to. Further, the disturbance inventory is not limited to the initial time frame investigated, but can easily be appended when images from additional years become available.

While our experience here demonstrates the effectiveness of the overall approach, the results are still subject to errors in the T0 reference map. Since the proposed framework does not alter the reference map outside disturbance features, errors present in the no change areas will persist throughout the time series. However, these errors remain consistent, and with the focus on reliable landscape monitoring, are much less troubling than the stochastic spatial errors dealt with in our approach. Linke et al. (2009) showed that boundary-delineation errors arising from the mismatched integration of change
features had a large impact on landscape metrics, and led to significant distortions in landscape pattern analysis. These errors were successfully suppressed in this work by matching the boundaries of change features, both to each other and to corresponding objects in the reference maps.

In addition to the internal dynamics of specific disturbance features, the size and shape of a ground feature may also change through time. Within the context of our framework, these modifications constitute discrete disturbance events which are spatially adjacent to, or contained by, the ground feature in question. As a result, these occurrences are dynamic features themselves. For example, the *increase* (e.g. a fire-driven expansion of a barren cutblock area through the burning of an adjacent forest section) or *decrease* (e.g. the advanced forest succession of a fenced section in a cutblock to reduce deer-browsing) in area of a ground feature with time can be represented by means of *feature insertions* and *feature removals*, as overlaid in context to adjacent dynamic features. However, it should be noted that the MMW requirements for the detection of areal dynamic features (Step 14, Figure 4.7) prevents any representations of feature increases or decreases below these minimum specifications.

### 4.6 Conclusions

A framework for generating temporally and categorically dynamic forest land-cover maps has been presented. The work constitutes an innovative approach designed to enable the seamless updating and backdating of existing map products based on a combination of different types of disturbance features, delineated by manual or automatic methods, stored in a disturbance-inventory database and conditioned with boundary-matching procedures and overlay orders. By implementing the framework over an eight-
year time interval across a large, multi-use study area in western Alberta, we
demonstrated that the resulting products are reliable, and free of artifacts generated
through the mismatched integration of change features. Furthermore, by accommodating
both categorical and continuous-variable maps, the approach allows for flexible
monitoring at any categorical scale of interest: an important consideration for specific
wildlife and environmental applications. While our framework does not eliminate pre-
existing errors in the reference maps, it successfully enables the production of reliable,
spatially consistent representations of landscape dynamics through time by suppressing
the introduction of new errors.

4.7 ACKNOWLEDGEMENTS

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4.8 REFERENCES


CHAPTER 5: THE RELATIVE ABUNDANCE OF GRIZZLY BEARS IN WEST-CENTRAL ALBERTA: ASSESSING THE IMPACTS OF HUMAN-INDUCED DISTURBANCE

5.1 ABSTRACT

The grizzly bear (*Ursus actos*) population of Alberta, Canada is threatened by human-induced disturbances that degrade and disrupt their habitat and increase the risk of human-caused mortality. However, the details surrounding the impact of cumulative human effects are not yet fully understood. This paper deals with a subpopulation of 42 grizzly bears dwelling in the Yellowhead region, located in the west-central portion of the province in an area that is undergoing rapid development from timber harvest, petroleum extraction, and coal-mining. We used relative-abundance information from a grizzly bear DNA census conducted in 2004 alongside a disturbance-inventory database documenting changes in land cover and human footprint over the preceding seven years, in order to gain insight into the relative importance of disturbance and landscape processes on the spatial distribution of individuals in this population. We found that the main factor explaining the spatial distribution of bears was the distance-to-colonizer source (i.e. Jasper National Park), though other disturbance variables indicative of long-term, medium-intensity human disturbance (e.g., gas wellsites), and short-term, high-intensity human use (e.g., logging operations or road construction), were significantly and negatively associated with grizzly bear abundance.

5.2 INTRODUCTION

Landscape modification through human-induced disturbance is one of the most important causes of contemporary habitat loss and fragmentation, represents an on-going threat to
wildlife species, and contributes to the decline of biodiversity throughout the world (Saunders et al. 1991, Kerr and Deguise 2004, Lindenmayer and Fisher 2006, Krauss et al. 2010). However, in studies conducted over large spatial extents, it is virtually impossible to observe the behavioural response of wildlife to discrete disturbance events directly. Instead, researchers often focus on the relationship between species occurrence or abundance and the presence and/or extent of so-called *disturbance features* (Burton 2007) on the landscape, which are collectively referred to as the *human footprint* (Janzen 1998, Leu et al. 2008). Remote sensing plays an indispensable role in these studies by providing a large array of spatial data-sets capable of characterizing the landscape systematically, and detecting changes in human footprint and other habitat-elements through time (Kerr and Ostrovsky 2003). With the growing availability of satellite-based time series of imagery, such as the freely available Landsat archive (Woodcock et al. 2008), combined with the development of new strategies for handling them effectively (Linke et al. 2009, Linke and McDermid in press), the door is open for new studies focused on multi-temporal analyses of landscapes and disturbance dynamics (Gillanders et al. 2008), and their resulting impacts on wildlife communities.

In the multi-use forested regions of Alberta, Canada, disturbance features associated with oil and gas development, forestry, and mining operations exert a strong influence on the landscape (Schneider 2002, Linke et al. 2005, 2008). In these same areas, native grizzly bear (*Ursus arctos*) populations have suffered serious declines, from historical speculations that numbered them in the thousands, to current population estimates of less than 600 (ASRD/ACA 2010). Based on these low numbers, grizzly bears are now officially listed as a *threatened* species in Alberta. Habitat alteration and
the accompanying increase in human access are the main issues of concern surrounding
this population, since wide-scale landscape conversion for the purpose of settlement or
agriculture is currently limited in the area (ASRD/ACA 2010). While previous studies
have shown that grizzly bears in general tend to avoid roads (Mattson 1987, McLellan
and Shackelton 1988, Mace et al. 1996, Wieglus et al. 2003), forestry clearcuts (Waller
1992, McLellan and Hovey 2001) and other human-activity centres (Mace et al. 1999),
there is also recent evidence in the literature that suggests the true impact of human-
disturbances is more complicated. For example, Wieglus and Vernier (2003) observed
that grizzly bears in the Selkirk mountains of British Columbia select for regenerating
clearcuts in proportion to their availability, while Nielsen et al. (2004a) found that grizzly
bears in Alberta can select for clearcuts preferentially during the early summer, due to the
availability of high-quality foraging resources (Nielsen et al. 2004b). However, this
selection behaviour, when combined with the increased risk of human-caused mortality
brought about by associated road networks and increased human access (Nielsen et al.
2004c), can serve to heighten the threats faced by grizzly bears in these disturbed
environments (Nielsen et al. 2006). Another study in Alberta by Berland et al. (2008)
found no evidence for grizzly bear avoidance of new disturbance features, indirectly
underscoring the high risk associated with this behaviour.

With the exception of human-caused mortality risk models (e.g. Nielsen et al.
2004c), the current body of knowledge concerning disturbance effects on grizzly bears
stems predominantly from investigations on the relationship between individual
disturbance features and the presence and/or absence of bears. However, one important
limitation of this approach is that it does not explicitly account for the effects of
disturbance magnitude at the landscape scale (i.e. the density or total area occupied by disturbance features in different parts of a study area), or the cumulative impact of combined disturbance features. The issue of cumulative effects is particularly relevant, since single disturbances observed in isolation may have a negligible – or, as demonstrated by the above studies – even a positive impact on habitat selection, but the accumulation of these individual changes over time may constitute a major negative impact (Theobald et al. 1997). While it seems obvious that at some upper threshold of disturbance density, grizzlies would have no secure space remaining on the landscape and become extirpated, the effects of varying levels of cumulative disturbance patterns over space and time is unclear, and remains an important issue for conservation management. Further insights into this problem may be gained by incorporating a multi-temporal landscape perspective, which includes observations surrounding the rate-of-change of various types of human-disturbance features, as well as their cumulative abundance, on observed patterns of grizzly bear abundance.

The overall goal of this study was to better understand the relative importance of human disturbance and landscape processes on the spatial distribution of Alberta’s threatened grizzly bear populations. In order to pursue this goal, we formulated two main research objectives: first, to quantify the status and trends of major human-footprint categories, both individually and cumulatively, across the multi-use Yellowhead landscape of west-central Alberta between 1998 and 2004; and second, to assess how human-induced disturbance processes relate to the region’s current distribution of grizzly bears. To achieve the second objective, we tested theoretical models designed to relate several metrics as indicators of selected disturbance and landscape processes, using a
model-selection approach based on Akaike’s Information Criterion (Burnham and Anderson, 2002).

5.2 MATERIALS AND METHODS

5.2.1 Study Area

The 8721-km$^2$ study area for this research is located within the Rocky Mountain foothills of western-central Alberta, Canada (Figure 5.1). The area increases in topographic elevation from east to west, ranging from around 1000m in the east to maximum peaks of 2400m along the western boundary. At lower elevations (below ~1450 m), the area is primarily dominated by closed-canopied forests, made up of spruce ($Picea glauca$), lodgepole pine ($Pinus contorta$), and poplar ($Populus$ spp.) occurring in both pure and mixed stands. In the upper elevations, the forests are primarily coniferous, with Engelmann spruce ($Picea engelmannii$) and subalpine fir ($Abies lasiocarpa$) co-dominating along-side lodgepole pine (Strong 1992, Beckingham et al. 1996).

With the exception of two small human settlements, Robb (30 dwellings) and Cadomin (81 dwellings) (Statistics Canada 2007), the human footprint in the study area is comprised primarily of human-disturbance features associated with resource extraction. The five main types of disturbances features are a) cutblocks created by forest clear-cutting; b) surface or open-pit mines for coal extraction; c) wellsites, which consist typically of a gas well surrounded by a ~1-ha patch of cleared terrain; d) pipelines, for transporting oil and gas along ~30m-wide herbaceous corridors; and e) roads, ranging in size from one-lane dirt or gravel roads for accessing cutblocks and wellsites, to multi-lane highways for general travel. Seismic cutlines represent another prominent form of linear disturbance features in this area (Linke et al. 2008), but they were not included in our
5.2.2 Relative Abundance of Grizzly Bears

The study area coincides roughly with the Yellowhead grizzly bear population unit, which is one of seven regionally distinct populations in the province, each based on differences in human-induced habitat alterations and slight deviations in genetic structure.
The range of the Yellowhead population is bounded in the north and south by highways 16 and 11, respectively. The boundary along the east extends into open land, consisting mainly of settlements and agriculture, where bears generally no longer roam. The western boundary contains no physical barriers, except for steep and high-elevation terrain. However, east/west-oriented river valleys allow ready movement, and include access to the protected area of Jasper National Park. The population has been exposed to varying levels of industrial disturbances, particularly coal-mining and forestry, as far back as the 1910s (AAR 2005). Widespread petroleum extraction represents a more recent set of disturbance trends.

In the early summer of 2004, the population size and spatial distribution of grizzly bears in the study area was estimated using a mark-recapture sampling design based on hair-snag DNA methods (Boulanger et al. 2005a, 2006). The sampling was carried out between the 6th of June and 27th of July, during the hypophagia and early hyperphagia foraging seasons. During this time period, bears feed on a variety of foods, including horsetail (*Equisetum* spp.), roots of cow parsnip (*Heracleum maximum*) and sweet vetch (*Hedysarum* spp.), graminoids, sedges, insects, and ungulate calves or carrion (Hamer and Herrero 1987, Nagy et al. 1989, Nielsen 2005, Munroe et al. 2006). The general foraging behaviour and more even distribution of the food supply during this time frame is assumed to minimize seasonal foraging effects on bear distribution. Furthermore, sex- and age-segregations in habitat preferences have been found to be negligible (Nielsen and Boyce 2005), allowing the use of a population-level approach to estimating abundance.

A systematic sample grid with 178 cells was overlaid onto the study area (Figure 5.1). Within each 49-km² grid cell, hair samples from barbed-wire surrounding bait sites
were collected within four two-week intervals; one sample from a fixed bait site, and one from a bait site that was moved throughout the last three sessions. Each site was placed in high-quality bear habitat to promote adequate trap-encounter probability (Boulanger et al. 2005a, 2006). That study resulted in a total population estimate of 42 grizzly bears, of which 39 were “captured” by the hair samples (Boulanger et al. 2005a). For the purposes of our study, these data were transformed into the total number of unique individuals detected within each 7-by-7-km cell. The resulting count data represents the relative abundance of grizzly bears across landscape cells (Figure 5.2).

Figure 5.2: Relative abundance of grizzly bears in 2004 as derived from counts using DNA hairsampling.
5.2.3 Variables for Spatio-temporal Landscape and Disturbance Processes

In order to quantify the status and trends of disturbance and landscape processes within the study area in the years preceding the DNA hair sampling, we computed 18 variables (Table 5.1) from an annual time series of landcover and disturbance maps representing the study area from 1998 to 2005 (Linke et al. 2009). Overall, these metrics deal with disturbance magnitude, disturbance change, disturbance proximity, disturbance neighbourhood effect, bear colonizer source, and landscape/habitat characteristics. The timing of this detailed data set covers the time frame of grizzly-bear telemetry data collected by the Foothills Research Institute Grizzly Bear Research Program in a related study (Stenhouse and Graham 2007). The disturbance-inventory time series consists of annual maps of all five disturbance types (i.e. cutblocks, mines, wellsites, roads & pipelines, and fires) that were discernable from 30m-resolution Landsat Thematic Mapper and Enhanced Thematic Mapper Plus imagery (Figure 5.3). The landcover time series depicts the spatio-temporal distribution of land-cover across the study area, including the disturbance features, using a broad 10-class land cover classification (Figure 5.1). A thorough description of the assembly and validation of both data sets can be found in Linke et al. (2009).

In order to summarize the spatial and temporal distribution of changes occurring within the study area between 1998 and 2004, we measured the amount and proximity of each specific disturbance type alone, and all disturbance types combined for each of the 178 sample cells using ArcGIS 9.3 (Esri 2008). The mean value of each metric was then tracked temporally across the landscape. In the following sections, we provide a detailed description of each metric, the theoretical meaning behind them, and the anticipated
Figure 5.3 Distribution of cumulative disturbances present in the study area in the year 2004.

5.2.3.1. Disturbance Magnitude

The accumulation of all land-cover disturbances brought about by human activities is described as disturbance magnitude, and is measured as the proportion of each sample cell occupied by disturbance features. Although this metric assumes (conservatively) that the area occupied by any given disturbance feature has the same functional impact across all disturbance types and ages (i.e., elapsed time since the disturbance occurred), it was chosen for its simplicity as a measure of overall disturbance quantity per unit cell. We calculated disturbance magnitude for the years 2004 and 1998 (DD04 and DD98,
Table 5.1: Metrics used to quantify changes and disturbance and landscape processes across the sampled landscape cells with preprocessing details for regression model selection (* indicates metrics used in model selection).

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Definition</th>
<th>Metric Preprocessing</th>
<th>Metric Acronym</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Disturbance Magnitude</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disturbance Density 04</td>
<td>Total area of all disturbances accumulated by 2004 (ha/km²)</td>
<td>transformed to log (x+1)</td>
<td>DD04*</td>
</tr>
<tr>
<td>Disturbance Density 98</td>
<td>Total area of all disturbances existing in 1998 (ha/km²)</td>
<td>transformed to log (x+1)</td>
<td>DD98*</td>
</tr>
<tr>
<td>New Disturbances 04</td>
<td>Total area of all disturbances new in 2004 (ha/km²)</td>
<td>transformed to log ((x+1)^{0.25})</td>
<td>DDN04*</td>
</tr>
<tr>
<td>Wellsite Density</td>
<td>Total number of all wellsites accumulated by 2004 (100#/km²)</td>
<td>transformed to log (x+1)</td>
<td>WD04*</td>
</tr>
<tr>
<td>Cutblock Density</td>
<td>Total area of all cutblocks accumulated by 2004 (ha/km²)</td>
<td>Excluded due to very high collinearity with DD04</td>
<td>CD04</td>
</tr>
<tr>
<td>Mine Density</td>
<td>Total area of all surface mines accumulated by 2004 (ha/km²)</td>
<td>Excluded due to low frequency</td>
<td>MD04</td>
</tr>
<tr>
<td>Linear Features Density</td>
<td>Total length of roads and pipelines accumulated by 2004 (km/ha)</td>
<td>Excluded due to high collinearity with DD04</td>
<td>LD04</td>
</tr>
<tr>
<td>Burn Density</td>
<td>Total area burnt accumulated by 2004 (ha/km²)</td>
<td>Excluded due to low frequency</td>
<td>BD04</td>
</tr>
<tr>
<td><strong>Disturbance Change</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual Change</td>
<td>Mean annual increment of change in density of all disturbances between 1998 and 2004 (ha/km²/yr)</td>
<td>transformed to (x^{0.25})</td>
<td>DDCh*</td>
</tr>
<tr>
<td><strong>Disturbance Proximity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disturbance Proximity</td>
<td>Mean distance to any nearest disturbance feature accumulated by 2004 (m)</td>
<td>Excluded due to high collinearity with DD04</td>
<td>CDP</td>
</tr>
<tr>
<td>New Disturbance Proximity</td>
<td>Mean distance to any nearest disturbance feature new in any year between 1998 and 2004 (m)</td>
<td>transformed to log (x+1)</td>
<td>NDP*</td>
</tr>
<tr>
<td><strong>Neighbourhood Effect</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disturbance Density Context Difference</td>
<td>Difference in total disturbance density at the context (ha/km²)</td>
<td>transformed to log (x+1)</td>
<td>DDCD*</td>
</tr>
<tr>
<td><strong>Colonizer Source</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance to Protected Area</td>
<td>Distance to Jasper National Park protected area (km)</td>
<td>None</td>
<td>DTP*</td>
</tr>
<tr>
<td><strong>Landscape Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSF habitat rank</td>
<td>Mean value of the resource selection function habitat ranking (from lowest to highest 0-10)</td>
<td>None</td>
<td>RSF*</td>
</tr>
<tr>
<td>Area of Forest</td>
<td>Total area occupied by forest (ha/km²)</td>
<td>((1000/x)^{0.25})</td>
<td>AF*</td>
</tr>
<tr>
<td>Largest Patch Inside Cell</td>
<td>Largest contiguous patch of forest inside the landscape cell (ha)</td>
<td>None</td>
<td>LPI*</td>
</tr>
<tr>
<td>Elevation</td>
<td>Mean elevation as derived from the digital elevation model (m)</td>
<td>Excluded due to very high collinearity with DD04</td>
<td>E</td>
</tr>
<tr>
<td>Ruggedness</td>
<td>Standard deviation of elevation</td>
<td>Excluded due to very high collinearity with DD04</td>
<td>R</td>
</tr>
</tbody>
</table>
Table 5.1). Any disturbance metric quantified for the year 1998 represents landscape condition six years prior to the bear survey, and serves as the initial point of reference for any mid-term temporal change assessment. In contrast, disturbance magnitudes for 2004 indicate *cumulative habitat alteration* up to the point at which the bear population was sampled. Because of the associated relative degree of human access, these metrics were expected to be negatively associated with grizzly bear abundance.

The total amount of new disturbances, specifically those features occurring between 2003 and 2004, was measured as *habitat disruption*, and is meant to characterize the high-intensity use by humans and machinery that occurs while the disturbance features are being created (DDN04, Table 5.1). It was expected that these short-term disturbances would be negatively related to grizzly bear abundance. However, this impact was anticipated to have a lower overall importance than the longer-term disturbance magnitude, since other factors may confound its effects (e.g. high habitat disruption magnitude but spatially clumped together, leaving space for avoidance).

The magnitude of specific disturbance types across the study area, such as the cumulative densities of cutblocks (CD), surface mines (MD), and burns (BD) were computed as areal metrics (ha/km²), while linear features, such as the roads and pipelines (LD), were measured as a linear metric (km/km²). Wellsite density (WD) was measured as a point metric (#/100km²) (Table 5.1). In preliminary assessments, we found cutblocks and linear features to be highly correlated with overall disturbance (DD04) (Pearson’s correlations 0.92 and 0.8, respectively). As a result, these variables were only used as descriptors of change of the study area (objective 1), and were excluded from the subsequent modelling of bear abundance. Surface mines and natural burns were also
excluded from modelling, since both of these features occurred in less than 5% of the sample cells.

With regular facility checks (frequent human presence) and frequently high noise level related to gas flaring, we treated WD as a specific indicator of habitat degradation, brought about by long-term, medium-intensity disturbance, and anticipated it to be negatively associated with grizzly bear abundance. We expected this metric to be of similar or higher importance than overall disturbance density to bear abundance, due to its association with continuous medium-intensity human and industrial use.

5.2.3.2 Disturbance Change

In addition to the quantification of the long-term cumulative disturbances, we also calculated the mean annual change in disturbance magnitude to capture annual habitat alteration after 1998. This metric was calculated as the mean total density of all features that originated each year between 1998 and 2004 (DDCh, Table 5.1). While we did not anticipate this metric to be strongly related to bear abundance by itself, it was expected that annual disturbance would interact with cumulative disturbance from 1998, such that established, older disturbances (i.e. locations with space and light for the growth of forage) would be positively associated with bear abundance, so long as the magnitude of recent disturbance (i.e. short-term, high-intensity use) was low.

5.2.3.3 Disturbance Proximity

We calculated the mean distance to the nearest disturbance feature for each landscape cell (CDP, Table 1) to represent the overall configuration of disturbances on the landscape, and capture the average potential travel distance without encountering disturbance.
However, new disturbance proximity (NDP, Table 5.1), which measures the mean distance to any new annual disturbance feature occurring between 1998 and 2004, was highly correlated ($r>0.8$) to this metric, and was judged to be a more specific measure of short-term, high-intensity use by humans and machinery. As a result, we used NDP in subsequent abundance-modelling. The disturbance process indicated here is therefore the overall degree of habitat exposure to short-term, high-intensity human and industrial use.

We expected close proximity to new disturbances to be negatively associated with grizzly bear abundance, since undisturbed space is required for resting, security from humans, and activities related to mating and the rearing of young.

### 5.2.3.4 Neighbourhood Disturbance

A perspective that looks slightly beyond the immediate area of interest (i.e. the landscape cell) can provide additional insight into the landscape effects on population dynamics (Dunning *et al.* 1992), and was achieved here through consideration of the disturbance magnitude in the surrounding neighbourhood. We calculated the *neighbourhood disturbance effect* (DDCD, Table 1) as the difference between the total disturbance density in a 3.5-km buffer surrounding each cell, and that occurring within the cell.

Higher values of DDCD should amplify the anticipated negative effect of disturbance magnitude within a given cell, since a positive context difference implies at least some minimum level of disturbance density inside a given cell. It was therefore expected that higher positive context differences would be related to lower bear abundances, since such neighbourhoods would provide little supplemental shelter or free space.
5.2.3.5 Colonizer Source

Another large-scale process extending beyond the landscape cell is the source-sink dynamics of this bear population (Dunning et al. 1992). Since movement is generally unrestricted from the west, where grizzly bears live under the protected status of Jasper National Park, this neighbouring population constitutes a source of colonizers. The effect is readily apparent in the bear count data (Figure 5.2), with high relative-abundance values strongly clustered along the western boundary of the study area. In order to account for this effect of a colonizer source, we measured the distance to the eastern boundary of the protected area, Jasper National Park, from any cell within the study area (DTP, Table 5.1). We expected a strong negative association between this metric and grizzly bear abundance.

5.2.3.6 Landscape and Habitat Characteristics

Mean elevation and terrain ruggedness (the standard deviation of elevation) were computed from a 30m digital elevation model (DEM) in order to quantify the terrain inside each landscape cell (E, R, Table 5.1). As expected, these variables were highly correlated (r > -0.75) with disturbance density and were therefore excluded from the abundance modelling.

In order to account for the effect of local habitat quality, we calculated the relative habitat rank of each cell (RSF, Table 5.1, Figure 5.4). The measure was based on a fine-scale resource selection function, computed from early summer telemetry-based point location data from collared grizzly bears inhabiting the area from 1999 to 2003. The function was developed using landcover, forest-canopy composition and density,
distance-to-edge, distance-to-streams, and terrain as the main predictor variables (Nielsen 2005).

In order to characterize the available area of undisturbed forest in each sample cell, we calculated the total area belonging to the ‘upland trees’ category of the 2004 landcover map (AF, Table 5.1, Figure 5.4). Since the amount of forest area is limited not only by disturbance, but also by elevation and soil-moisture regime, the metric represents a unique descriptor of the total effective area available for shelter and secure space.

Minimum security area is thought to play an important role in the reduction of human-encounter probability (Gibeau et al. 2001). In addition to forest area, we also calculated the size of the largest-contiguous forest patch within each cell (LPI, Table 5.4,

**Figure 5.4**: Landscape characteristics, in form of mean bear habitat ranking, total area of forest, and largest contiguous forest patch, across all landscape cells at the year 2004.
Figure 5.4). All of the three landscape characteristics – RSF, AF and LPI – indicate aspects of habitat availability and pattern, and were expected to have positive associations with grizzly bear abundance. Since RSF measures the probability of occurrence, and AF describes the total effective security area, these two metrics were expected to be more important to abundance than LPI.

5.2.4 Candidate Models, Selection, and Statistical Approach

It is important to note that the purpose of this study was not to describe the relative abundance of grizzly bears for predictive purposes, but rather to test alternative models of bear abundance based on hypotheses that are well-grounded in theory. Once again, our overall goal was to better understand the relative importance of disturbance and landscape processes on bear abundance in multi-use landscapes, using the information at hand. Such a model-based inference framework is provided by candidate-model comparison and selection methods using Akaike’s Information Criterion (AIC) as a measure of goodness-of-fit (Burnham and Anderson 2002, Johnson and Omland, 2004). We took a semi-mensurative research approach for pursuing this goal, since we could not control the disturbance factors experimentally at such a large spatial scale. We were able to access multi-temporal disturbance data from remote sensing, but the distribution of bears was sampled for just one time frame. However, since this study was carried out within the identified range of grizzly bears, absences and low relative abundance values were assumed to arise from negative impacts related to disturbance.

Since not all of the measured disturbance and landscape processes are mutually exclusive (e.g., the features used to indicate cumulative habitat alteration include the features indicating habitat degradation), a global model combining the additive effect of
all processes would here be at risk of redundancy and overfitting. Instead, our goal was to formulate simple models, containing as few model terms as possible (following the principle of parsimony) to investigate the relative importance of the various processes in explaining relative bear abundance.

With 66% of the 178 landscape cells containing zero counts, the abundance data, like many other species data sets (e.g. Melles et al. 2010), was so-called zero-inflated. Such an excess of absence values violates the data-distribution assumptions of a standard Poisson regression model, where the mean of the response variables must equal the variance (Cameron and Trivedi 1998). In these cases, a zero-inflated Poisson regression (ZIP) constitutes a good, alternative model, since the count data are treated as a mixture of a point mass at zero, and a Poisson distribution (Lambert 1992, Martin et al. 2005). When fitting a zero-inflated poisson regression, essentially two processes are modeled simultaneously: one determining if the landscape cell is zero or non-zero (logistic process), and the other determining the count (Poisson process), which can also include zeros. The final parameter estimates result in separate terms, one set of explanatory variables and coefficients to explain the excess absences, and the other set to explain the counts.

Since the study area is located within the natural range of Alberta’s grizzly bear population and the inherent landscape/habitat characteristics are assumed not to have changed unfavourably over the past decade or two, it was hypothesized that the excess absences were driven primarily by human-induced disturbance processes. Therefore, the initial step in model selection was to fit each of the six disturbance processes to the relative abundance count data individually using univariate models, with the goal of
identifying the processes with the highest goodness-of-fit (models I, 1–6, Table 5.2). Based on this initial model comparison, the process that fit the excess absences better than the other disturbance processes could be identified. Then, in order to understand the role of the landscape processes in driving abundance (without the consideration of any disturbance processes), we constructed a few simple models using the intercept-only model for the logistic process (models II, 7-9, Table 5.2).

Ten complete ZIPS were formulated, where both the count and excess-zero components were modeled, using univariate or few additive linear terms, but all using the “best” disturbance process (as identified from models I) for explaining excess absences (models III, 10 to 19, Table 5.2). Models 10 to 14 represented the individual effects of all five other disturbance processes on relative bear abundance. Model 15 represented the combined effects of only the two main landscape processes, habitat availability and colonizer source; without any disturbances. Two plausible interaction models were also constructed to test (1) the hypothesis that areas with older disturbances and none or low amounts of newer disturbances would have a positive impact on abundance by fitting the interaction between habitat alteration in 98 (DD98) and subsequent annual habitat alteration (DDCh) (model 16, Table 5.2); and (2) the hypothesis that the potential negative impact of cumulative habitat alteration (DD04) could be offset by the availability of high-quality habitat (model 17, Table 5.2). Finally, the last two models tested whether or not disturbance processes could further explain grizzly bear abundance beyond landscape processes alone. The two disturbance processes found to be most important in the univariate analysis – neighbourhood disturbance effect, (model 18, Table 5.2), and habitat degradation (model 19, Table 5.2) – were used for this purpose.
Table 5.2: Disturbance and landscape processes expected to affect grizzly bear relative abundance.

<table>
<thead>
<tr>
<th>Theoretical Models</th>
<th>Disturbance Processes</th>
<th>Landscape Processes</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZIP Model Component</td>
<td>Specific Model terms</td>
<td>Cumulative Habitat Alteration</td>
</tr>
<tr>
<td>I) Disturbance for “Excess Absences” (intercept only for Poisson model)</td>
<td>1) Cumulative disturbance 2) Wellsites 3) Newest disturbances 4) Annual change 5) Distance to new annual features 6) Neighbourhood disturbance</td>
<td>X</td>
</tr>
<tr>
<td>II) Landscape for “Counts” (intercept only for binomial model)</td>
<td>7) Landscape characteristics 8) Distance to Colonizers 9) Colonizer &amp; Landscape ch.</td>
<td>X</td>
</tr>
</tbody>
</table>
5.2.5 Statistical Modelling Details and Evaluation

Eleven metrics (Table 5.1) were used as indicators to test the hypothesized effects of disturbance and landscape processes. Since simple linear-regression analysis assumes that the explanatory variables are normally distributed, most of these metrics had to be transformed to remove the positive or negative skew in their distribution (Quinn and Keough 2002) (Table 5.1). Then, in order to ease the interpretation and comparability of regression coefficients, the transformed explanatory variables were standardized to z-scores by calculating the deviations from the mean in standard deviation units (Menard 2001; Quinn and Keough 2002). The final standardized explanatory data set contained some disturbance variables that were correlated with other variables \( (r > 0.7) \) (Table 5.3), underscoring that the disturbance indicators are not mutually exclusive. However, since the goal was not to build a global model, and since, despite their correlations, they quantified different disturbance processes, all of the correlated variables were kept. Even so, correlated variables were certainly not used jointly within any given model, except if used for modelling the different components of the ZIP.

<table>
<thead>
<tr>
<th></th>
<th>DD98</th>
<th>DD04</th>
<th>DDN04</th>
<th>WD04</th>
<th>DDCh</th>
<th>NDP</th>
<th>DDCD</th>
<th>DTP</th>
<th>RSF</th>
<th>AF</th>
<th>LPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>DD98</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DD04</td>
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<td>1.00</td>
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<td></td>
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<td></td>
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<td></td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>WD04</td>
<td>0.52</td>
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<td>0.54</td>
<td>1.00</td>
<td></td>
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<td></td>
<td></td>
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</tr>
<tr>
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</tr>
<tr>
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<td>-0.65</td>
<td>-0.75</td>
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<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>DDCD</td>
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<td>0.24</td>
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<td>0.35</td>
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<td>-0.37</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DTP</td>
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<td>0.57</td>
<td>0.37</td>
<td>0.53</td>
<td>0.50</td>
<td>-0.60</td>
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<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSF</td>
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<td>-0.17</td>
<td>-0.22</td>
<td>-0.17</td>
<td>0.26</td>
<td>-0.18</td>
<td>-0.59</td>
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</tr>
<tr>
<td>AF</td>
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<td>-0.07</td>
<td>-0.14</td>
<td>-0.02</td>
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<td>-0.15</td>
<td>-0.15</td>
<td>-0.02</td>
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<td></td>
</tr>
<tr>
<td>LPI</td>
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<td>-0.61</td>
<td>-0.30</td>
<td>-0.42</td>
<td>-0.54</td>
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<td>-0.18</td>
<td>-0.30</td>
<td>-0.04</td>
<td>-0.49</td>
<td>1.00</td>
</tr>
</tbody>
</table>
The ZIP models were constructed using R statistical software (version 2.10.1, R Development Core Team, 2009) equipped with the ‘pscl’ package with the ‘zeroinfl’ function (Jackman 2010, Zeileis et al. 2008). For each fitted model, regression coefficients, standard errors, and p-values were used to assess the significance of the model terms (intercept and explanatory variables). Only the explanatory variables with significant coefficients (p<0.1) were retained for any given model. The relative support of each statistical model was assessed using Akaike’s Information Criterion index of model fit for small sample sizes (AICc, Burnham and Anderson 2002, Johnson and Omland, 2004). We also considered the corresponding AIC differences (Δi), Akaike weights (wi which indicate the probability of a given model being the best model in the full set that is being compared and provides therefore an indication of relative model fit), and evidence ratios (which indicate the amount of evidence favouring one model over another). The best-fitting final models were identified using a Δi between 0 and around 2 as a guide (Burnham and Anderson 2002). For the best-ranking models, the relative improvement of the zero-inflated Poisson model over the corresponding standard Poisson model was assessed using Vuong’s closeness tests (Vuong 1989) under the null hypothesis that the models were indistinguishable. As an indication of explanatory power, a pseudo-$R^2$ measure was estimated for the best-ranking models, calculated as the fraction of the maximally achievable, potential log-likelihood gain that was attained with the inclusion of the explanatory regression variables of the particular model (Cameron and Trivedi 1998).
5.3 RESULTS AND DISCUSSION

5.3.1 Disturbance Changes in the Study Area between 1998 and 2004

Significant changes in disturbance magnitude occurred over the six-year time span between 1998 and 2004. On average, the overall disturbance density increased by nearly 60%, from 6.3 to 9.9 ha/km$^2$ (Table 5.4). The variation in disturbance densities found across the 178 landscape cells was large, with maximum density reaching 38 ha/km$^2$ by 2004, with only 20 cells remaining completely undisturbed along the western boundary (Figure 5.5A,B). New disturbances generally occurred within the same or nearby landscape cells, but with highly variable annual rates-of-change across space, ranging up to a maximum annual rate of 16.7 ha/km$^2$ (Figure 5.5C). We observed an overall mean annual rate-of-change in disturbance density of 0.6 ha/km$^2$/yr (Table 5.4).

Table 5.4: Temporal comparison of disturbance magnitude and proximity, including summary statistics of the observed annual rate of total disturbance, proximity to new annual features between 1998 and 2004, and the neighbourhood disturbance effect in 2004 across the entire study area (n=178 landscape cells).

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<tbody>
<tr>
<td>Density of all cumulative total disturbance (ha/km$^2$)</td>
<td>6.30</td>
<td>9.90</td>
<td>&lt;0.000</td>
</tr>
<tr>
<td>Density of all cumulative cutblocks (ha/km$^2$)</td>
<td>2.99</td>
<td>6.09</td>
<td>&lt;0.000</td>
</tr>
<tr>
<td>Density of all cumulative surface mines (ha/km$^2$)</td>
<td>0.42</td>
<td>0.53</td>
<td>0.32</td>
</tr>
<tr>
<td>Density of all cumulative wellsites (#/100km$^2$)</td>
<td>10.66</td>
<td>16.89</td>
<td>0.005</td>
</tr>
<tr>
<td>Density of cumulative linear features (km/km$^2$)</td>
<td>0.56</td>
<td>0.68</td>
<td>0.006</td>
</tr>
<tr>
<td>Total cumulative area burnt (ha/km$^2$)</td>
<td>0.00</td>
<td>0.04</td>
<td>n/a</td>
</tr>
<tr>
<td>Mean proximity to any nearest disturbance feature (m)</td>
<td>1474</td>
<td>1309</td>
<td>0.202</td>
</tr>
<tr>
<td>Mean proximity to any nearest new disturbance feature 1998-2004 (m)</td>
<td>Mean: 7,162</td>
<td>S.E.: 489</td>
<td></td>
</tr>
<tr>
<td>Mean annual rate of change of all cumulative total disturbances (ha/km$^2$/yr)</td>
<td>Mean: 0.6</td>
<td>S.E.: 0.07</td>
<td></td>
</tr>
</tbody>
</table>
Over the studied time frame, the area occupied by cutblocks doubled on average (Table 5.4), with cutblocks occurring in more landscape cells, and reaching densities of up to 28 ha/km². Cut blocks were mainly distributed along the lower-elevation, eastern half of the study area (Figure 5.6A). The absolute area occupied by locally occurring (i.e. in 11 cells in 2004) surface mines increased from 3621 ha in 1998 to 4644 ha in 2004, corresponding to an average 0.11 ha/km² increase across the study area (Table 5.4). The highest mine density was 18 ha/km² (Figure 6B). The number of wellsites increased on average by more than 50% (Table 5.4), mainly through additional wells along the middle and eastern boundary of the study area. The maximum wellsites density was 187 wells/100km² (Figure 5.6C). The density of roads and pipelines increased by one-fourth to an average of 0.68 km/km² (Table 5.4), mainly through the addition of new features to landscape cells with existing linear disturbances (Figure 5.6D). Over the course of the time frame, only one fire was recorded with an extent of 340 ha (Table 5.4, Figure 5.6E).

Accompanying the significant increase in overall disturbance magnitude was a substantial but non-significant increase in disturbance proximity (Table 5.4). The mean proximity increase was non-significant due to the high variation across the landscape in both years. However, on average, movement was undisturbed up to about 1500 m in 1998, while in 2004, disturbances feature could be encountered on average every 1300 m. Except in the few landscape cells where no disturbances were recorded between 1998 and 2004, all the others experienced decreases in mean distance to disturbance ranging from a few meters to as much as 2000m (Figure 5.7A,B). The proximity to new annual disturbance features was substantially lower than the proximity to any cumulative disturbance, with an overall average distance of around seven km across the six years,
Figure 5.5: Distribution of A) the disturbance density of all features accumulated by the years 1998 and 2004, the B) increase in disturbance density between 1998 and 2004, and C) the disturbance density of any new features occurring in a specific year between 1998 and 2004.

approximating the spacing of each landscape cell (Table 5.4). Proximity to new annual features was consistently below five km within the southwest quadrant of the study area, while the proximity in the northwest quadrant varied across years, but was never below one km (Figure 5.7C). The highest proximities to new features occurred in the eastern two quadrants of the study area, where landscape cells exhibited consistent mean distances of less than five km, ranging as close as 440m (Figure 5.7C).
Figure 5.6: Distribution of cumulative densities across landscape cells for the specific disturbance types, such as A) cutblocks, B) surface mine, C) wellsites, D) roads and pipelines, and D) natural burns, in 1998 and 2004.
5.3.2 Impacts of Disturbance and Landscape Processes on Bear Abundance

Visual assessments of the relative abundance of grizzly bears in the study area (Figure 5.2) reveals an obvious general trend: most bears were detected along the western study area boundary, near Jasper National Park, where fewer disturbances occur and the terrain is on average higher and more rugged. There were, however, some bears detected in the more disturbed parts of the upper and lower foothills to the east. Further insight into the relative importance of the disturbance and landscape processes driving the excess absences and relative abundance across this study area has been gained from a statistical model selection approach (Table 5.5), and is explained below.
From the six sub-models that specifically tested the effect of disturbance on excess absences (ZIPs 1 to 6, Table 5.5), the lowest AICc was achieved by model 5, which fitted new annual disturbance proximity (NDP) as a metric indicating habitat exposure. Among the three models that related landscape processes to relative abundance (ZIPs 7 to 9, Table 5.5), the most-supported model parameter was colonizer source (DTP), which substantially reduced the AICc in combination with habitat availability (AF) and by itself (ZIPs 8 and 9, Table 5.5).

Regarding the final sub-set of combined models, where complete ZIPs were fitted with explanatory variables from both model components, three out of 19 conceptual models provided the best explanations for overall grizzly bear abundance (Table 5.5). Model 19, which contained terms for colonizer source, habitat exposure and habitat

| Table 5.5: Small-sample adjusted AICc, Akaike weights, and ranks of tested statistical model (AICc for the null model = 378.0; best-ranking models appear in bold, k stands for the total number of parameters incl. the intercept). |
|---|---|---|---|---|---|---|
| Model | Variables | k | AICc | ΔAICc | Model Likelihood Akaike Weight (wi) | Evidence Ratio | Model Rank |
| ZIP 1 | | 3 | 353.7 | 41.18 | 0.00 | 0.00 | 15 |
| ZIP 2 | | 3 | 356.9 | 44.38 | 0.00 | 0.00 | 16 |
| ZIP 3 | | 3 | 358.0 | 54.29 | 0.00 | 0.00 | 17 |
| ZIP 4 | | 3 | 366.81 | 45.48 | 0.00 | 0.00 | 19 |
| ZIP 5 | | 3 | 340.5 | 27.98 | 0.00 | 0.00 | 13 |
| ZIP 6 | | 4 | 360.0 | 47.48 | 0.00 | 0.00 | 18 |
| ZIP 7 | RSF + AF + LPI | 5 | 348.0 | 35.48 | 0.00 | 0.00 | 14 |
| ZIP 8 | DTP | 3 | 318.3 | 5.78 | 0.06 | 0.03 | 18.59 | 5 |
| ZIP 9 | DTP + AF | 4 | 318.1 | 5.58 | 0.06 | 0.03 | 16.81 | 4 |
| ZIP 10 | DD04 | NDP | 4 | 337.33 | 24.81 | 0.00 | 0.00 | 11 |
| ZIP 11 | WD04 | NDP | 4 | 327.9 | 15.38 | 0.00 | 0.00 | 7 |
| ZIP 12 | DDN04 | NDP | 5 | 336.21 | 23.69 | 0.00 | 0.00 | 10 |
| ZIP 13 | DDCh | NDP | 4 | 339.48 | 26.96 | 0.00 | 0.00 | 12 |
| ZIP 14 | DDCD | NDP | 4 | 334.63 | 22.1 | 0.00 | 0.00 | 9 |
| ZIP 15 | DTP + AF | NDP | 4 | 314.64 | 2.12 | 0.35 | 0.19 | 2.88 | 3 |
| ZIP 16 | DD98+DDCh+D98:DDCh|NDP | 7 | 333.83 | 31.31 | 0.00 | 0.00 | 8 |
| ZIP 17 | RSF + DD04 + RSF:DD04 | NDP | 6 | 327.35 | 15.07 | 0.00 | 0.00 | 6 |
| ZIP 18 | DTP + DDCD | NDP | 5 | 314.53 | 2.01 | 0.37 | 0.20 | 2.73 | 2 |
| ZIP 19 | DTP + WD04 | NDP | 5 | 312.52 | 0 | 1.00 | 0.55 | 1 | 1 |
degradation, had the highest weight of evidence ($w_{19} = 0.55$). Alternative models replacing habitat degradation with neighbourhood effect ($w_{18} = 0.20$) and habitat area ($w_{15} = 0.19$) also provided reasonable explanations of bear abundance. These models had similar evidence ratios of 2.73:1 and 2.88:1, respectively, but the first-ranking model with habitat degradation was about 3 times more likely than models that excluded this process. Furthermore, the likelihood of a bear abundance model that excluded both habitat exposure and habitat degradation, and that only contained colonizer source and habitat availability was only about 17:1 (ZIP 9, Table 5.5). This strongly supports the relatively high importance of habitat degradation and exposure to current patterns of grizzly bear abundance, and confirms the visual observation that colonizer source is by far the most supported model parameter, since it occurred in all of the highest-ranking models (Ranks 1 to 5, Table 5.5).

Even without having accounted for other biotic processes such as predator-prey interactions or mating associations, this study was able to explain a considerable amount of the variability in bear abundance across the range of this population unit (~45%), using just a small number of disturbance and landscape processes. Above all, abundance decreased with increasing distance to Jasper National Park, from where bears can colonize the study area (ZIPs 19, 18, 15, Table 5.6). This decrease in abundance observed with increasing distance from park was amplified further by increasing habitat degradation, which was indicated by growing densities of long-term, medium-intensity disturbance, which was presumably accompanied by gas flaring noise and frequent amounts of human presence (ZIP 19, Table 5.6). In the second-ranking model, the neighbourhood disturbance effect had a similar amplifying effect on abundance, with
lower abundance values associated with higher cumulative habitat alterations in the
neighbourhood of a landscape cell (ZIP18, Table 5.6). This result supports the
importance of maintaining a wider landscape perspective beyond the individual landscape
cell level; particularly since cumulative habitat alteration at the landscape cell alone was
not highly supported (ZIP10, Table 5.5).

In the third-ranking model, the negative effect of increasing distance to colonizer
source was mitigated by increasing habitat availability in the form of area of undisturbed
forest (ZIP 15, Table 5.6). This metric was empirically uncorrelated to other disturbance
metrics, but is conceptually related inversely to cumulative habitat alteration, especially
at the upper spectrum of this metric. Lastly, habitat exposure (NDP) appeared
consistently as a significant variable explaining the excess amount of absences across the
study area, and for improving the model fit of all the best-ranking models (Vuong’s

| Table 5.6: Standardized coefficients, standard errors, significance level, pseudo-R² and Vuong’s closeness tests for the three best-ranking regression models. |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| Statistical Model Components | Variables | 1st ranking Model (ZIP19) | 2nd ranking Model (ZIP18) | 3rd ranking Model (ZIP15) |
| | | β | SE | p | β | SE | p | β | SE | p |
| Count Model (poisson) | (Intercept) | -0.61 | 0.21 | <0.01 | -0.55 | 0.20 | <0.01 | -0.46 | 0.20 | <0.05 |
| | DTP | -0.74 | 0.18 | <0.001 | -0.79 | 0.18 | <0.001 | -0.77 | 0.19 | <0.001 |
| | WD04 | -0.32 | 0.14 | <0.05 | - | - | - | - | - | - |
| | DDCD | - | - | - | -27 | 0.15 | <0.1 | - | - | - |
| | AF | - | - | - | - | - | - | 0.09 | 0.05 | <0.1 |
| Zero-inflated Model (binominal) | (Intercept) | -0.65 | 0.43 | <0.1 | -0.54 | 0.39 | <0.1 | -0.51 | 0.40 | 0.2 |
| | NDP | -0.64 | 0.38 | <0.1 | -0.78 | 0.37 | <0.05 | -0.98 | 0.45 | <0.05 |
| Pseudo-R² of overall Model: | | 0.46 | | | 0.45 | | | 0.44 | | |
| Vuong’s closeness test (zip > poisson GLM) | | 0.04 | | | 0.04 | | | 0.03 | | |
closeness tests $Z_{19,18,15} p<0.05$, Table 5.6). In cells where mean distances to new, annual disturbance features were large, the habitat was presumably less exposed to the short-term high-intensity human and machinery use that accompanies these new disturbances when they first originate, hence leading to lower probabilities of excess bear absences.

Newly updated census estimates (e.g. Boulanger et al. 2005a, 2005b and others) suggest that the vastly differing grizzly bear densities observed across the seven population units in Alberta are negatively correlated to the level of human access. As a result, this observation has been considered as a strong support for the argument that habitat alteration through forestry, mining, and hydrocarbon development is related to the decline in grizzly bear numbers (ASRD/ACA 2010). The multi-temporal disturbance data set used in this study provides empirical support for this argument, and offers insight into the specific processes that may be driving the spatial distribution of relative abundance across the range of this population unit.

It could be argued that the impact of the colonizer source could be visually observed up-front, preempting the need for any statistical analysis. Indeed, bears occur only in relatively rare numbers in areas further away from Jasper National Park, where disturbances are common and the risk of human-caused mortality is high (Nielsen et al. 2004c, 2006). However, this study demonstrates how a statistical model-selection approach can be used to assess the relative importance of other disturbance and landscape processes, and provides a tool for explaining the extra variability in relative abundance beyond the distance to protected area. Furthermore, while some studies have documented bear avoidance and displacement from areas with high human presence associated with
recreational or industrial activity (e.g., McLellan 1989, Mace et al. 1999), this study shows, for the first time, the direct negative impact of habitat degradation and exposure on the relative abundance of grizzly bears at the landscape scale.

The results of this study stand in apparent contrast to Berland et al.’s (2008) spatio-temporal homerange use study, which concluded that grizzly bears do not avoid sites that were disturbed within the past year, and instead preferentially use them, especially during the hypophagia foraging season. Contrary to this, we documented non-negligible support for the observation that abundance was lowest in areas with high amounts of recent disturbances, and highest in areas with older, regenerating disturbances (on average > 6 years) and lower amounts of recent disturbances (ZIP 16, Table 5.5, Table 5.7). These apparently contrasting differences in findings may be considered especially relevant since the study was undertaken in the same Alberta foothills region, and over a similar time frame (between 1999 and 2003). However, Berland et al.’s (2008) analysis related grizzly bear occurrence (from telemetry) to new (for each year) disturbance features. A 30m cell, buffered by 500m, was considered ‘used’ if it fell within a bear’s annual homerange (estimated annually with GPS data), measuring on average ~6000 km². The fact that a cell of such small size lies inside the homerange does not necessarily entail that it was actually used by a grizzly bear, and since the disturbance features were buffered by 500m, it is likely that there was some positive bias in both the number of used and disturbed cells represented by that study.

Nevertheless, other studies of this region have also found that bears use areas of regenerating clearcuts (Nielsen et al. 2004a) and nearby roads (Roever et al. in press), which act as attractive sinks (Nielsen et al. 2006) and exert an indirect negative impact on
the population through the increased risk of human-caused mortality (Nielsen et al. 2004c). In the current study, the densities of clearcuts and linear features were found to be highly correlated to the overall level of habitat alteration (i.e. cumulative disturbance density), and appears to negatively affect relative abundance (ZIP 10, Table 5.5). Furthermore, there was some non-negligible support for the positive interaction between habitat quality and cumulative habitat alteration with abundance in this study (ZIP 17, Table 5.5, Table 5.7). While increasing disturbance density was associated with decreasing abundance overall, high-quality habitat was found to offset this trend; an observation consistent with previous work in southern Alberta by Gibeau et al. (2002).

While many of the findings in this study are corroborated by other research, the new inferences drawn should still be interpreted within the context of the data used to model both disturbances and bear abundance. There is little uncertainty associated with the disturbance data set, whose accuracy was assessed previously at 100% (Linke et al. 2009). However, it could be argued that the cumulative habitat alteration was represented conservatively, since all disturbance feature types were treated with the same

<table>
<thead>
<tr>
<th>Statistical Model Components</th>
<th>Variables</th>
<th>Habitat Quality Interaction (ZIP 16)</th>
<th>Variables</th>
<th>Disturbance Age Interaction (ZIP 17)</th>
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</thead>
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<tr>
<td>Count Model (poisson)</td>
<td>(Intercept)</td>
<td>-0.38</td>
<td>0.20</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>DD04</td>
<td>-0.53</td>
<td>0.15</td>
<td>&lt;0.001</td>
</tr>
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<td>0.15</td>
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<tr>
<td></td>
<td>DD04:RSF</td>
<td>0.40</td>
<td>0.15</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Zero-inflated Model (binomial)</td>
<td>(Intercept)</td>
<td>-0.35</td>
<td>0.40</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>NDP</td>
<td>-1.15</td>
<td>0.42</td>
<td>&lt;0.01</td>
</tr>
</tbody>
</table>
relative importance, as measured by their areal extent. For example, the areal coverage of a linear disturbance feature such as a road is on average much lower than the area occupied by a cutblock, though the importance of roads to potentially negative factors of human access is likely much higher. However, this factor is not expected to lead to a significant bias in the analysis of disturbance impact on grizzly bear abundance, since cutblocks and linear features are highly correlated, and should be accounted for by overall disturbance magnitudes.

In regards to relative bear abundance, it was estimated that only three individuals from the population were missed during sampling (Boulanger et al. 2005a). The sample grid cells were 49 km² and covered at minimum one quarter of the bears’ homeranges (smallest homerange 200km²), and therefore represented a very high trap-encounter probability. In addition, each cell was sampled four times, which, since these were pooled as total counts of individuals, was anticipated to have yielded representative relative counts. The fact that the absolute numbers are likely slightly different (three bears were missed in the sampling) could be of concern if the three bears resided in the same general area, or were habituated to traps and high levels of disturbance. However, it is not expected that this bias would cause any significant changes to the model results.

One substantial limitation of the mensurative approach used in this study is the fact that the reported evidence was not experimentally supported with multi-temporal bear data. The causal drivers were inferred by means of model fitting, but it is possible that the bear distribution in 2004 was actually the result of local extirpations in the open foothills, and not directly related to landscape and disturbance processes. As previously mentioned, human-caused mortalities are most commonly associated with roads and
cutblocks, and these disturbances were represented together through *cumulative habitat alteration*, or total disturbance magnitude (DD04) (please see section 2.3.1). While cumulative habitat alteration did result in a significant model fit with abundance (ZIP10, Table 5), this was not the best model. It could also be argued that in the top model, the landscape process *colonizer source* is actually indicative of the same local extirpations in the open foothills (i.e. more roads and cutblocks away from the park and hence higher human access and risk for human-bear encounters). While such concern should not be neglected, the variable indicative of *colonizer source* (DTP) was found to be relatively independent of cumulative habitat alteration (DD04) ($r=0.57$, Table 3), so it is therefore not expected that the entire pattern of bear distribution can be attributed to mortality alone. The strong support for several disturbance processes at the very least emphasizes the need to avoid underestimating the direct effects of disturbance features on the observed abundance of bears. However, additional studies focused on the collection of multi-temporal bear data in this region, as well as in other less-disturbed areas, will be needed to provide further insight into this issue.

5.4. Conclusions

A multi-temporal remote-sensing based disturbance data set has supported the investigation of the relative importance of select spatio-temporal disturbance processes on a threatened grizzly bear population in west-central Alberta. Rather than focusing on presence and absence of human-footprint features alone, this study investigated varying degrees of human-induced disturbances from across the study area. The inclusion of the temporal dimension further allowed the differentiation among different processes that may act upon the resident population. While we found the main driver to be the distance
to a bear colonizer source (Jasper National Park), a few disturbance processes were found to play additional roles impacting the relative abundance of grizzly bears across the study area. Increasing amounts of habitat degradation caused by long-term, medium-intensity disturbances, and disturbance-neighbourhood effects caused by an even higher degree of habitat alterations in the immediate surroundings, were found to have a negative impact on relative bear abundance. Further, increasing degrees of habitat exposure caused by close distances to short-term, high-intensity disturbances was negatively associated with relative bear abundance. Overall, the variation in abundance was relatively low and zero-inflated, but a substantial 45% of this variability could be explained by our best models. This study provides first-time empirical support for the argument that the decline in Alberta grizzly bears is associated with human-induced landscape alterations. Since the Alberta landscape is expected to undergo further changes in the future, more insight may be gained by repeating similar studies in other population units, especially in areas where cumulative habitat alteration is lower, and the variability in bear abundance is higher, or by repeating this study when a new DNA hair-sampling campaign has been completed.

5.5 ACKNOWLEDGEMENTS

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CHAPTER 6: SUMMARY AND CONCLUSIONS

Human activities and disturbances are the source of much contemporary land-cover change, and have been identified as one of the major causes of wildlife population declines and the loss of biodiversity around the world. The Alberta forest landscape is changing quickly due to exposure to human-induced disturbances, including intensive oil and gas development, mining, forestry, and road construction. Since this area is also host to a threatened grizzly bear population, conservation management relies in part on improved knowledge regarding landscape change and its impact on grizzly bears. Remote sensing plays a critical role in environmental monitoring over large areas, but our strategies for handling these data are not yet fully developed. In particular, multi-temporal map products generated from automated processing strategies are still challenged by spatial inconsistencies through time. Prior to this research, a framework for creating spatially consistent, multi-temporal land-cover data suitable for supporting multiple research and management applications had yet to be developed.

The overall goal of this research was to develop a reliable and flexible remote-sensing-based approach to tracking landscape change in Alberta’s multi-use forest environments, in order to gain an improved understanding of the associated disturbance impacts on grizzly bears and the landscape they inhabit. In summary, five research objectives were formulated to address this goal:

1) To assess the impacts of slivers generated during the backdating and updating of raster-based land-cover maps on the types of quantitative metrics commonly used in landscape-monitoring programs;
2) To develop a conceptual model that outlines an automated map backdating- and updating-approach capable of creating a spatially consistent time series;

3) To develop and implement an overarching framework for performing flexible and reliable landscape monitoring using remote sensing;

4) To quantify the status and trends of recent disturbances in the west-central Alberta foothills; and

5) To assess how human-induced disturbance processes explain the spatial distribution and relative abundance of the region’s threatened grizzly bear population.

This PhD research has successfully accomplished each of these five objectives. Brief descriptions of the work surrounding each objective are provided below, highlighting their progress towards a cohesive, over-arching research program:

1) At the beginning of this research, it was important to understand the effects of small, seemingly inconspicuous slivers that are often present in multi-temporal map products on quantitative landscape monitoring. I approached this using a theoretical example, which conceptually and graphically demonstrated how slivers can manifest themselves during both map updating (i.e. projecting forward in time) and map backdating (i.e. projecting backward in time). I then used an experimental approach and data from three small case-study areas in west-central Alberta to quantify the impact of slivers on multi-temporal landscape pattern analysis. As part of this work, I developed an automated methodological procedure for suppressing slivers in both backdated and updated map products. By comparing corrected and uncorrected annual landscape maps, this research
demonstrated that slivers can lead to significant distortions in the magnitude and
direction of multi-temporal landscape pattern trajectories, despite their relatively
small and inconspicuous size. This investigation highlighted the need to suppress
slivers from multi-temporal maps to ensure reliable monitoring.

2) With the insights gained from the previous investigations, I developed a
conceptual model that described how a spatially consistent time series of land
cover could be generated. An innovative new monitoring approach was presented
that combined object-based classification and change-detection strategies with
feature boundary conditioning routines designed to maximize the spatial and
thematic integrity of the finished products. Of central importance is the use of a
vector database, the so-called disturbance inventory, which efficiently and
transparently stores all change features according to specific overlay orders. The
boundary conditioning performed for these features ensure their subsequent
seamless integration in the existing map in order to yield sliver-free, spatially
consistent, but temporally dynamic new map products, without the need for
manual interference. This model is able to handle all the basic landscape
dynamics, including feature appearance, disappearance, succession, expansion,
and shrinkage, leading to realistic and meaningful representation of land-cover
trends over time.

3) In addition to reliability, there is a need for flexibility in multi-temporal map
representations: an important consideration for wildlife and environmental
applications which must often serve a variety of purposes. This research
component was based on the preceding conceptual model (described above) and
introduced an overarching methodological framework designed to accommodate maps with either categorical or continuous attributes; a quality that provides an adaptable foundation for monitoring of land cover and vegetation structure at any categorical scale of interest. In implementing this approach, I formulated efficient, transparent, and automated data-handling methods that were tested across a 40,000 km² study area in the Rocky Mountain foothills of west-central Alberta from 1998 to 2005. These methods were furthermore adaptable to deal with change features identified either manually (digitizing) or automatically (image differencing): a trait that is highly desirable for operational applications. The framework resulted in the successful, semi-automated generation of annual maps depicting land cover and vegetation structure with both continuous and categorical attributes.

4) In order to demonstrate the potential of the new monitoring framework and its utility as a powerful tool for analyzing and tracking change, I quantified the recent status and trends in disturbances in the Alberta foothills. Focusing on the central portion of the annual map series (~ 8800km²), I documented substantial changes in density and configuration of human-induced disturbance features related to resource extraction and industrial development. These changes took place over a relatively short time frame (less than seven years), and serve to highlight the rapid development taking place within Alberta’s public landscapes, which experience mean annual rates of landscape change of 0.6 ha/km².

5) In addition to simply describing the rate of landscape change in Alberta’s foothills, I also set out to assessing the impact of anthropogenic disturbance
features on the region’s population of grizzly bears. I used a systematic sampling
design to partition the landscape into grid cells. Each cell was used to measure
relative grizzly bear abundance (based on a 2004 DNA census) and landscape
disturbance. Several variables from the multi-temporal disturbance inventory
were used to measure selected disturbance processes, while other variables
quantified landscape processes. I used a model-selection approach to highlight
the potential role of habitat degradation and habitat exposure as negative drivers
of grizzly bear abundance, providing empirical evidence for long-speculated
consequences of industrial development for the first time at the landscape scale.
However, this particular portion of the province contains a long history of
accumulated disturbance features, and the role of other effects on bears such as
increased human-caused mortality were not directly accounted for in my study,
perhaps limiting the extent to which these findings can be generalized. In order to
confirm these results, we need to conduct repeated studies in the Yellowhead over
time, and expand the work to neighbouring populations with different patterns of
disturbance and abundance. Nevertheless, this study demonstrated that the multi-
temporal disturbance inventory provides an important database allowing fine-
tuned analysis surrounding the impact of rates and directions of multi-temporal
environmental change.

In conclusion, the multi-temporal framework for flexible and reliable landscape
monitoring developed in this thesis constitutes an effective strategy for generating
spatially consistent, temporally and categorically dynamic land-cover maps over large
areas. The disturbance-inventory database concept serves as a powerful tool for assessing and tracking disturbance features and landscape change, both now and for future applications.

6.1 Research Contributions

This thesis research resulted in a number of theoretical and methodological contributions to the fields of landscape ecology and remote sensing. First, the thorough examination of slivers and their impacts on landscape monitoring was published in the international journal of *Landscape Ecology* as Linke et al. (2009a). The new awareness created by this work was acknowledged by remote sensing practitioners during a presentation given at the annual conference of the American Society for Photogrammetry and Remote Sensing (ASPRS) in Portland, Oregon in May of 2008. The reception of my work at that conference led to a subsequent invitation to an international workshop on multi-temporal image analysis (Multi-Temp) in Connecticut during July of 2009.

It was at the Multi-Temp workshop, where the most significant contribution of this research program – the new framework for flexible and reliable landscape monitoring – was presented for the first time to an international audience of multi-temporal remote sensing scientists. The work was published as Linke and McDermid (*in press*) in a special issue on multi-temporal imagery analysis arising from the workshop. The application of this framework to tracking changes across a 40,000-km² study area in west-central Alberta between 1998 and 2005 was published as Linke et al. (2009b) in *Photogrammetric Engineering and Remote Sensing*: one of the most widely read journals in the field of remote sensing. This work was recognized by Dr. Marvin Bauer (Editor *Remote Sensing of Environment*, pers. comm. July 30, 2008) as one of the most
innovative contributions of the year, and received the third place ERDAS award for Best Scientific Paper in Remote Sensing in 2010.

Finally, the results from the implemented framework were used to track disturbances and assess their impacts on grizzly bears within the multi-use foothills landscape of Alberta. The work constitutes one of the first demonstrations of this type of landscape-monitoring activity in the field of wildlife ecology. The detailed multi-temporal disturbance inventory has allowed us to document the rapid changes occurring within this region, and facilitated a first-time analysis on the impacts of the various disturbance processes on Alberta’s threatened grizzly bear population. This latest study constitutes a research tool for investigating potential relationships between multi-temporal disturbance and wildlife, and will be submitted to an applied ecological journal.

Aside from these immediate contributions, this work has also contributed to collaborative research applications within the Foothills Research Institute Grizzly Bear Research Program. For example, the disturbance database generated in my work was used as validation data for collaborative research on Landsat-MODIS data fusion procedures for high spatial- and temporal-resolution mapping (Hilker et al. 2009). In addition, the mapping framework has so far been applied to two other regions of comparable size within the province: one just north of the current study area, and another in the Kakwa region of northern Alberta. Other research by MGIS student Andrea Ram, is currently underway to extend the monitoring horizon back to 1980s, and will allow the overall quantification and comparison of human-induced changes in the Alberta Foothills across three decades.
6.2 SUGGESTIONS FOR FUTURE RESEARCH

While this thesis contains a number of substantial research contributions, some specific research issues require further study, and a large number of potential research applications exist. The research issues and applications deemed most relevant are suggested below.

During the course of the thesis work, much attention was paid to the desirable spatial and thematic consistency of the resulting time series. It was beyond the already challenging scope of this research to address variable rates of regeneration within each disturbance feature; the application of strict decision-rules for assigning land-cover attributes to specific disturbance features through time constituted a necessary but unrealistic simplification. Furthermore, the relatively short time-spans investigated in the applied phases of this project did not require accommodations that would allow disturbance features to return back to their original status (e.g. regenerating cut-blocks back to mature forest). As a result, the full spectrum of forest succession was absent from this approach. These two related issues deal with some of the more subtle aspects of thematic changes, and are deemed important research topics. It is anticipated that issues surrounding the representation of thematic attributes would present spatial-consistency challenges similar to those encountered with the representation of geographic entities, because of spurious changes arising from classification differences. Future research should investigate the usefulness of biophysical modelling of vegetation succession within this context.

Related issues surround the long-term backdating or updating of maps depicting continuous attributes of vegetation structure such as forest crown closure or tree-species
composition. For the needs of the time frame dealt with in the presented framework, the reference map for the continuous variables was kept as the standard throughout the monitoring horizon. However, in cases where the monitoring horizon exceeds the time needed for forest stands to undergo substantial change in the respective attribute, a further expanded updating procedure would be needed. Future research should focus on this issue if longer monitoring horizons are important.

One specifically well-suited application of the currently existing data set is the investigation of independent and cumulative effects of stand-replacing disturbances on landscape structure in the Alberta foothills. Advances have been made in this relevant area of research by differentiating the relative and combined contributions of fire and forest harvesting on the formation of overall landscape configuration (Wang and Cumming in press) through the explicit removal and overlay of the respective disturbance features. Such analyses could be readily expanded through the inclusion of other disturbance features, such as wellsites, roads, and pipelines using the data set assembled in the present work; a research objective that has been previously limited by the necessary time-consuming, manual procedures.

Another highly relevant area of research surrounds questions about the importance of multi-temporal landcover gradients. To date, most species-distribution models have used only categorical landcover data as habitat-related covariates, wherein landcover is represented as a mosaic of discrete patches, each belonging to a single landcover class. However, ecosystems are comprised of a complex interplay of continuous gradients of variation (Wiens 1994), and may not be well-characterized by single catch-all map products (McDermid et al. 2005). This approach assumes that
landcover types are suitable surrogates of the environmental conditions required by multiple species (Noon et al. 2003). However, this may be an unsupported assumption for most taxa in most ecosystems (Cushman et al. 2008). An alternative approach is to use continuously varying gradients of some measurable characteristics on which these classifications are based (e.g. species composition) (McGarigal and Cushman 2005). A specific advantage of this gradient concept is that by avoiding the truncation of landcover variation into a discrete set of classes, ecologists can use a reduced set of high-measurement-level predictor variables to model species distribution. Future research is urged to seek further evidence for the alternative, continuous way of representing landcover attributes and its application to species distribution modelling. The data needed for such an undertaking have been generated from the results of this thesis.

In summary, the data set created in this research now allows for many opportunities to apply them to other applications. Within the scope of this thesis, the application focus for tracking and assessing change was limited to the categorical representation of land cover and disturbance; however, with the possibility for creating any composite map product based on the combined categorical and continuous attributes for land-cover and vegetation structure (i.e. crown closure and species composition), this multi-annual data set could further be explored for many other wildlife species or biodiversity data existing in the region. More application examples include the use of this large-area, multi-annual data set for addressing questions about the relative importance of landscape composition and configuration for additional wildlife population attributes, including spatial distribution, abundance, occurrence, or survival (Fahrig 2003, McGarigal and Cushman 2002). We can gain new insights into population-level
processes by incorporating new approaches based on multivariate landscape pattern trajectory analysis, through the integration and spatial analyses of multiple sources of temporal variability (Cushman and McGarigal 2007). Many questions exist that can further advance the contributions made in this research. These represent a wealth of exciting research opportunities for the future.
BIBLIOGRAPHY


