Satellite Image Classification and Spatial Analysis of Agricultural Areas for Land Cover Mapping of Grizzly Bear Habitat

A Thesis Submitted to the College of Graduate Studies and Research in Partial Fulfillment of the Requirements for the Degree of Master of Science in the Department of Geography University of Saskatchewan

Saskatoon

By

Adam Collingwood

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Abstract

Habitat loss and human-caused mortality are the most serious threats facing grizzly bear (Ursus arctos L.) populations in Alberta, with conflicts between people and bears in agricultural areas being especially important. For this reason, information is needed about grizzly bears in agricultural areas. The objectives of this research were to find the best possible classification approach for determining multiple classes of agricultural and herbaceous land cover for the purpose of grizzly bear habitat mapping, and to determine what, if any, spatial and compositional components of the landscape affected the bears in these agricultural areas. Spectral and environmental data for five different land-cover types of interest were acquired in late July, 2007, from Landsat Thematic Mapper satellite imagery and field data collection in two study areas in Alberta. Three different classification methods were analyzed, the best method being the Supervised Sequential Masking (SSM) technique, which gave an overall accuracy of 88% and a Kappa Index of Agreement (KIA) of 83%. The SSM classification was then expanded to cover 6 more Landsat scenes, and combined with bear GPS location data. Analysis of this data revealed that bears in agricultural areas were found in grasses / forage crops 77% of the time, with small grains and bare soil / fallow fields making up the rest of the visited land-cover.

Locational data for 8 bears were examined in an area southwest of Calgary, Alberta. The 4494 km² study area was divided into 107 sub-landscapes of 42 km². Five-meter spatial resolution IRS panchromatic imagery was used to classify the area and derive compositional and configurational metrics for each sub-landscape. It was found that the amount of agricultural land did not explain grizzly bear use; however, secondary effects of agriculture on landscape configuration did. High patch density and variation in distances between neighboring similar patch types were seen as the most significant metrics in the abundance models; higher variation in patch shape, greater contiguity between patches, and lower average distances between neighboring similar patches were the most consistently significant predictors in the bear presence / absence models. Grizzly bears appeared to prefer areas that were structurally correlated to natural areas, and avoided areas that were structurally correlated to agricultural areas. Grizzly bear presence could be predicted in a particular sub-landscape with 87% accuracy using a logistic regression model. Between 30% and 35% of the grizzlies’ landscape scale habitat selection was explained.
Acknowledgments

This research was funded by the Natural Sciences and Engineering Research Council of Canada and the Foothills Model Forest. I would like to thank my committee members, Dr. Steven Franklin, Dr. Xulin Guo, and Dr. Marc Cattet, for all of their help, advice, and encouragement. I am also indebted to my summer field assistant, Amanda Davies, who made the field data collection possible, and Dr. Gordon Stenhouse and the rest of the Foothills Model Forest team for their time, ideas, and the use of their data.
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1. Introduction and Overview

This chapter will provide an introduction and overview of the concepts that are used in the following chapters. The objectives of the thesis will be established, and placed within the larger context of existing literature.

1.1 Grizzly Bear Background

1.1.1 Importance

There has recently been a growing trend in North America, as well as other places in the world, to recognize the value of intact, healthy ecosystems that contain native plants and animals. Grizzly bears (*Ursus arctos* L.) could be considered a well-recognized poster child for this developing ecological consciousness (Peak *et al.*, 2003). In addition to this cultural value, grizzly bears are also an important ecological asset. Grizzly bears are an umbrella species, meaning that ecosystems and landscapes that are viable for grizzly populations are also viable for a large number of other species (Peak *et al.*, 2003), and they are therefore an important indicator of ecosystem health. Grizzly bears can also influence ecosystem health and variability directly, through processes such as seed dispersal and transportation of nutrients from marine to inland ecosystems (Hilderbrand *et al.*, 1999). In addition, complex ecological relationships can be affected by a lack of grizzly predation on ungulates. Berger *et al.* (2001) showed how an increased ungulate population caused by lack of predation after a local grizzly extinction caused damage to riparian areas from overgrazing, which in turn affected migratory bird
diversity. Grizzly bears can also be a cause of local vegetation diversity. By overturning earth in search of roots and small mammals, they provide disturbance patches that become good sites for pioneering plant species (Peak et al., 2003). Grizzly bears play an important role in the environments which they inhabit; unfortunately, they are under threat, due mainly to conflict with humans. Grizzly bears require wilderness and seclusion from humans, as well as high quality, contiguous habitat (McLellan and Shackleton, 1988).

Grizzly bears occupied the entire western half of North America at the time of European settlement, with their territory even including much of the Great Plains (Kansas, 2002). In the last 200 years, however, grizzly range has shrunk by as much as two-thirds. Their range south of the Arctic Circle is limited to mountainous areas, isolated pockets, and national parks (Figure 1.1, adapted from Kansas, 2002). They are now classified as a ‘threatened’ species (likely to become endangered in the near future in a significant portion of its range) in the contiguous United States (grizzly bears in Yellowstone National Park in the U.S.A. have been delisted, however), and it has been recommended by Alberta’s Endangered Species Conservation Committee that the species be elevated from ‘may be at risk’ status (believed to be at risk, but needing a detailed assessment for confirmation) to ‘threatened’ status in Alberta as well (McLellan and Shackleton, 1988; Stenhouse et al., 2003).

1.1.2 Habitat and fragmentation

The term ‘habitat’ in this thesis will be defined as “the sum and location of the specific resources needed by an organism for survival and reproduction”, which is the definition put forward by McDermid et al. (2005). ‘Fragmentation’ in this thesis refers to
the more general principle of land transformation in which a large habitat is broken into smaller pieces by a spatial process (Forman, 1995). Fragmentation will therefore lead to an overall loss of habitat and increased isolation of the remaining habitat pieces. Habitat loss can also occur without fragmentation, if the use of the land changes. Fragmentation is often measured with ‘landscape metrics’, which for the purposes of this thesis will follow the definition as outlined by McGarigal (2002). Landscape metrics refers to indices developed for categorical maps, and “is focused on the characterization of the geometric and spatial properties of categorical map patterns represented at a single scale.” (McGarigal, 2002) Landscape metrics act as the quantitative link between spatial
patterns of the landscape and ecological or environmental processes, such as animal
movement and habitat selection. (O’Neill et al., 1988; Narumalani et al., 2004).

There are two primary effects of fragmentation on the landscape: an alteration of
the remnant habitat microclimate, and isolation of previously connected areas of the
landscape. Fragmentation therefore causes both biogeographical and physical effects on
the landscape (Saunders et al., 1991). It often has dramatic consequences for species
richness and complex ecosystem interactions, and can lead to a decrease in biodiversity
(Saunders et al., 1991; Hoffmeister et al., 2005).

Biogeographical effects of fragmentation, such as changes in microclimate, result
from changes in the physical fluxes, or movements of energy, across the landscape.
Alterations in solar radiation, wind, and water can all be caused by fragmentation of the
landscape, and have important effects on remnant populations. For example, changes in
the radiation balance can affect large animals by altering resource availability due to
changes in vegetation type, growth rates, and phenology. Altered solar radiation fluxes
can also destabilize predator-prey and other complex interactions though direct changes
in temperature. Similar effects can be caused by wind, as fragmented landscapes are
more susceptible to this process; wind can damage vegetation, and is responsible for the
transfer of materials such as dust, seeds, and nutrients (Saunders et al., 1991).
Fragmentation may also interrupt natural processes that have important biological
consequences, such as fire. These processes are often essential to creating habitat and
promoting ecosystem health (Leach and Givnish, 1996). However, natural processes
only operate at a limited scale in fragmented landscapes, often being confined to
individual patches.
Fragmentation also causes direct physical effects on the landscape. Both reduction of total habitat area and the spatial structure of the remaining habitat are important factors for the survivability of the remaining native populations. Habitat (and therefore species) isolation is one of the most important factors to examine. Populations that are isolated from neighboring populations are subject to inbreeding and genetic drift (Peak et al., 2003; Hoffmeister et al., 2005). Inbreeding and genetic drift in turn increases the population’s susceptibility to long term climate variability, pathogen-induced changes in ecosystem carrying capacity, and, eventually, extinction (Mattson and Reid, 1991; Hoffmeister et al., 2005). Species can no longer survive these habitat changes by normal means (i.e., migration and dispersal) because of a lack of travel corridors or contiguous habitat in fragmented landscapes (Mattson and Reid, 1991; Saunders et al., 1991; Rosenberg et al., 1997). Suppressed migration and dispersion is especially problematic for grizzly bears, with their large natural range and relatively low population numbers (Kansas, 2002). Habitat fragmentation may also lead to evolutionary changes in a species, due to changes in their encounters with mutualists, competitors, enemies, and prey (Hoffmeister et al., 2005). The size, shape, and position in the landscape of the remaining habitat are all important modifying variables for these direct physical effects on the landscape (Fahrig and Merriam, 1994).

Probably the most significant impact fragmentation has on grizzly bears is an increased exposure to humans, due to greater amounts of edge habitat and an associated increase in access by people to formerly remote areas of grizzly habitat (Mattson and Reid, 1991; Gibeau et al., 2002; Kansas, 2002; Nielsen et al., 2004).
1.1.3 Impacts on grizzly bears

Human-caused mortality, along with habitat loss, are the most serious threats facing grizzly bear populations (Gibeau et al., 2002; Kansas, 2002). Habitat loss is most often caused by uncontrolled human access and industrial development activity in bear habitat. Activities such as oil and gas exploration and extraction, forestry, agriculture, and recreation all contribute to grizzly bear habitat fragmentation and loss (Garshelis et al., 2005). Another important factor is the network of roads and trails that all of the aforementioned activities depend on, as well as the seismic exploration lines that are cut for oil and gas exploration (Mace et al., 1996; Linke et al., 2005). These linear features allow access to otherwise remote areas by people, which leads to conflict and a declining bear population (Kansas, 2002). Roads and trails not only fragment the landscape, but reduce the total area of habitat and limit grizzly bear movement. Roads, for example, can act as barriers or even increase mortality for grizzly bears (Gibeau et al., 2002). Not all fragmentation is bad, however - natural habitat variability can be favorable, as it provides more potential resources for different activities such as feeding and bedding (Linke et al., 2005).

Oil and gas exploration and extraction is a very large part of fragmentation of forested areas in the Rocky Mountains, especially in the Alberta foothills region. One of the major components of oil and gas exploration is the creation of seismic cutlines, which dissect the landscape and contribute to the fragmentation of existing patches of forest. The network of cutlines can be quite dense, and the lines themselves 5 – 10m wide (Linke et al., 2005). Linke et al. (2005) investigated the role that seismic cutlines and landscape structure play in determining grizzly bear use of an area in the foothills of the
Alberta Rocky Mountains. They found no direct relationship between landscape use and proportion of cutlines, which is the same result obtained by McLellan and Shackleton (1989) in southern British Columbia. However, Linke et al. (2005) did find an indirect relationship: grizzly bear use was linked to physical landscape metrics that included mean patch size, proportion of closed forest, and variation in mean nearest neighbor distances between patches of the same type. These landscape metrics are all affected by the dense network of seismic cutlines through forested areas.

Grizzly bears are known to prefer areas that include both forested and non-forested habitat (Apps et al., 2004), but with increasing human presence, natural causes of forest variability, such as fire, are suppressed or eliminated. Elimination of natural disturbance results in forest habitat with relatively few openings, which can result in bears instead using anthropogenic openings caused by forestry activity (Nielsen et al., 2004). Data from bears in the central Alberta Rocky Mountain foothills region shows that grizzly bear use could be predicted by landscape metrics, distance-to-edge, and edge-to-perimeter ratio. Grizzly bears were found closer to clear-cut edges, selected clear-cuts that had an irregular shape, and generally used these areas at night (Nielsen et al., 2004). While generally suitable habitat, bear use of clear cuts leads to increased conflict with humans, which often results in high bear mortality (Nielsen et al., 2006).

While less conspicuous than other forms of fragmentation, linear features such as roads can have very large impacts on grizzly bear populations (McLellan and Shackleton, 1988; Mace et al., 1996; Wielgus et al., 2002; Chruszcz et al, 2003; Waller and Servheen, 2005). The impacts are large due to the bears’ great mobility and extensive spatial requirements for survival (Chruszcz et al, 2003). Roads may increase landscape
connectivity for people, but they decrease it for bears and other wildlife; decreased connectivity can have many detrimental effects. Some of the direct effects of roads on grizzly bears include increased access for hunters and poachers, increased probability of vehicle-bear collisions, and increased frequency of bear flight responses, the stress of which can negatively impact the health of the bear (McLellan and Shackleton, 1988).

Indirect effects of roads on grizzly bears can occur because of long-term displacement of bears from areas adjacent to roads; roads in the Rocky Mountains are usually located along valley bottoms, and pass through riparian areas and other highly productive areas of bear habitat. Loss of these areas of productive habitat can lead to increased pressure on similar habitats in regions that are not fragmented by roads, as well as the loss of overall habitat (McLellan and Shackleton, 1988; Singleton et al., 2004).

Agriculture and its associated activities are also causes of habitat fragmentation and increased conflict between bears and humans. Kansas (2002) identified reducing human-grizzly conflict on agricultural lands as a priority for mitigating the long term decline of the species. In a study of grizzly-human conflict on agricultural lands in Montana, Wilson et al. (2005; 2006) found that there were many different attractants for bears on private lands that are a part of the natural bear habitat. One of the most important factors was the use of riparian areas by bears as both habitat and transportation corridors (Wilson et al., 2005). The bears use these areas to reach anthropogenic attractants, such as cattle, sheep, beehives, and boneyards. The more attractants that were in an area, and the closer that area was to wetlands or riparian areas, the more likely the bears were to use that area as habitat. When barriers such as fences were introduced, the rate of bear use of these areas dropped considerably. For example, beehives that were
protected by fencing were much less likely to be “attacked” by the bears than unprotected hives (Wilson et al., 2006). In many cases in Montana, the original bear habitat has not been fragmented, but its use has been changed, which brings the bears into conflict with people, and can be seen as an effective loss of habitat. Effective habitat loss is defined as an unwillingness of the bear to use suitable habitat because of “high levels of sensory disturbance or mortality risk” (Kansas, 2002).

The province of Alberta, Canada, also has a large agricultural footprint. Agriculture and related activities exist right up to the edge of the foothills of the Rocky Mountains. The recommendation by Alberta’s Endangered Species Conservation Committee that grizzly bears be elevated to ‘threatened’ status (Stenhouse et al., 2003) means that appropriate management and conservation planning will be required. Effective and current habitat maps will be necessary for this planning (Nielsen et al., 2006). A problem currently facing grizzly bear habitat mapping in Alberta is the lack of a classification scheme that differentiates between agricultural and herbaceous areas. An accurate classification of such areas will be necessary in order to further understand the relationships between the grizzly bears and these agricultural areas. However, the current area of interest for grizzly bear population viability analysis in Alberta is most of the western half of the province (Nielsen et al., 2006), rendering traditional field based analysis methods problematic for land cover classification purposes. Therefore, another technique is needed. Due to their spatial and temporal flexibility, remote sensing methods of land cover classification are well situated to handle this problem of land cover classification over a large spatial range (McDermid et al., 2005).
1.2 Land Cover Classification

One of the most common uses for remotely sensed satellite data is land cover classification, the process of creating a thematic map by attributing a particular class identity to image objects or discrete pixels within the image (Cihlar et al., 1998; Foody, 2002). Each separate class can be defined by its individual spectral response within the available spectral bands registered by the satellite sensor being used. The spectral response of a band is a measurement of the amount of reflected solar radiation in a particular wavelength, with the wavelength being determined by the band. Classes can also be defined based on textural or spatial measures, such as homogeneity or distance to other features. Land cover classification can be executed in a variety of ways, and for a variety of purposes. Land cover classification can also be accomplished at a variety of different scales: from the continental and global level (e.g., Friedl et al., 1999; Agrawal et al., 2003; Cihlar et al., 2003; Joshi et al., 2006) to local and regional studies (e.g., Brook and Kenkel, 2002; Reese et al., 2002; Van Niel and McVicar, 2004). Satellite sensors are commonly grouped by spatial resolution, and coarse, medium, and fine resolution sensors have all been used for land cover classification studies (see Table 1.1).

However, McDermid et al. (2005) note that “while landcover maps may contain useful predictive power, they are often not capable of revealing the underlying mechanisms and dynamic nature of complex natural landscapes”. To help increase the accuracy and usefulness of land cover maps, a small selection of classification methods were tested in this thesis. An exhaustive look at all of the available classification methods and satellite remote sensing systems is beyond the scope of this thesis. However, some attention will be given to medium resolution sensors, especially Landsat
Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and the Indian Remote Sensing (IRS) 1-C/D sensors, as images from these satellites were used in the thesis.

Table 1.1: Common satellite sensors used for land-cover classification

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<tr>
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<th>Common Land Covers Studied</th>
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<tr>
<td></td>
<td>Advanced Very High Resolution Radiometer (AVHRR) (1.1 km)</td>
<td>Various – continental to global scale cover</td>
<td>Friedl et al., 1999; McIver and Friedl, 2002</td>
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<tr>
<td></td>
<td>Systeme Pour l'Observation de la Terre (SPOT) Vegetation sensor (1.15 km)</td>
<td>Vegetation, Agriculture</td>
<td>Agrawal et al., 2003; Kerr and Cihlar, 2003</td>
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<th>Medium Resolution</th>
<th>Satellite Sensor (resolution)</th>
<th>Common Land Covers Studied</th>
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<tr>
<td></td>
<td>Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) (30m)</td>
<td>Forest fragmentation, semi-arid vegetation, National Park land cover, habitat</td>
<td>Franklin et al., 2002; Brown de Colstoun et al., 2003; Camacho-De Coca et al., 2004; Bock et al., 2005</td>
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<tr>
<td></td>
<td>SPOT (20m)</td>
<td>Crop yield, Agricultural land cover</td>
<td>Cohen and Shoshany, 2002; Raclot et al., 2005</td>
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<th>Fine Resolution</th>
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<td>Indian Remote Sensing (IRS)-1A/B/C/D (5m, 23.5m, 36.25m, 72.5m, or 188m, depending on sensor and spectral band used)</td>
<td>Wheat crop, crop cover, wetland</td>
<td>Murthy et al., 2003; De Wit and Clevers, 2004; Shanmugam et al., 2006</td>
</tr>
<tr>
<td></td>
<td>European Space Agency ESA-1 Synthetic Aperture Radar (SAR) (26m)</td>
<td>Crop mapping</td>
<td>Michelson et al., 2000; Ban, 2003; Blaes et al., 2005</td>
</tr>
<tr>
<td></td>
<td>IKONOS (4m)</td>
<td>Forest inventory parameters, Mangrove swamps</td>
<td>Wang et al., 2004; Chubey et al., 2006</td>
</tr>
</tbody>
</table>
1.2.1 Medium-resolution cropland and grassland classification

The Landsat 5 and Landsat 7 satellites are commonly used for medium-resolution land cover classification studies (Table 1.1). The Landsat 5 TM sensor and the Landsat 7 ETM+ sensor are very similar. Details regarding the capabilities of these sensors are given in Table 1.2, along with details about the IRS satellites. Images from these three satellites were used in this thesis. The 5m resolution PAN sensor was the only component used from the IRS satellites.

<table>
<thead>
<tr>
<th>Band</th>
<th>Landsat 5 TM Spectral Wavelength (μm)</th>
<th>Spatial Resolution (m) at Nadir</th>
<th>Landsat 7 ETM+ Spectral Wavelength (μm)</th>
<th>Spatial Resolution (m) at Nadir</th>
<th>IRS-1C and 1D Spectral Wavelength (μm)</th>
<th>Spatial Resolution (m) at Nadir</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.45-0.52</td>
<td>30x30</td>
<td>1</td>
<td>0.45-0.52</td>
<td>30x30</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.52-0.60</td>
<td>30x30</td>
<td>2</td>
<td>0.52-0.60</td>
<td>30x30</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.63-0.69</td>
<td>30x30</td>
<td>3</td>
<td>0.63-0.69</td>
<td>30x30</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.76-0.90</td>
<td>30x30</td>
<td>4</td>
<td>0.76-0.90</td>
<td>30x30</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1.55-1.75</td>
<td>30x30</td>
<td>5</td>
<td>1.55-1.75</td>
<td>30x30</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>10.4-12.5</td>
<td>120x120</td>
<td>6</td>
<td>10.4-12.5</td>
<td>60x60</td>
<td>Pan 0.50-0.75</td>
</tr>
<tr>
<td>7</td>
<td>2.08-2.35</td>
<td>30x30</td>
<td>7</td>
<td>2.08-2.35</td>
<td>30x30</td>
<td>WiFS 1 0.62-0.68</td>
</tr>
<tr>
<td>-</td>
<td>Pan</td>
<td>15x15</td>
<td>-</td>
<td></td>
<td>WiFS 2 0.77-0.86</td>
<td>188x188</td>
</tr>
</tbody>
</table>

Swath Width 185 km 185 km 142 km for bands 2,3,4; 148 km for band 5; Pan = 70 km; WiFS = 774 km

Revisit Period 16 days 16 days 24 days for bands 2-5; 5 days (off-nadir) for Pan; 5 days for WiFS

Many studies of land cover classification have focused on agricultural applications, such as crop yield prediction (e.g., Lobell and Asner, 2003; Ferencz et al., 2004), nitrogen content (e.g., Boegh et al., 2002), stress (e.g., Estep et al., 2004), as well as simple crop classification (e.g., Aplin and Atkinson, 2001; Turker and Arikan, 2005). Grasslands have also been studied (e.g., Price et al., 2002; Baldi et al., 2006), for similar reasons. There has been comparatively little research on delineating natural herbaceous cover from crop or managed meadow cover. A few studies have briefly mentioned how to delineate between cropland and natural herbaceous or grassland areas (e.g., Reese et
al., 2002; Bock et al., 2005); others have simply included classes such as meadow (e.g., El-Magd and Tanton, 2003) and grassland (e.g., De Wit and Clevers, 2004) in their classifications of agricultural areas.

Remote sensing of cropland has used a variety of methods and techniques, including multi-temporal analysis, object-based analysis, and classification methods such as supervised and unsupervised approaches.

1.3 Methods of classification
1.3.1 Multi-temporal analysis

One of the problems in using remote sensing data for land cover classification is the separability of vegetation types, especially agricultural croplands (hereafter: crops). For a single-date image, different vegetation types often show very similar spectral responses, possibly resulting from very similar leaf area index values and internal structure. Crops at the same phenological stage are especially hard to discriminate (Guerschman et al., 2003). One solution to this problem has been to use multi-temporal image analysis; that is, combining multiple images of the same area from different dates or phenological stages (e.g., Murthy et al., 2003; Van Niel and McVicar, 2004; Yuan et al., 2005). There are many different techniques for the combination and analysis of multi-temporal scenes. Two techniques, known as iterative multi-date (Van Niel and McVicar, 2004) and sequential masking (Turker and Arikan, 2005), give better results than others; however, no matter the technique, there is a consensus their use improves vegetation separability and can reduce problems caused by clouds, for example. More importantly, multi-temporal techniques can increase classification accuracy (e.g., Murthy et al., 2003; Van Niel and McVicar, 2004; Reese et al., 2002; Joshi et al., 2006). It has
been shown that a minimum of two, and preferably three, images taken over a single growing season are necessary to distinguish many different crop and grassland types (e.g., Reese et al., 2002; Guerschman et al., 2003; Van Niel and McVicar, 2004; Wunderle et al., 2005)

Despite these benefits, many studies, including this one, do not use multi-temporal methods (e.g., Latifovic et al., 1999; Vescovi and Gomarasca, 1999; Lobell and Asner, 2003; Baldi et al., 2006). There are often limitations on available imagery, or financial resources are not available to obtain more scenes. In addition, multi-temporal analysis may not be best for all areas or land cover types. For example, Langley et al. (2001) found that uni-temporal classification outperformed multi-temporal classification in their study of a semi-arid grassland. They also concluded that single date imagery involves less time and money, both in data acquisition and processing. In some research, the authors acknowledge the potential usefulness of multi-temporal imagery, but choose not to implement it (e.g., Brook and Kenkel, 2002). While there is general consensus about the potential usefulness of multi-temporal analysis, its use should be analyzed on a case-by-case basis. It may not be suitable to adopt this method in all situations. For example, operational constraints on image acquisition or a lack of availability of cloud-free imagery often make it impossible to use multi-temporal analysis even in situations that would benefit from it. In other cases, such as in this thesis, classification results may be sufficiently accurate with single date imagery, in which case it would not make sense to complicate the study with multi-temporal analysis.
1.3.2 Object-based classification

While most traditional remote sensing land cover classification is pixel-based, many newer studies are turning to object-based classification methods as a way to improve accuracy (e.g., Aplin and Atkinson, 2001; Smith and Fuller, 2001; Lloyd et al., 2004; Walter, 2004; Bock et al., 2005). Object-based classification divides the satellite image into objects or segments that represent a homogenous unit on the ground. The entire object is classified based on the overall statistical properties of the pixels that make up the object, instead of classifying each pixel separately as in pixel-based classifications (e.g., McIver and Friedl, 2002). Pixel-based methods have two main weaknesses: first, the end products do not relate well to the actual landscape structure, often having a speckled appearance due to misclassification of individual pixels within a homogenous area such as an agricultural field (Smith and Fuller, 2001; De Wit and Clevers, 2004). Second, there is a problem with ‘mixed’ or ‘edge’ pixels; these are pixels located on the boundaries between discrete land covers. An example would be the boundary between two different agricultural fields. In a pixel-based agricultural classification, the spectral properties of boundary pixels will not resemble the properties of either of the two crops of which it consists, but a mixture of the two, which causes them to be falsely classified as alternate land cover types (Smith and Fuller, 2001; De Wit and Clevers, 2004).

Object-based methods are not immune to these problems, as mixed pixels can lead to problems with creating the initial objects, and can affect the values of the object properties (such as mean reflectance values). For some applications however, such as an agricultural classification as done in Chapter 2 of this thesis, object-based classification has minimal drawbacks when compared to pixel-based classification. The relatively
large, homogenous fields of an agricultural setting are one reason that these problems are
minimized. Object-based classification also has the added benefit of easier integration
into vector-based GIS systems (Raclot et al., 2005).

The major difficulty with the object-based approach is the delineation of
meaningful objects. For large scale projects, it is not feasible to hand digitize, for
example, tens of thousands of field boundaries. One option is to use commercially
available software that can automatically segment an image into discrete objects based on
some spectral, spatial, or statistical measure. For large areas, this could be an efficient
method. However, there are potential problems associated with this automated
segmenting. For example, all of the natural boundaries may not be found, and those
boundaries that are found may not correspond to either the objects of interest or real
world objects. Methods of segmentation can also be highly subjective, requiring a
laborious set of training data and prior knowledge of the area. Also, elements such as
roads and streams may be included in other objects, and therefore cause overestimation of
area (De Wit and Clevers, 2004). As the capabilities of the available software improve,
however, more researchers are turning toward this technique (e.g., Wang et al., 2004;
Bock et al., 2005; Chubey et al., 2006). Automated segmentation was used in this thesis.

Object-based methods are usually used in combination with other classification
techniques. These techniques can be separated into two main types, supervised and
unsupervised, though often the two are joined in what is known as a hybrid approach
(e.g., Reese et al., 2002; Yuan et al., 2005). Many of the newer techniques, such as the
use of Artificial Neural Networks (ANNs) (e.g., Murthy et al., 2003), Support Vector
Machines (SVMs) (e.g., Keuchel et al., 2003) and decision trees (e.g., Brown de
Colstoun et al., 2003; Chubey et al., 2006), are supervised techniques, though they can be hybrid techniques as well, depending on their specific implementation.

1.3.3 Supervised Classification Methods

Supervised classification is most often used when *a priori* knowledge of the area to be mapped is extensive, as supervised classification schemes require knowledge of all cover types to be mapped. Supervised methods also use intensive training methods to define spectral signatures and information classes from the explanatory variables, which will then be applied to the whole scene (Cihlar, 2000; McDermid et al., 2005).

Supervised classification methods therefore rely heavily on both the quality and representation of the training data (Chubey et al., 2006), though ways have been suggested to automate, or at least simplify, this training data collection, especially in regards to mapping of large areas that represent varying ecosystems (Franklin and Wulder, 2002). For example, one method, known as ‘boosting’, weights observations in the training algorithm based on their accuracy in previous iterations of classification. It puts higher weights on classes that were improperly classified in the previous iteration, thereby forcing the classification algorithm to focus on those observations that are more difficult to classify. The boosting method was also found to increase classification accuracy (e.g., Friedl et al., 1999; Brown de Colstoun et al., 2003).

There are two basic types of supervised classification. Parametric methods depend on the data having a certain probability distribution. An example of this type is the popular maximum likelihood classifier (MLC) (e.g., Hunter and Power, 2002; Keuchel et al., 2003; Yunhao et al., 2006). MLC is a well-known mathematical decision
rule used for classification. It uses band means and standard deviations from training data to reproduce land cover classes as centroids in a multi-dimensional feature space, surrounded by probability contours (Bolstad and Lillesand, 1991). A feature space is a combination of features represented in a multi-dimensional space, where each feature is an orthogonal axis within the space. MLC assumes that the sample values for each class are normally distributed. The unclassified pixels from the image are then plotted in this same feature space; the pixels are then assigned to the class for which they have highest membership probability (the class whose centroid they are closest to) (Shanmugan et al., 2006). Non-parametric methods, conversely, make no assumptions about the statistical distribution of the data, which can sometimes be an advantage. Problems still arise with these non-parametric methods, however. For example, difficulties often arise with ANNs that are related to the dependence of the results on the training conditions, and to properly interpreting the network’s behavior (Serpico et al., 1996). Also, a useful property of parametric classifiers, the theoretical estimation of classification error from the assumed distributions, is not possible with non-parametric classifiers (Schowengerdt, 2006).

Despite these drawbacks, however, non-parametric methods are becoming popular (e.g., Murthy et al., 2003; Yang et al., 2003; Chubey et al., 2006). Non-parametric methods include decision trees, ANNs, and SVMs.

Decision trees are a commonly used non-parametric classifier (e.g. Brown de Colstoun et al., 2003; Franklin et al., 2002; Friedl et al., 1999) that have a number of advantages (Franklin and Wulder, 2002; Brown de Colstoun et al., 2003; Chubey et al., 2006):
They are capable of handling high-dimension data sets. That is, they can use ancillary data about the area to aid in classification, including non-remotely sensed data.

- They can handle both categorical and continuous data.
- They are non-parametric, so no assumptions have to be made about the distribution of the data.
- They are transparent (for example, compared to an ANN, in which you see the inputs and outputs, but don’t know what is happening in between).
- They can be simple to implement.
- They have been shown to outperform both MLC and other non-parametric classifiers (e.g., Yang et al., 2003; Xu et al., 2005; Chubey et al., 2006).

Decision trees also have a disadvantage however; they rely heavily on the quality of the training data, and accuracy can be dependent on the training data sample size (Chubey et al., 2006).

1.3.4 Unsupervised classification methods

Unsupervised methods generate natural groupings or clusters that are already present in the mapping variables (usually radiometric variables, i.e. different spectral bands), and require no prior knowledge of the study area (McDermid et al., 2005). Unsupervised classification allows for the exploitation of all the information content of satellite data, regardless of the geographic extent or surface characteristics, though the analyst still must have enough knowledge to label the resulting clusters (Cihlar et al., 2003). Another advantage is repeatability and consistency of the classification. With
unsupervised methods the same result can be obtained for the same data set by different analysts. However, there are also some disadvantages. For example, unsupervised classification can miss very small, but possibly important, classes in the data set that would not be missed by supervised classification if the analyst were aware of them (Cihlar et al., 1998). Certain unsupervised methods have also been found to give results that are dependent on the parameters guiding the classification process (Cihlar et al., 1998; Latifovic et al., 1999).

There are two basic unsupervised classification strategies, iterative and sequential (Cihlar et al., 2000). In an iterative method, a starting number of desired clusters is selected, and the centroid locations of the clusters are then moved around until a proper fit is obtained (Cihlar et al., 2000). Iterative methods commonly used include the K-means (e.g., Wulder et al., 2004a, 2004b; Tateishi et al., 2004; Joshi et al., 2006), ISODATA (e.g., Thompson et al., 1998; Shanmugam et al., 2006), and ISOCLASS (e.g., Agrawal et al., 2003) algorithms. Sequential algorithms, on the other hand, gradually reduce the large number of spectral combinations by merging the clusters using various proximity measures (Cihlar et al., 2000). The main sequential method is Classification by Progressive Generalization (CPG) (Cihlar et al., 1998). CPG has been found to be more accurate than other unsupervised methods in classifying land cover over large areas of Canada, with many classes. CPG has additional advantages such as greater robustness, reduced dependence on control parameters, and the possibility of the analyst’s input in the final clustering stages, which gives greater control over the final classes (Cihlar et al., 1998; Latifovic et al., 1999). A combination of K-means and CPG was found to be even
more useful in a Canadian boreal landscape setting (Cihlar et al., 2003; Kerr and Cihlar, 2003).

1.4. Research Objectives

The objectives of this thesis were twofold. The first objective is to find the most appropriate classification method for the classification of herbaceous and agricultural areas in Alberta. The most appropriate method will be found by selecting and testing a small number of classification schemes from among the many available to find the method that gives the most useful results. The second objective is to determine if landscape composition and spatial configuration was significantly different between agricultural areas in which the bears have been present, and similar areas where they have not been present, and to determine which landscape metrics or compositional elements have the greatest relationship with grizzly bear presence, absence, and location density.

Due to their spatial and temporal flexibility, remote sensing methods of land cover classification are well situated to handle the problem of large spatial range (McDermid et al., 2005). Approaches to large-scale, medium resolution (Landsat, for example) land cover mapping are still not well developed (McDermid et al., 2005). Land cover classification of a large geographic extent (for example, covering multiple Landsat scenes), particularly in a Canadian agricultural context, has been studied, but significant room remains for improvement. The specific goals of the remote sensing classification (Chapter 2) are:

(i) to find the best possible classification approach from a limited selection of methods for determining multiple classes of agricultural and herbaceous land cover, and
(ii) to create land cover maps of agricultural and herbaceous areas which will be integrated into existing grizzly bear habitat maps for western Alberta.

Landscape metrics have been shown to be an important element in grizzly habitat selection (Linke et al., 2005). Therefore, the specific goals of the second objective (Chapter 3) are to:

i) identify landscape composition and spatial configuration in the agricultural areas of western Alberta,

ii) determine if landscape composition and spatial configuration are related to grizzly presence or absence in an area,

iii) determine which landscape metrics have the strongest relationships with certain grizzly population and biological measures that are available from collared bear GPS datasets, and

iv) determine the extent of the difference between landscape metric values when calculated at different spatial and thematic scales.

Accomplishing these objectives will allow for the creation of a more accurate and detailed land cover map covering areas of grizzly bear habitat. A more accurate map could contribute to more accurate resource selection models (Boyce et al., 2002; Nielsen et al., 2002) and would give a better understanding of bear activity in agricultural areas. The increased thematic resolution (increased number of classes) of this map would also contribute to more robust calculation of landscape metrics in agricultural areas. Landscape metrics have been shown by others (e.g. Linke et al., 2005) to be an important consideration when trying to understand grizzly bear presence in a landscape. Applying these metrics to an agricultural area could play a role in further understanding the
relationship between the spatial configuration and composition of the landscape and grizzly presence in that landscape.

1.5 Organization of Thesis

The thesis has been divided into four parts, with the above literature review being the first. Two research manuscripts have resulted from this study. The first manuscript (Chapter 2) deals with testing a small selection of medium-resolution land cover classification techniques, and selecting and applying the most appropriate one for large-area agricultural mapping in Alberta. The second manuscript (Chapter 3) deals with analyzing the relationships between landscape metrics and grizzly bear presence or absence in agricultural areas. It is linked with the first manuscript in that it further explores the relationship between bears and agricultural areas from a landscape ecology point of view. Unfortunately, the results from Chapter 2 were not available at the time that the research in Chapter 3 was being conducted. However, a brief comparison between the older land cover map and the newly classified (higher thematic resolution) agricultural areas from Chapter 2 was examined in the context of calculating landscape metrics. The overall contribution can be considered to encompass both remote sensing science and landscape ecology. Finally, a fourth chapter integrates the findings of these manuscripts, focuses on the application of this work to wildlife habitat analysis, and discusses limitations of the research and future directions of study.
1.6 References


2. A Medium-Resolution Remote Sensing Classification of Agricultural Areas in Grizzly Bear Habitat

2.1 Abstract

Habitat loss and human-caused mortality are the most serious threats facing grizzly bear (*Ursus arctos* L.) populations in Alberta, with conflicts between people and bears in agricultural areas being especially important. To help manage and mitigate these effects, current habitat maps are needed. The objectives of this research were to find the best possible classification approach from a limited selection of methods for determining multiple classes of agricultural and herbaceous land cover, and to create land cover maps of agricultural and herbaceous areas which will be integrated into existing grizzly bear habitat maps for western Alberta. Spectral and environmental data for five different land-cover types of interest were acquired in late July, 2007, from Landsat TM satellite imagery and field data collection in two study areas in Alberta. Three different object-based classification methods, one unsupervised and two supervised methods, were analyzed with these data to determine the most accurate and useful method. The best method was the Supervised Sequential Masking (SSM) technique, which gave an overall accuracy of 88% and a Kappa Index of Agreement (KIA) of 83%. Three of the 5 classes had an average KIA of greater than 95%, with the other two classes being above 72%. The SSM classification was then expanded to cover 6 more Landsat scenes, and when combined with bear GPS location data, it was discovered that bears in agricultural areas were found in Grass / Forage crops 77% of the time, with Small Grains and Bare Soil / Fallow fields making up the rest of the visited land-cover. The bears were found in these areas primarily in the summer months.
The results of this research will allow for the creation of a more accurate and detailed land cover map covering areas of grizzly bear habitat. A more detailed map could contribute to more accurate resource selection models and would give a better understanding of bear activity in agricultural areas. The increased thematic resolution of the map compared to current maps could also contribute to more robust calculation of landscape metrics in agricultural areas.

2.2 Introduction and Background

Grizzly bears require wilderness and seclusion from humans, as well as high quality, contiguous (connected) habitat (McLellan and Shackleton, 1988). The term ‘habitat’ in this manuscript will be defined as “the sum and location of the specific resources needed by an organism for survival and reproduction”, which is the definition put forward by McDermid et al. (2005). Grizzly bears previously occupied the entire western half of North America, with their territory even including much of the Great Plains, but in the last 200 years their range has shrunk by as much as two-thirds. Their range south of the Arctic Circle is limited to mountainous areas, isolated pockets, and national parks. They are now classified as a ‘threatened’ species (likely to become endangered in the near future in a significant portion of its range) in the contiguous United States (grizzly bears in Yellowstone National Park in the U.S.A. have been delisted, however), and it has been recommended by Alberta’s Endangered Species Conservation Committee that the species be elevated from ‘may be at risk’ status (believed to be at risk, but needing a detailed assessment for confirmation) to ‘threatened’ status in Alberta as well (McLellan and Shackleton, 1988; Stenhouse et al., 2003).
Agriculture and its associated activities is a major cause of increased conflict between bears and humans, and a decline in bear populations. Kansas (2002) identified reducing human-grizzly conflict on agricultural lands as a priority for mitigating the long term decline of the species. In a study of grizzly-human conflict on agricultural lands in Montana, Wilson et al. (2005; 2006) found that there were many different attractants for bears on private lands that are a part of the natural bear habitat. One of the most important factors was the use of riparian areas by bears as both habitat and transportation corridors (Wilson et al., 2005). The bears use these areas to reach anthropogenic attractants, such as cattle, sheep, beehives, and boneyards. The more attractants that were in an area, and the closer that area was to wetlands or riparian areas, the more likely the bears were to use that area as habitat. When barriers such as fences were introduced, the rate of bear use dropped considerably. For example, beehives that were protected by fencing were much less likely to be “attacked” by the bears than unprotected hives (Wilson et al., 2006). In many cases in Montana, the original bear habitat has not been fragmented or physically modified. However, its use has been changed, which brings the bears into conflict with people, and can be seen as an effective habitat loss. Effective habitat loss is defined as an unwillingness of the bear to use suitable habitat because of “high levels of sensory disturbance or mortality risk” (Kansas, 2002).

The province of Alberta, Canada, also has a large agricultural footprint. Agriculture and related activities exist right up to the edge of the foothills of the Rocky Mountains. The recommendation by Alberta’s Endangered Species Conservation Committee that grizzly bears be elevated from ‘may be at risk’ status to ‘threatened’ status (Stenhouse et al., 2003) means that appropriate management and conservation
planning will be required. Effective and current habitat maps will be necessary (Nielsen et al., 2006). However, one problem currently facing grizzly bear habitat mapping in Alberta is the lack of a classification scheme that differentiates between different agricultural and herbaceous areas. By finding an appropriate classification scheme for this purpose, the current land cover maps being used by the Foothills Model Forest Grizzly Bear Research Program (FMFGBRP) for grizzly habitat analysis will be updated with greater thematic resolution, which could lead to increased resource modeling accuracy. The current area of interest for grizzly bear population viability analysis in Alberta is most of the western portion of the province, a huge area that renders traditional field based methods problematic for land cover mapping purposes; another technique is needed. Due to their spatial and temporal flexibility, remote sensing methods of land cover classification are better situated to handle this problem of land cover classification over a large spatial range than field-based methods alone (McDermid et al., 2005). Many studies of medium-resolution land cover classification have focused on agricultural applications (see Table 2.1).

<table>
<thead>
<tr>
<th>Application</th>
<th>Study</th>
</tr>
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<tbody>
<tr>
<td>Crop yield prediction</td>
<td>Lobell and Asner, 2003; Ferencz et al., 2004</td>
</tr>
<tr>
<td>Crop nitrogen content</td>
<td>Boegh et al., 2002</td>
</tr>
<tr>
<td>Crop stress</td>
<td>Estep et al., 2004</td>
</tr>
<tr>
<td>Crop classification</td>
<td>Aplin and Atkinson, 2001; Turker and Arikan, 2005</td>
</tr>
<tr>
<td>Grassland discrimination / agricultural classification</td>
<td>Price et al., 2002; Reese et al., 2002; El-Magd and Tanton, 2003; De Wit and Clevers, 2004; Bock et al., 2005; Baldi et al., 2006</td>
</tr>
</tbody>
</table>

Approaches to large-scale, medium-resolution (Landsat, for example) land cover mapping, such as that done in this study, are still not well developed, however (McDermid et al., 2005). There are many issues still to be overcome.
classification of a large geographic extent (for example, covering multiple Landsat scenes), particularly in a Canadian agricultural context, has been studied, but significant room remains for improvement. The purpose of this research is to demonstrate the use of remote sensing for land cover classification in western Alberta, specifically focusing on the classification of herbaceous and agricultural areas in grizzly bear habitat. The specific goals of this manuscript are:

(i) to find the best possible classification approach from a limited selection of methods for determining multiple classes of agricultural and herbaceous land cover.

(ii) to create land cover maps of agricultural and herbaceous areas which will be integrated into existing grizzly bear habitat maps for western Alberta.

Accomplishing these objectives will allow for the creation of a more accurate and detailed land cover map covering areas of grizzly bear habitat. A more accurate map could contribute to more accurate resource selection models (Boyce et al., 2002; Nielsen et al., 2002), and would give a better understanding of bear activity in agricultural areas. The increased thematic resolution of this map would also contribute to more robust calculation of landscape metrics in agricultural areas.

2.3 Study Area and Methods

2.3.1 Study area and Imagery

The research was conducted as part of the Foothills Model Forest Grizzly Bear Research Program (FMFGBRP) in west-central Alberta, Canada. The study area for this project covers sections within the greater 228 000 km² study area that contain
herbaceous and agricultural areas, and that are within the natural range of the grizzly bear (Figure 2.1). Two areas were examined in detail: one in the northern part of the province, located west of Grand Prairie (the ‘North study area’), and one in the south, located around the Nanton / Chain Lakes area (the ‘South study area’). The two study areas were selected from agricultural areas that are within the current range of grizzly bears in the province, and that have bear GPS collar location data present within them. Large portions of both of these study areas were also located within Landsat scene overlaps, which made cloud-free image acquisition more likely.

The landscape of the North and South study areas are fairly similar, with both study areas consisting primarily of grassland and agricultural crops, with small patches of forest and shrubs scattered throughout. The crops are predominately cereals (wheat varieties, barley, and oats), tame hay, and canola, with a scattering of others, such as legume crops (Agri-Food Statistics Update, 2007). Both study areas have a high road density, mostly gravel grid roads, but also a few highways. The South study area surrounds the Porcupine Hills, a region of moderate topographic relief that is not directly used for agriculture. It acts as an extension of the foothills, but is surrounded on all sides by pasture and agricultural crops. The South area has greater topographic relief than the North because of its proximity to the Rocky Mountain foothills. The western portion of the South study area, the area that borders the foothills, is used primarily as natural pasture for cattle. In the North study area, the Wapiti River is a major feature, bisecting the area west-to-east. The area along the river is dominated primarily by Aspen trees (*populus tremuloides*) with some conifers mixed in, and has not been cleared for agriculture.
There was excessive soil moisture in the study locations in the spring of 2007; this delayed seeding, or prevented it altogether, especially in the North study area, resulting in more fallow and bare fields than normal. The north area was hit harder in general by
poor weather, and the crop quality was lower than that of the south area (Bergstrom, K., 2007). High temperatures in July and a lack of precipitation caused slower growth for pasture and tame hay, and poor conditions for non-irrigated field crops (Bergstrom, K., 2007). Average precipitation in May and June for the south study area was much higher than the 30 year mean, while for July and August it was lower. July temperatures were also well above normals. For the north study area, precipitation was above normal for May – August, but this precipitation was not evenly distributed across the region, leaving some areas very dry. Average July temperatures were above, and August temperatures were below, monthly 30-year normals (Environment Canada, 2008).

The imagery used was from the Landsat 5 TM sensor. The spatial and spectral resolution of Landsat TM imagery is well suited for land cover classification at the level of detail required for this research, and has been used for other medium-resolution classification studies (e.g., Camacho-De Coca et al., 2004; Ferencz et al., 2004; Franklin and Wulder, 2002), with good results. Landsat is also more efficient at covering large regions (as are present in this research) than sensors with greater spatial resolution, such as SPOT or IKONOS, due to amount of area that each image covers (170 x 185 km Landsat scene size vs. 60x60 km for the SPOT HRV sensor, for example). Landsat is also the sensor being used for most of the Foothills Model Forest Grizzly Bear Research Program’s land classification efforts, so it will match with previous and on-going work. Portions of both the North and South study areas were located within Landsat scene overlaps. Overlapping scene paths effectively doubles the possible temporal resolution, and increases the chances of getting cloud-free images.
One scene was collected for each of the North and South Study areas. In addition to these 2 scenes, 5 additional Landsat TM scenes and one Landsat ETM+ scene were used. (Table 2.2, Figure 2.4). These additional scenes covered the remainder of the agricultural areas in western Alberta that are currently being mapped by the FMFGBRP.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Path / Row</th>
<th>Acquisition Date (dd/mm/yy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM</td>
<td>47 / 21.62 (shifted) North study area</td>
<td>26/07/07</td>
</tr>
<tr>
<td>TM</td>
<td>42 / 25 - South study area</td>
<td>23/07/07</td>
</tr>
<tr>
<td>TM</td>
<td>45 / 21</td>
<td>03/09/03</td>
</tr>
<tr>
<td>TM</td>
<td>44 / 22</td>
<td>13/08/04</td>
</tr>
<tr>
<td>TM</td>
<td>44 / 23</td>
<td>17/09/05</td>
</tr>
<tr>
<td>TM</td>
<td>43 / 24</td>
<td>25/08/05</td>
</tr>
<tr>
<td>TM</td>
<td>41 / 26</td>
<td>27/08/05</td>
</tr>
<tr>
<td>ETM+</td>
<td>46 / 21</td>
<td>22/08/99</td>
</tr>
</tbody>
</table>

2.3.2 Existing datasets

A large database of grizzly bear GPS (Global Positioning System) location data was provided by the FMFGBRP. In order to collect the data for this database, the FMF captured, immobilized, and radio-collared a sample of the grizzly bear population located throughout the bear’s Alberta range. Collars were placed on both male and female grizzly bears. The resulting telemetry data from these collars was then transmitted to the FMF through a satellite uplink, a process that started in 1999 and is on-going. A detailed methodology and results of this program can be found in Hobson (2005, 2006).

GPS locations in purely agricultural locations (i.e., areas classified in this study) consist of 1270 locations, or 0.84% of the total of 151575 bear locations. These 1270 locations represent 18 different bears (10 male and 8 female). The true number of bears
in these areas may be underestimated due to possible capture bias. Bear capture attempts are not made in agricultural areas, but in more isolated areas (Hobson, 2005).

A 10-class, object-based land cover classification of the FMF study area (Franklin et al., 2001; McDermid et al., 2006) was used as a starting point for the classification of the agricultural areas. The classes in this base map (hereafter: FMF land cover map) include: Upland Trees, Wetland Trees, Upland Herbs, Wetland Herbs, Shrubs, Water, Barren Land, Snow/Ice, Cloud, and Shadow. Using the Barren, Upland Herbs, and Wetland Herbs classes from the FMF land cover map along with a manually delineated agricultural mask (also now included on the FMF land cover map as an ‘Agriculture’ mask), a herbaceous/agricultural mask was created and used to define the area to be classified (Figure 2.2). The mask was later limited to areas that could be visually confirmed (either from satellite images or from field visits) to be currently under agricultural use. The results of the classification described in this chapter will then be applied to the FMF land cover map to increase its thematic resolution.

2.3.3 Field methods

A stratified random sample scheme was used to collect field level data in late July, 2007, which corresponds to the week in which the images that cover the North and South study areas were taken (the stratification of the classes was done with an exploratory 10-class unsupervised k-means clustering classification). A random sampling design was chosen for a number of reasons. First, as its name implies, it is a random sampling scheme, which reduced the probability of operator bias in selecting plots. Also, by using the stratified method, it could be assured that a number of samples
from each class were obtained, from which individual conclusions about each class could then be drawn. Most importantly, this sampling design allowed statistical analyses to be applied to the results. The stratified random sampling scheme is commonly used in land cover classification research (e.g., Ban, 2003; Brown de Colstoun et al., 2003). A target of 35 sample plots per class was used during data collection, which is following results by Van Niel et al. (2005), who found that, while it is usually recommended to have $n =$
$30p$ (where $p =$ number of spectral bands being used for the classification) samples for each class, 95% of that information can be found in only $3p$ or $4p$ for each class. Using Landsat TM bands 1-7 (excluding the thermal band, 6), $3p - 4p$ gives 18 - 24 samples for each class. Additional samples were added (30% of the total) for validation purposes, giving 24 - 35 samples ideally needed per class. In addition, samples of opportunity were taken wherever possible to offset random plots that could not be accessed on the ground. An effort was made to make selection of these samples of opportunity as random as possible, while preserving the stratified nature of the dataset. The total number of opportunistic samples was small, and for the purposes of this study will be considered part of the random dataset. Data collected consisted of ground cover type of the field as it related to the selected classes. The ground information was gathered visually, with locations confirmed by GPS.

A total of 5 classes were used, consisting of Bare Soil/Fallow, Canola, Grass/Forage, Legumes, and Small Grains (which includes barley, wheat, and oat varieties). The sample sizes for each class are not equal, but are representative of the overall amount of area covered by those classes in the study regions (Agri-Food Statistics Update, 2007). The Legume class did not meet the target of 35 samples, but the 15 samples collected were enough to derive a meaningful spectral response for the class. All other classes met the minimum target. A total of 506 samples were collected, with 30% of the samples from each class being saved for validation (Figure 2.3).
The classes were chosen because they corresponded with the land cover types that represent the most land area in the agricultural region of Alberta (Agri-Food Statistics Update, 2007). Five classes were chosen based on an initial exploration of the data, which revealed that certain crop types, such as wheat and barley, were spectrally almost identical. To enable greater classification accuracy, crops such as barley, wheat and oats were combined into a single class, Small Grains, an approach that has been taken by others (e.g., Martinez-Casanovas et al., 2005), for similar reasons.

The average spectral reflectance values of each classes were examined for Landsat bands 1-5 and 7, and compared for the two study areas. The spectral analysis
was used as part of an initial exploration of the data, and to help determine the most distinct classes, which is helpful for one of the classification methods. The differences in the reflectance values between the two studies was also helpful for determining differences in crop status between the two areas.

2.3.4 Image pre-processing

The Landsat scenes (both TM and ETM+) were orthorectified using 5th order polynomial geometric correction in PCI OrthoEngine. Ground control points (GCPs) were collected from existing geo-referenced scenes of the same areas; a minimum of 30 GCPs were used for each image. Root Mean Square (RMS) error for all images was lower than 0.2 pixels (6m). Radiometric and atmospheric correction was performed using the ATCOR-2 algorithm in PCI Geomatica 10. ATCOR-2 (Richter, 2008) uses a sensor-specific atmospheric database of look-up tables containing the results of pre-calculated radiative transfer calculation (using the MODTRAN4 radiative transfer code; see Berk et al., 1999) to remove the effects of the atmosphere from the spectral values of the data, as well as correcting the influences of solar illumination and sensor viewing geometry. Output from this algorithm is surface reflectance for each Landsat band 1-5 and 7. Surface reflectance is a true measure of reflected radiation at the ground surface. It takes into account factors such as the interaction of the solar radiation with the atmosphere, terrain elevation, sun illumination angle, and sensor viewing geometry (Richter, 2008; Song et al., 2001). Surface reflectance was used for a couple of reasons. First, it is required for the use of a non-linear vegetation index (NDMI), which was used as one of the input channels for the classification methods (Song et al., 2001). Secondly, as the application of these data is over a large area, it is beneficial to have a classification
system for one place / time, and be able to apply that same classification to other places / times (Song et al., 2001); this can be accomplished by having actual surface reflectance rather than top-of-atmosphere reflectance, which can vary depending on place and time. Using surface reflectance also allows the classification to be extended to other Landsat scenes for which ground data are not available.

In addition to the 6 Landsat bands, The tasseled cap transformation of Crist and Ciccone (1984) was used to generate the standard orthogonal components brightness, greenness, and wetness. The spectral features of the tasseled cap transform can be directly related to important physical parameters of the ground surface (Crist and Ciccone, 1984). Tasseled cap values for the Landsat 5 TM scenes were generated using the Tassel algorithm, with L5 (Landsat 5) modifier, in PCI Geomatica 10; the Landsat 7 ETM+ Tassel values were generated with same algorithm, but used the L7 (Landsat 7) modifier. The Normalized Difference Moisture Index, or NDMI (equation 2.1), was also calculated for each scene. The NDMI (Wilson and Sader, 2002) takes advantage of the strong absorption of Landsat band 5 (a short-wave infrared band) by soil water, and the strong reflectance of Landsat band 4 (a near-infrared band) by healthy green vegetation (Jensen, 2000). A total of 10 bands, or channels, were therefore used (Landsat 1-5, 7, brightness, greenness, wetness, NDMI).

\[
\text{NDMI} = \frac{\text{band4} - \text{band5}}{\text{band4} + \text{band5}} \tag{eq. 2.1}
\]

\begin{align*}
\text{band4} & = \text{TM or ETM+ band 4} \\
\text{band5} & = \text{TM or ETM+ band 5}
\end{align*}
2.3.5 Classification

While most traditional remote sensing land cover classification is pixel-based, many newer studies are turning to object-based classification methods as a way to improve accuracy (e.g., Aplin and Atkinson, 2001; Smith and Fuller, 2001; Lloyd et al., 2004; Walter, 2004; Bock et al., 2005). Object-based classification divides the satellite image into objects or segments that represent a homogenous unit on the ground. The entire object is classified based on the overall statistical properties of the pixels that make up the object, instead of classifying each pixel separately as in pixel-based classifications (e.g., McIver and Friedl, 2002). Three different object-based classifications were performed and analyzed: one unsupervised classification, and two supervised classifications.

The classification was initially only carried out over the two North and South 2007 study areas. The North and South study areas were classified separately to reduce differences relating to weather conditions, moisture levels, and phenology.

The unsupervised classification method used the PCI Geomatica 10 implementation of the fuzzy k-means classifier (Bezdek, 1973). Fuzzy k-means is an iterative process that uses fuzzy membership grades to assign each pixel membership to each of the classes in the spectral feature space, based on the Euclidean distance between the spectral value of the pixel and the mean spectral value of each class (Wiemker, 1997). The pixel is assigned to the class to which it has the highest membership. Fuzzy k-means was chosen as it is one of the most accurate unsupervised methods that is available in commercial software packages (Cihlar et al., 2000). Unsupervised methods in general have also given good classification results for agricultural areas (e.g., Cohen and
Shoshany, 2002). The fuzzy k-means classifier was used to first create a 30 class pixel-based classification. Sample classes and expert knowledge were used to merge those classes down to the 5 to be used for the classification. The fuzzy k-means classification was then combined with the image objects for the scenes, derived from Definiens software, and the modal class of the unsupervised classification was then calculated and assigned for each object using the VIMAGE algorithm in PCI Geomatica 10. Using the modal class to assign pixel classifications to an object has been used by others, such as Turker and Arikan (2005), with good results.

Two supervised classification methods were also analyzed, both completed using Definiens Professional software. The first of these was a nearest neighbor (NN) fuzzy membership classification using an automated feature space optimization based on selected class samples (70% of field samples, with 30% saved for validation). Nearest neighbor classification has been used by Bock et al. (2005) for habitat mapping, with good results, as well as by Wang et al. (2004), who used it for mapping Mangrove forests, and also got good results. The NN classification method first defines a feature space in which each image object becomes a point. A feature space is a combination of features represented in a multi-dimensional space, where each feature is an orthogonal axis within the space. The distance in the feature space to the nearest sample of each class is calculated for every object in the image, and class is assigned based on the smallest distance (Definiens AG, 2006). The distance values are shown in a distance matrix, which is simply a way of representing the largest distance between the closest samples of classes in the feature space (Definiens AG, 2006). Distances in the distance matrix were analyzed as relative values; that is, a distance of 2 (for example) from an
Object to the nearest sample would mean that the object was twice as close in the feature space than if it was at a distance of 4 from the nearest sample. The distances themselves are unit-less. The feature space in which this occurs was calculated from the mean and standard deviation values of each object in each of the 10 channels used. The optimum feature space dimension could therefore be between 1 and 20, with any combination of channels and their mean or standard deviation. Texture measures were not included in the feature space calculation, as it was found when testing them that they did not significantly change the feature space distances between the classes; i.e., adding texture measures did not increase the accuracy of the resulting classification.

The second supervised classification was a manually delineated sequential masking process that masked out the most highly separable crops as they were classified. This second classification technique will be called the Supervised Sequential Masking (SSM) classification. The SSM classification was chosen because it is similar in theory to a decision tree classifier, with many of the same benefits (Franklin and Wulder, 2002; Brown de Colstoun et al., 2003; Chubey et al., 2006):

- It is capable of using ancillary data about the area to aid in classification, including non-remotely sensed data.
- It can handle both categorical and continuous data.
- It is transparent, in that it is possible to see every calculation being done.
- It is simple to implement.

The SSM classification is done using sequentially executed processes based on mean values for the different channels (TM bands, Tasseled Cap results, NDMI) in the image. The means and standard deviations of the objects in each band were examined to
determine the best way to separate the classes, similar to the process used in the NN classification, only done manually. The classes that were the easiest to distinguish were then identified, based on analysis of the feature (mean, standard deviation) values and the spectral response curves of the classes in each Landsat band (section 2.3.2). The classes that were most easily distinguishable were Canola and Bare Soil / Fallow, so these classes were classified first, followed by Legumes, Grass / Forage, and Small Grains, in that order. Once a class is classified, it is masked out and cannot be changed later in the classification process. In this way, each class is sequentially masked out of the classification, until nothing is left unclassified (hence the Supervised Sequential Masking nomenclature). A similar sequential masking process, though with a different classifier, was used to good effect by Turker and Arikan (2005) in their agricultural classification. The process works backwards, in a way, by classifying all unclassified objects as the class being examined. A rule set is then developed that determines what is not characteristic of that class, based on the spectral properties of the channels being examined, and the sample training data; objects that are found to not be characteristic of the class are made ‘unclassified’ again. Eventually, all that is left classified is the objects that belong to the class being examined. The SSM classification accuracy may be influenced by the analyst’s channel and feature selection.

2.3.6 Validation

Validation, or the assessment of accuracy, was carried out using quantitative statistical tests. There is much discussion in the literature about what constitutes a ‘good’ accuracy assessment for a thematic map (e.g., Foody, 2002; McDermid et al., 2005).
There is agreement that there is not one single, universally accepted measure of accuracy; rather, it is better to use a combination of tests, each sensitive to different properties of the data.

Validation of the results was done using both the standard error matrix and the Kappa Index of Agreement (KIA) for both overall and class specific results. The error matrix is a site-specific measure of the correspondence between the image classification result and the measured ground conditions, and is a standard first step for accuracy assessment (Foody, 2002). From the error matrix, user’s, producer’s, and overall accuracies were obtained. User’s accuracy is a measure of reliability, or the probability that a pixel or object classified on the map actually represents that class on the ground. Producer’s accuracy indicates the probability of a reference pixel being correctly classified. Overall accuracy is determined by dividing the total number of correctly classified pixels by the total number of pixels in the error matrix. Overall accuracy is therefore a measure of accuracy of all classes, whereas user’s and producer’s accuracy measure the accuracy of individual classes.

KIA is a discrete multivariate technique used to statistically evaluate the accuracy of the classification maps and error matrices. One of the attractive features of KIA analysis is that it takes into account the effect of chance agreement in the error matrix; it also takes into account unequal class sizes. KIA can be a measure of both overall accuracy and of individual class accuracy.

Each of these statistics (user’s, producer’s, overall, and KIA) are useful not only for accuracy assessment, but also for comparisons of accuracy between different analysts and different classification methods (Langley et al., 2001; Foody, 2002).
The field data were used as the “ground truth” for the purpose of the accuracy assessment, with 30% of the total field data collected from each class saved for validation purposes and not used as training data during the classification process.

2.3.7 Application

The most accurate and useful classification method from among those tested was applied to the additional six Landsat scenes. Figure 2.4 shows the coverage area of these additional scenes, plus the two scenes covering the north and south study areas. The complete classification of the eight Landsat scenes was then added to the FMF land cover map, with the new classification being overlain on top of the existing classification as one large image mosaic.

Figure 2.4: Blue areas show outlines of the 8 Landsat scenes used to classify the agricultural area. The red area is the agricultural mask.
The Grizzly bear location data were also analyzed to determine if there were any relationships between bear locations in agricultural areas and crop / land cover type. The analysis was done by selecting every newly classified image object that contained a bear location point. The class of each selected image object was then noted, as well as the month in which the bear location data were recorded for that particular image object. Bear locations were also analyzed separately for each class in which they were present, to look for any seasonal visit patterns.

2.4 Results and Discussion

2.4.1 Spectral properties

There are some minor differences between the spectral responses of the crops between the north and south study areas (Figures 2.5 and 2.6). The classes are separated more in the North study area, especially in TM band 4. Different spectral responses are to be expected, as the two areas are nearly 700 km apart, and have different weather patterns and moisture levels. Planting dates, crop phenologies, and crop conditions varied significantly throughout both the northern and southern areas, even for the same crop type among adjacent fields. The Small Grains class cannot be separated into its constituent crop types (wheat varieties, barley, oats) without a severe drop in classification accuracy due to these varying spectral properties; there is so much spectral overlap between these different cereal crops that they become nearly indistinguishable. The peaks for the Legumes and Small Grains classes are much lower in the North image as well. There are similarities in the shapes of the curves of the Grass / Forage and Bare
Figure 2.5: Spectral values (in surface reflectance) of the different classes in the main Landsat TM bands for the South study area.

Figure 2.6: Spectral values (in surface reflectance) of the different classes in the main Landsat TM bands for the North study area.
Soil/Fallow classes. The three other classes have higher TM band 4 and lower TM band 5 values.

2.4.2 Classification results

The average overall accuracy for the unsupervised classification was 59.4%, with the accuracy of the north scene (65.7%) being higher than that of the south scene (53.1%). The average Kappa Index of Agreement (KIA) was also low, at 46.40%, with the north scene again doing better than the south (56.4% versus 36.4%). Certain classes had a higher accuracy than others, and there were large variations between producer’s and user’s accuracy within the same class. The Bare Soil / Fallow class, for example, had

![Class Accuracy Results - Unsupervised](image)

*Figure 2.7: Class accuracy results for the unsupervised classification. Overall accuracy was 59.4%.*
an average producer’s accuracy of 97.3%, and an average class KIA of 97.0%, but a lower user’s accuracy of 26.5%. Figure 2.7 details these unsupervised results (see Appendix E for tabled data).

The supervised classifications gave higher accuracy results than the unsupervised classification. The supervised NN classification had an overall average accuracy of 85.7%, with an average KIA of 80.1%. The accuracy of the north scene was again higher than that of the south, with an overall accuracy of 86.7% and a KIA of 82.4% compared to the south scene’s 84.8% overall accuracy and 77.8% KIA. Figure 2.8 gives these details. The feature space with dimension 8 (8 object features) was found to have the

![Class Accuracy Results - Supervised NN](image)

*Figure 2.8: Class accuracy results for the supervised NN classification. Overall accuracy was 86.7%.*
highest average separation distance (0.567) for the South study area. The features used can be seen in Table 2.3, and the distance matrix showing the separability of each class using this feature space can be seen in Table 2.4. The feature space and distance matrix for the North study area can be seen in Tables 2.5 and 2.6.

**Table 2.3**: South NN feature space. The best separation distance is the largest distance between the closest samples of classes within this feature space.

<table>
<thead>
<tr>
<th>Standard deviation:</th>
<th>Mean:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wetness</td>
<td>Wetness</td>
</tr>
<tr>
<td>Greenness</td>
<td>TM 2</td>
</tr>
<tr>
<td>TM 2</td>
<td>TM 3</td>
</tr>
<tr>
<td>TM 3</td>
<td></td>
</tr>
<tr>
<td>TM 4</td>
<td></td>
</tr>
</tbody>
</table>

Dimension: 8
Best separation distance: 0.57

**Table 2.4**: South NN distance matrix

<table>
<thead>
<tr>
<th>Class / Class</th>
<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grass / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare Soil / Fallow</td>
<td>0</td>
<td>8.9</td>
<td>0.7</td>
<td>7.2</td>
<td>2.6</td>
</tr>
<tr>
<td>Canola</td>
<td>8.9</td>
<td>0</td>
<td>6.0</td>
<td>0.6</td>
<td>2.9</td>
</tr>
<tr>
<td>Grass / Forage</td>
<td>0.7</td>
<td>6.0</td>
<td>0</td>
<td>5.0</td>
<td>0.6</td>
</tr>
<tr>
<td>Legumes</td>
<td>7.2</td>
<td>0.6</td>
<td>5.0</td>
<td>0</td>
<td>2.1</td>
</tr>
<tr>
<td>Small Grains</td>
<td>2.6</td>
<td>2.9</td>
<td>0.6</td>
<td>2.1</td>
<td>0</td>
</tr>
</tbody>
</table>

**Table 2.5**: North NN feature space.

<table>
<thead>
<tr>
<th>Standard deviation:</th>
<th>Mean:</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDMI</td>
<td>NDMI</td>
</tr>
<tr>
<td>Brightness</td>
<td>Greenness</td>
</tr>
<tr>
<td>Greenness</td>
<td>TM 1</td>
</tr>
<tr>
<td>Wetness</td>
<td>TM 2</td>
</tr>
<tr>
<td>TM 1</td>
<td>TM 3</td>
</tr>
<tr>
<td>TM 2</td>
<td>TM 4</td>
</tr>
<tr>
<td>TM 3</td>
<td>TM 5</td>
</tr>
<tr>
<td>TM 4</td>
<td>TM 7</td>
</tr>
<tr>
<td>TM 5</td>
<td></td>
</tr>
<tr>
<td>TM 7</td>
<td></td>
</tr>
</tbody>
</table>

Dimension: 18
Best separation distance: 0.58
The supervised sequential masking (SSM) technique gave the highest classification accuracies of the methods tested, with the highest average overall accuracy (88.0%) and KIA (83.4%) values. Figure 2.9 gives these results in more detail. The accuracy of the south scene was higher than that of the NN method, but the north scene

<table>
<thead>
<tr>
<th>Class / Class</th>
<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grass / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare Soil / Fallow</td>
<td>0</td>
<td>7.9</td>
<td>1.5</td>
<td>10.1</td>
<td>4.3</td>
</tr>
<tr>
<td>Canola</td>
<td>7.9</td>
<td>0</td>
<td>3.7</td>
<td>0.9</td>
<td>2.1</td>
</tr>
<tr>
<td>Grass / Forage</td>
<td>1.5</td>
<td>3.7</td>
<td>0</td>
<td>4.9</td>
<td>0.6</td>
</tr>
<tr>
<td>Legumes</td>
<td>10.1</td>
<td>0.9</td>
<td>4.9</td>
<td>0</td>
<td>1.6</td>
</tr>
<tr>
<td>Small Grains</td>
<td>4.3</td>
<td>2.1</td>
<td>0.6</td>
<td>1.6</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 2.6: North NN distance matrix

![Class Accuracy Results - Supervised Sequential Masking](image)

Figure 2.9: Class accuracy results for the SSM classification. Overall accuracy was 88%.
had slightly lower accuracy results than the NN method (Figure 2.10). Individual class accuracies were also very good, with classes such as Bare Soil / Fallow, Canola, and Peas having average KIA per class values above 95%. The lowest accuracy was the southern Bare Soil / Fallow class user’s accuracy, at 44%. The process trees used for the North and South images (as well as the additional Landsat scenes) can be seen in Appendix C.

The unsupervised classification gave lower than expected results, with the North study area classification accuracy being higher than that of the South study area. These relatively low accuracy figures could be the result of the varying crop conditions. Two

![Figure 2.10: Overall accuracy and KIA for all three classification methods](image)

Figure 2.10: Overall accuracy and KIA for all three classification methods
adjacent fields could contain a homogenous cover of identical crops, but be in two different stages of growth. Differences in crop phenology such as these can result in the classifier identifying the crops as different, when they are in fact the same. Early stage cereal crops are closer spectrally to grasses than to late stage cereal crops, so there is much class confusion with this method. Training samples were used to help amalgamate the unsupervised classes into the final 5 classes examined, but often a homogenous field would be made up of multiple classes with this classifier.

Another factor in the lower accuracy was the confusion between Grass / Forage and Bare Soil / Fallow. Confusion between these classes was due to some grass pasture fields being heavily overgrazed, which results in very low biomass, and spectral properties that mimic fallow fields. The same confusion effect can also be seen in the supervised Nearest Neighbor classification, as well as the spectral response curves for the classes.

The distance matrices for the NN classification are good indicators of crop separability levels for all of the classifications. Canola and Legumes have a relatively low class separation distance, when compared to classes such as Canola and Bare Soil / Fallow. Grass / Forage and Small Grains also have a low class separation, in addition to the Grass / Forage and Bare Soil / Fallow relationship mentioned above. The Grass / Forage class is itself very diverse, containing many different types of natural grasses, planted feed crops, and herbaceous forage. The Grass / Forage class is therefore a very broad class that contains elements of many of the other classes, hence the spectral similarity with other classes. Canola and Legumes generally have a high class separation distance from other classes (except with each other, as mentioned above). For the Canola
class, this is most likely due to the bright yellow flowers that are present on the canola plant. These flowers appear to have a very high spectral reflectance, and canola fields can often be identified on unmodified Landsat images shown in true color, showing up as a bright yellow-green color. Legumes also have a distinct green color, and can be spotted on true-color imagery. A higher separability for some classes is reflected in the class accuracy results, with Canola, Legumes, and Bare Soil/Fallow having, on average, the highest classification accuracies. Classes that are more confused with others, such as Small Grains and Grass/Forage, generally have lower classification accuracies.

The difference in the accuracy between the North and South study areas using both of the supervised classifications likely has a number of explanations. First of all, the differences in the average spectral values of the crops, though slight, is enough to show that there are different growing conditions between the two areas. The north area was hit harder by poor weather, and the crop quality was lower than that of the south. Differences in crop quality mean that there is again more confusion between the crops, as poor quality crops move farther away spectrally from their class. There may also have been differences in the quality of the training sites chosen for each area. That is, some training sites may be more representative of a crop type than others, depending on the factors such as the condition of the field, planting date, or soil moisture content. The SSM classification in particular is unique in that classification accuracy can be increased or decreased depending on the analyst’s ability to correctly identify the best channels and features to use for class discrimination. The specific values of those features that are chosen to represent each class can also affect the accuracy. Thus the classification accuracy will vary depending on differences in homogeneity of the crops, weather and
moisture patterns, crop phenology, crop condition, and the abilities of the analyst to
determine those differences.

The SSM classification is the best classification of those tested to reach the
stated goals of this research, for a number of reasons. The SSM classifier had the highest
average overall accuracy and the highest overall KIA value. It was also the most
adaptable classification scheme; it can be extended to cover areas where on-the-ground
training data is not available. In a project such as the FMFGBRP, which covers a large
amount of land and needs multiple Landsat scenes to cover it all, this is a very important
factor. Training sites from other scenes can be used to train the classifier, which can then
be adapted to better suit the current area being looked at. The process trees upon which
the SSM classification is based are easy to change or refine based on new information,
which is something that cannot be easily done with the other classification methods
examined. The SSM classifier is also able to adapt to different climatic, biophysical, and
phenological conditions across the entire mosaic of scenes. The basic theory behind this
classification can also be applied to other land-cover types, such as wetlands. In short,
the SSM classification allows for increased flexibility for current and future mapping
needs, while at the same time reducing operational costs by eliminating the need for a
massive field campaign across a large area.

2.4.3 Completed Mosaic

Due to the higher average accuracies, as well as other benefits, such as easy
adaptation to new areas without training sites, the SSM method was chosen as the best
method of classification, and was applied to the other six Landsat scenes (5 TM, 1
ETM+) that make up the agricultural area in the Foothills Model Forest Grizzly Bear
Research Program (FMFGBRP) study area. The complete mosaic, with the SSM agricultural classification can be seen in Figure 2.11. The agricultural classification was added to the existing FMF land cover map, increasing its thematic resolution. There are some class similarities between the SSM and FMF classified parts of the map. For example, the SSM Bare Soil / Fallow class is spectrally similar to the Barren class of the FMF map, though the SSM class represents a different use of the land cover. Another example is the SSM Grass / Forage class, which is similar spectrally to the Upland Herbs class of the FMF map, though again the use of the land cover is different between these two classes, with the SSM class existing within an agricultural framework. The new SSM land cover map could contribute to more accurate resource selection models (Boyce et al., 2002; Nielsen et al., 2002) and would give a better understanding of bear activity in agricultural areas. The increased thematic resolution of this map could also contribute to more robust calculation of landscape metrics in agricultural areas (see Chapter 3).

2.4.4 Grizzly Location Data:

A total of 502 agricultural image objects from the SSM classification contained grizzly bear location data. Of those, 23 (4.6%) were classified as Bare Soil / Fallow, 386 (76.9%) as Grass / Forage, and 93 (18.5%) as Small Grains (Figure 2.12). The location of these points was in or near the foothills region of the province, which means that most of the Grass / Forage polygons would be represented on the ground by natural prairie grasses and shrubby areas, rather than planted hay or feed crops as are more common in the eastern areas of the study region.
Many of the bear locations skirt the edge of the agricultural area without actually entering it. The bears appear to prefer the forested regions, entering agricultural land only at the margins, or travelling through the river corridors that dissect the landscape.

Figure 2.11: Completed mosaic with SSM classification, showing new agricultural classes (top 5 in legend) with those of the FMF land cover map.
These points were collected from the GPS collars of 18 different bears, 10 male and 8 female. The majority of the points (66.9%) represent data from the months of July, August, and September. Figure 2.13 breaks down the monthly locations of the bears within the agricultural area. The same seasonal pattern also holds true when the classes Small Grains and Grass / Forage are looked at separately, with the majority of the points located in these classes being from the mid-late summer months of July, August, and September. The Bare Soil / Fallow class, which makes up only 4.6% of the total, is more uneven in monthly distribution (class specific breakdowns of monthly bear location can be found in Appendix D).
While the percentage of total bear location points appearing in agricultural areas is low, the actual number of GPS collar location points that do appear (1270 points representing 18 different bears) is still significant, especially when the type of land-cover visited and the time of the visits is considered.

The majority of the locations occurred in the Grass / Forage class, which, in the marginal areas where the bears are present, usually consists of natural grasses, pastures, and planted feed crops such as oats and alfalfa. The bears also visit areas classified as Small Grains. The bears visit these locations most frequently in the summer months of July, August, and September, which is the time of year when the crops and grasses are mature. The Bare Soil / Fallow class, which makes up only 4.6% of the total agricultural
areas visited by the bears, is more uneven in monthly distribution, with the majority of visits taking place in June, July, and September (see Appendix D). This uneven distribution could have resulted because these bare fields don’t contain a food supply; it may also be related to the relatively low visit rate to this class, which means the data available may not be a good representation of their presence in this land cover type.

2.5 Conclusion

The objectives of this research were to test a small selection of classification methods, and of those methods, find the one most appropriate for determining multiple classes of agricultural and herbaceous land cover for the purpose of land cover mapping in areas of grizzly bear habitat. The most appropriate method was determined to be the Supervised Sequential Masking classification, which gave an overall accuracy of 88% and a Kappa Index of Agreement (KIA) of 83%. It had the highest classification accuracies, was the most operationally useful, and it is flexible and easily expandable to other classification problems. The SSM demonstrated some of its utility with the examination of the grizzly bear locations within the agricultural areas in Alberta. The results from the analysis of this data show that food availability may play a part in the bears’ use of the agricultural area in Alberta, so the SSM land cover map may be useful for resource selection and food availability models that could help with grizzly bear management in the agricultural areas of the province.
2.6 References


3. Relationships Between Landscape Spatial Properties and Grizzly Bear Presence in Agricultural Areas in Alberta

3.1 Abstract
Management plans to reduce problem bear conflicts in agricultural areas are seen as one of the strategies with the greatest potential to mitigate human-induced harmful effects on grizzly bear (*Ursus arctos*) populations in Alberta. Agricultural practices change the physical structure and composition of the landscape. The purpose of this research was to determine which, if any, landscape configurational and compositional metrics are related to grizzly bear presence or abundance in an agriculture-dominated landscape. Locational data for 8 bears was examined in an area southwest of Calgary, Alberta. The 4494 km² study area was divided into 107 sub-landscapes of 42 km². Five-meter spatial resolution IRS panchromatic imagery was used to classify the area and derive compositional and configurational metrics for each sub-landscape. It was found that the amount of agricultural land did not explain grizzly bear use; however, secondary effects of agriculture on landscape configuration did. High landscape patch density and variation in distances between neighboring similar patch types were seen as the most significant metrics in the abundance models; higher variation in patch shape, greater contiguity between patches, and lower average distances between neighboring similar patches were the most consistently significant predictors in the bear presence / absence models. Grizzly bears appeared to prefer areas that were structurally correlated to natural areas, and avoided areas that were structurally correlated to agricultural areas. Grizzly bear presence could be predicted in a particular sub-landscape with 87% accuracy using a logistic regression model. Between 30% and 35% of the grizzlies’ landscape scale
habitat selection was explained using these models. Landscape metric values are dependent to some degree upon the spatial and thematic resolution of the imagery used to generate them.

3.2 Introduction and Background

Human-caused mortality, along with habitat loss, are the most serious threats facing grizzly bear (*Ursus arctos* L.) populations in Alberta (Gibeau *et al.*, 2002; Kansas, 2002). Mortality and habitat loss is most often caused by uncontrolled human access and industrial development activity in bear habitat. The term ‘habitat’ in this manuscript will be defined as “the sum and location of the specific resources needed by an organism for survival and reproduction”, which is the definition put forward by McDermid *et al.* (2005). ‘Fragmentation’ in this thesis refers to the more general principle of land transformation in which a large habitat is broken into smaller pieces by a spatial process (Forman, 1995). Fragmentation will therefore lead to an overall loss of habitat and increased isolation of the remaining habitat pieces.

Activities such as oil and gas exploration and extraction, forestry, agriculture, and recreation all contribute to grizzly bear habitat fragmentation and loss (Garshelis *et al.*, 2005). Another important factor is the network of roads and trails that all of the aforementioned activities depend on, as well as the seismic exploration lines that are cut for oil and gas exploration (Mace *et al.*, 1996; Linke *et al.*, 2005). These linear features allow access to otherwise remote areas by people, which leads to conflict and a declining bear population (Kansas, 2002). Fragmentation not only fragments the landscape, but reduces the total area of available habitat, and may limit grizzly bear movement.
Management plans to reduce problem bear conflicts in agricultural areas were mentioned by Kansas (2002) as one of the strategies with the greatest potential to mitigate human-induced harmful effects on grizzly bear populations in Alberta. It has also been recommended by Alberta’s Endangered Species Conservation Committee that the species be elevated from ‘may be at risk’ status to ‘threatened’ status (Stenhouse et al., 2003). Any change in status would require appropriate management and conservation planning, including management plans for agricultural areas that are a part of traditional grizzly habitat.

The purpose of this research is to investigate the possible relationships between metrics that represent landscape structure and grizzly bear (Ursus arctos) presence in agricultural areas. The characteristics of certain landscape elements and landscape composition and configuration are examined to identify their relationships with grizzly bear location information. Using satellite imagery, existing bear location GPS data, and a statistical landscape analysis program (FRAGSTATS) this research is designed to determine the configurational and compositional differences between areas that the bears use and areas that they avoid in the agricultural landscape. Information about these relationships between landscape and bear presence could be critical in determining land management practices in agricultural areas that border current grizzly bear habitat.

3.2.1 Landscape Modification and Fragmentation

This manuscript will follow the definition of ‘landscape metrics’ as outlined by McGarigal (2002), where it refers to indices developed for categorical maps, and “is focused on the characterization of the geometric and spatial properties of categorical map
patterns represented at a single scale.” Landscape metrics act as the quantitative link between spatial patterns of the landscape and ecological or environmental processes, such as animal movement and habitat selection. (O’Neill et al., 1988; Narumalani et al., 2004).

Landscape metrics have been grouped into four main categories, which describe different parameters about the landscape being examined: i) patch area, ii) edge and patch shape, iii) diversity, and iv) landscape configuration, which includes measures of connectivity, proximity, and dispersion, among others (Herzog and Lausch, 2001; Ivits et al., 2002). Patch shape, for example, can often be an indicator of human manipulation of the landscape (O’Neill et al., 1988; Narumalani et al., 2004), which results in more regular, geometric shapes and straight edges. Landscape configuration metrics can be used to measure the amount of fragmentation of the landscape, which is important in many habitat and ecology studies.

Landscape metrics have been shown to contribute to the explanation of species presence and abundance (McGarigal and McComb, 1995; Linke et al., 2005), habitat loss and fragmentation (Linke et al., 2005), and the effects of ecotones and corridors on species movement (Bowers et al., 1996). They have also been used extensively for describing habitat function and landscape pattern (Herzog and Lausch, 2001), especially in the field in landscape ecology. It has been well documented that grizzly bears are affected by landscape structure, especially when caused by anthropogenic landscape modification and fragmentation (Mace et al., 1996; Kansas, 2002; Garshelis et al., 2005; Linke et al., 2005). Anthropogenic effects on grizzlies have been shown in oil and gas exploration and extraction, (McLellan and Shackleton, 1989; Linke et al., 2005) forestry (Apps et al., 2004; Nielsen et al., 2004; Nielsen et al., 2006; Nams et al., 2006), road
development (McLellan and Shackleton, 1988; Mace et al., 1996; Wielgus et al., 2002; Chruszczy et al., 2003; Waller and Servheen, 2005), and agriculture (Wilson et al., 2005; 2006).

3.2.2 Agriculture

Agriculture and its associated land cover were the focus of this research. In a study of grizzly-human conflict on agricultural lands in Montana, Wilson et al. (2005; 2006) found that there were many different attractants for bears on private lands that are a part of the natural bear habitat. One of the most important factors was the use of riparian areas by bears as both habitat and transportation corridors (Wilson et al., 2005). The bears use these areas to reach anthropogenic attractants, such as cattle, sheep, beehives, and boneyards. The more attractants that were in an area, and the closer that area was to wetlands or riparian areas, the more likely the bears were to use that area as habitat. When fences were introduced, the rate of bear use dropped considerably. For example, beehives that were protected by fencing were much less likely to be “attacked” by the bears than unprotected hives (Wilson et al., 2006). In many cases in Montana, the original bear habitat has not been fragmented, but its availability for bear use has been reduced due to human presence. This human presence in the landscape brings the bears into conflict with people, and can be seen as bringing about an effective habitat loss.

3.2.3 Objectives

Landscape metrics have been shown to be an important element in grizzly habitat selection (Linke et al., 2005). Therefore, the specific goals of this research were to:
i) identify landscape composition and spatial configuration in the agricultural areas of western Alberta,

ii) determine if landscape composition and spatial configuration are related to grizzly presence or absence in an area,

iii) determine which landscape metrics have the strongest relationships with grizzly location data that are available from collared bear GPS datasets, and

iv) determine the extent of the difference between landscape metric values when calculated at different spatial and thematic scales.

### 3.3 Study Area and Methods

#### 3.3.1 Study Area

The study area for this project was the foothills region to the southwest of Calgary, Alberta. The area was chosen based on grizzly GPS location data that suggested that bears were present in agricultural areas in this part of the province. The landscape of this area is dominated by grassland and agricultural crops, with patches of forest, changing to largely forested areas further west in the foothills. Roads are a dominant feature in much of this landscape, with higher densities in the agricultural areas, and lower densities in the foothills.

The total study area covers 4494 km², which was made up of 107 square sub-landscapes of 42 km² each (see Figure 3.1), 71 of which contained bear occurrence points. The scale of the sub-landscapes in this research is based on the recommendations of Linke et al. (2005) and Nams et al. (2006), who found that grizzly bears move through and select habitat at a landscape scale of around 35 – 50 km². Nams et al. (2006)
found a strong selection preference at a scale of 16 - 64 km², with a peak preference at 36 km², while Linke et al. (2005) found a possible range from 31 – 49 km², and used a

Figure 3.1: Study area map showing the distribution of the 107 sub-landscapes in southern Alberta.
measure of 49 km$^2$. The use of sub-units of 42 km$^2$ is halfway between the two used values of 36 km$^2$ and 49 km$^2$, and well within the given ranges. It is important that this scale be defined and representative of the organism being studied; otherwise, the landscape patterns detected will have little meaning, and the conclusions reached may not be accurate (McGarigal and Marks, 1995). Each sub-landscape was analyzed separately in the FRAGSTATS program (McGarigal et al., 2002), and had its own landscape metrics generated.

3.3.2 Data Acquisition and Preprocessing

The imagery used for this research was from the Indian Remote Sensing (IRS) satellites (IRS-1C and IRS-1D) panchromatic sensors. The IRS imagery was acquired as 6 bit image data, resampled to 8 bit by the company Space Imaging (maximum number of distinct grey levels = 64). Each image has been orthorectified to Alberta provincial 1:20,000 vector data files. The imagery has a geometric accuracy of +/- 15 meters across each scene. The images are a compilation of scenes from as many as 7 dates, acquired between April and October, and some span more than one year (Table 3.1). The intent of

<table>
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<th>NTS map sheet area</th>
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<td>82J_01</td>
<td>July, 2001</td>
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this compilation was to produce images that were virtually cloud free, and that mirrored Alberta provincial 1:50,000 NTS map sheets. Radiometric correction and tonal balance were employed to maintain uniformity across each scene and adjoining scenes within each image compilation. Radiometric correction was done by the originating company, Space Imaging. Further radiometric and atmospheric correction was not conducted, as it was not necessary for the classification due to the images being classified separately, and accurate biophysical measurements not being needed (Song et al., 2001).

Also used in this study was an existing Landsat TM based land cover map (the same FMF land cover map used in Chapter 2) of the same area of the Alberta foothills. The FMF land cover map was created as part of the Foothills Model Forest Grizzly Bear Research Program, and consists of multiple scenes of Landsat TM data combined together into a mosaic and classified using an object-based classification method (Franklin et al., 2001; McDermid et al., 2006). The FMF land cover map has an overall accuracy of greater than 80% (Franklin et al., 2001). The classes used in the FMF land cover map are Upland Trees, Wetland Trees, Upland Herbs, Wetland Herbs, Shrubs, Water, Barren Land, Snow/Ice, Cloud, and Shadow.

GIS data were also used in this study, provided by the Foothills Model Forest. The data included a grizzly bear point location database, as well as vector data of roads and streams within the study area. In order to collect the bear GPS location data, the FMF captured, immobilized, and radio-collared a sample of the grizzly bear population located throughout the bear’s Alberta range. Collars were placed on both male and female grizzly bears. The resulting telemetry data from these collars were then transmitted to the FMF through a satellite uplink, with locations being recorded every
four hours or less (varies depending on year of bear capture). A detailed methodology and results of this program can be found in Hobson (2005, 2006). A total of 8 bears (5 male, 3 female) gave 1454 point locations (not evenly distributed among the bears or the study area) in the area of study. Specific bear behavior, such as foraging or mating, was not accounted for. The road and stream vector data were used to calculate the density of these features (km / km$^2$) within each sub-landscape. Stream density was included based on work by Nielsen et al. (2002) and Wilson et al. (2005, 2006) who demonstrated a relationship between grizzly habitat selection and distance to riparian areas. Road density was also included, as road density has been shown to play a large role in grizzly bear use or avoidance of an area (McLellan and Shackleton, 1988; Mace et al., 1996; Wielgus et al., 2002; Chruszcz et al, 2003; Waller and Servheen, 2005).

3.3.3 Image Classification

The panchromatic IRS images were classified using the Definiens Professional object-based image analysis software package. Each image was classified separately, using the same SSM classifier as described in Chapter 2. The SSM method was chosen for its relatively high accuracy and so that each image that was classified could simply use a modified version of the SSM classifier that was used on the previous image; the SSM classifier is easily adapted to suit each scene. A limited number of classes were used in this study, due to its focus on agricultural settings and limitations of interpretability for the panchromatic imagery. Panchromatic imagery contains only one image channel, or band, so the spectral responses of the land cover types are limited. Four classes were used: agriculture (which includes open shrubland, grassland, and pastureland in addition to agricultural crops), forest, water, and other (which includes
features such as roads, cities, bare rock, snow, etc.). An object-based approach for the classification was chosen, for a number of reasons. Using an object-based approach, images are separated into discrete, homogenous patches, which allows for easy and accurate interpretation of the land-cover information by the FRAGSTATS software. These homogenous landscape objects also reduce the “salt and pepper” effect that is often seen in pixel-based classification methods. Reduction of this “salt and pepper” effect is important for the derivation of landscape metrics, especially those dealing with connectivity, as a single incorrectly classified pixel in the center of an otherwise homogenous area could lead to inaccurate results (Ivits et al., 2002). Using an object-based classification also made assessment of the classification using the existing FMF Landsat TM-based land cover map of the area more straightforward. The classification assessment was done because it was not feasible at the time of this research to collect ground data to verify the accuracy of the IRS classification. A total of 150 random points were created, using a random point generator in the ArcMap 9 software program. The random points were located in all of the landscape sub-units. The classes of the FMF land cover map were combined to match the classes of the IRS imagery; the two forest classes (Upland Trees and Wetland Trees) were combined into a forest class; the Herbs, Shrubs, and Barren classes were combined into an agriculture class; Water remained water, and the rest of the classes were combined into the other class. The IRS objects matched up visually very well with the existing TM based map objects, with water features, general landscape pattern, and placement of classes matching well (Figure 3.2, points A, B, and C). The IRS map often had more detail because of the higher spatial resolution of the IRS imagery (5m) compared to the Landsat imagery (30m). The
random points were checked for accuracy against the 4-class FMF land cover map. The IRS map was in agreement with the FMF map 81% of the time.

3.3.4 Selection of Landscape Metrics

A variety of configurational and compositional landscape metrics were chosen for this analysis based on their simplicity and accuracy in measuring different elements of the landscape. Metrics were computed at the landscape level in the FRAGSTATS program; landscape level analysis measures the aggregate properties of the entire

Figure 3.2: Shows correlation between a classified IRS image (darker colored square in center) and the FMF land cover map (lighter colors), after combining the Landsat classes to match those used in the IRS image classification. Points A, B, and C are located at areas that showcase how the two images are in thematic agreement.
landscape mosaic for each sub-landscape (McGarigal et al., 2002). Individual grid cells of the same land cover type were merged to form discrete patches using the 8-cell patch neighbor rule (McGarigal et al., 2002), and the sub-landscape borders were not counted as edges, which are the same parameters used by Linke et al. (2005). The metrics were chosen to try to limit redundancy in the physical characteristics being measured, and to represent each of four main categories: i) patch area, ii) edge and patch shape, iii) diversity, and iv) landscape configuration. The ‘landscape configuration’ category was further sub-divided into measures of isolation/proximity, contagion/interspersion, and connectivity (Table 3.2). Some of the metrics were direct measures of some variable (e.g., Landscape Division Index), while others, such as the Shape Index, were aggregates of that metric across the entire sub-landscape in all classes. These aggregated metrics included the following statistical distributions of the measurement: mean (MN), area-weighted mean (AM), median (MD), range (RA), standard deviation (SD), and coefficient of variation (CV). Table 3.2 gives a complete list of the configurational metrics used for the analysis. Some of the metrics used (including the Euclidean Nearest Neighbor distance, the Shape Index, and Simpson’s Evenness Index) have shown promise in other studies (e.g., Linke et al., 2005) in describing the relationship between the spatial characteristics of the landscape and bear presence in that landscape.

Compositional metrics were also used, and included the percent composition of each class type (agriculture, forest, water, and other), as well as road and stream density, for each sub-landscape. Similar compositional components have been used in other grizzly landscape studies, with road density especially being seen as an important measurement to use (e.g., Apps et al., 2004; Singleton et al., 2004; Nams et al., 2006).
Including the configurational metrics, a total of 16 variables were included in the analysis, with 3 of those (Shape Index, Contiguity Index, and Euclidean Nearest Neighbor Distance) each having 6 different statistical distributions.

3.3.5 Statistical Analysis

An initial correlation analysis using Pearson’s r was conducted to identify variables which may be related to grizzly bear abundance (bear location points / km²).
Abundance as used in this manuscript refers to the number of grizzly GPS locations per km$^2$ in a specific sub-landscape. A Multiple Analysis of Variance (MANOVA) test was also conducted to find significant differences between identical variables with bear presence or absence (as a binary value; i.e., not abundance) as the controlling factor. Multiple regression analysis was conducted, using a stepwise approach, to see which metrics could be used to predict grizzly abundance, and how much of the variation can be explained by the given metrics. Finally, logistic regression based on presence/absence of bears was conducted, using a conditional forward stepwise method. Logistic regression was done to test predictions of the presence or absence of bears in a given area. Cushman and McGarigal (2004) found that coding for abundance data generally produced a more descriptive model, but uncommon species with a low frequency of occurrence (such as grizzly bears) can be better represented by presence / absence data. They also found that presence / absence models were more sensitive to analysis of spatial metrics at the patch- and landscape-scale than abundance models were. The results of the statistical analysis could therefore be somewhat dependent on the scale of the landscape and the way in which the species-response data are coded (Cushman and McGarigal, 2004).

A small selection of the sub-landscapes (39 of the 107) were used to generate landscape metrics for the class-combined FMF land cover map and the SSM land cover map (from Chapter 2). The metrics used were the same as those generated with the IRS land cover map. These additional metrics were generated to determine the impact of both spatial and thematic resolution on the values of the resulting landscape metrics. The class-combined FMF land cover map has the same thematic resolution (4 classes) as the IRS land cover map, but with lower spatial resolution (30m, compared to the 5m for the
IRS land cover map). The SSM land cover map has a higher thematic resolution than the FMF land cover map (15 classes versus 4 for the FMF class-combined map), but the same spatial resolution (30m). The metric values were compared by calculating the difference between each metric for the IRS map and the FMF map (IRS value – FMF value) and for the FMF map and the SSM map (FMF – SSM). The average, minimum, maximum, and range for these differences were then calculated, as well as the percent difference in the metric value.

### 3.4 Results

#### 3.4.1 Relationships Between Grizzly Abundance and Landscape Metrics

The Pearson correlation showed that a number of landscape metrics were significantly correlated (p < 0.05) with grizzly GPS location density in each landscape unit. These metrics included Patch Density, Edge Density, Landscape Shape Index, the mean of the Shape Index, the area-weighted mean of the Contiguity Index, the standard deviation of the Contiguity Index, the coefficient of variation of the Contiguity Index, the mean of the Euclidean Nearest Neighbor Distance, the coefficient of variation of the Euclidean Nearest Neighbor Distance, Percentage of Like Adjacencies, Connectance Index (100m) and Road Density (see Table 3.3). The highest correlation was with Patch Density (r = 0.509), which was significant at the p < 0.01 level.

The multiple regression analysis indicated that a model that included the metrics Patch Density, the area-weighted mean of the Contiguity Index, and the coefficient of variation of the Euclidean Nearest Neighbor Distance was a likely predictor of grizzly bear location density. All of these metrics were very significant (p < 0.01) in the model. The R value for the model was 0.61, with an adjusted R² value of 0.35, which indicates
that about 35% of the variance seen in the grizzly location density is explained by these metrics. The formula for this model is:

\[ Y = -35.041 + 0.453*PD + 34.245*CONTIG_AM + 0.002*ENN_CV. \]  

(eq. 3.1)

| Table 3.3: Landscape metrics correlated with Grizzly location density in each sub-landscape. |
|---------------------------------|---------------------------------|-----------------|-----------------|
| # Grizzly points in unit       |                                 | Pearson r       | p-value (2-tailed) |
| PD                             |                                 | .509(**         | 0.000            |
| CONNECT                        |                                 | -.287(**        | 0.003            |
| SHAPE_MN                       |                                 | -.250(**        | 0.009            |
| ENN_CV                         |                                 | .250(**         | 0.009            |
| ENN_AM                         |                                 | .243(*)         | 0.012            |
| Road Density                   |                                 | .227(*)         | 0.019            |
| CONTIG_AM                      |                                 | -.216(*)        | 0.025            |
| CONTIG_SD                      |                                 | -.213(*)        | 0.028            |
| PLADJ                          |                                 | -.207(*)        | 0.032            |
| ED                             |                                 | .207(*)         | 0.032            |
| CONTIG_CV                      |                                 | -.202(*)        | 0.037            |
| LSI                            |                                 | .198(*)         | 0.040            |

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

The coefficients of the model suggest that bear use of an area increases with increasing patch density (represented by Patch Density), increasing amounts of large, contiguous patches (represented by the area-weighted mean of the Contiguity Index), and increasing variation in the distances between similar patches (represented by the coefficient of variation of the Euclidean Nearest Neighbor Distance).

### 3.4.2 Relationships Between Grizzly Presence / Absence and Landscape Metrics

The results of the MANOVA test are shown in Table 3.4. A total of 15 configurational and 1 compositional metric (% forest) were found to be significantly different when bear presence or absence in the sub-landscape was the controlling factor.
Table 3.4: Landscape metrics that show a significant difference (p < 0.05) between sub-units with bears and sub-units without bears. A negative mean difference indicates that the mean was higher for bear presence. A positive mean difference indicates that the mean value was higher for bear absence. Equal variance is assumed.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Sig. (2-tailed) (p-value)</th>
<th>Bear presence</th>
<th>Mean</th>
<th>Mean Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Forest</td>
<td>0.020</td>
<td>no</td>
<td>20.5887</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>28.4446</td>
<td>-7.8559</td>
</tr>
<tr>
<td>PD</td>
<td>0.007</td>
<td>no</td>
<td>3.0369</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>3.8044</td>
<td>-0.7675</td>
</tr>
<tr>
<td>ED</td>
<td>0.001</td>
<td>no</td>
<td>84.1313</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>109.6331</td>
<td>-25.5019</td>
</tr>
<tr>
<td>LSI</td>
<td>0.001</td>
<td>no</td>
<td>14.6252</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>18.6820</td>
<td>-4.0568</td>
</tr>
<tr>
<td>SHAPE_AM</td>
<td>0.003</td>
<td>no</td>
<td>8.7114</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>11.0737</td>
<td>-2.3623</td>
</tr>
<tr>
<td>SHAPE_RA</td>
<td>0.001</td>
<td>no</td>
<td>14.3779</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>18.3333</td>
<td>-3.9555</td>
</tr>
<tr>
<td>SHAPE_SD</td>
<td>0.023</td>
<td>no</td>
<td>2.2538</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>2.4754</td>
<td>-0.2215</td>
</tr>
<tr>
<td>SHAPE.CV</td>
<td>0.006</td>
<td>no</td>
<td>74.9961</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>81.7614</td>
<td>-6.7653</td>
</tr>
<tr>
<td>CONTIG_AM</td>
<td>0.001</td>
<td>no</td>
<td>0.9744</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>0.9671</td>
<td>0.0073</td>
</tr>
<tr>
<td>CONTIG_MD</td>
<td>0.039</td>
<td>no</td>
<td>0.8607</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>0.8674</td>
<td>-0.0068</td>
</tr>
<tr>
<td>ENN_MN</td>
<td>0.000</td>
<td>no</td>
<td>224.5892</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>145.3429</td>
<td>79.2463</td>
</tr>
<tr>
<td>ENN_SD</td>
<td>0.018</td>
<td>no</td>
<td>649.3260</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>514.7290</td>
<td>134.5970</td>
</tr>
<tr>
<td>ENN_CV</td>
<td>0.011</td>
<td>no</td>
<td>304.9093</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>361.8683</td>
<td>-56.9590</td>
</tr>
<tr>
<td>PLADJ</td>
<td>0.001</td>
<td>no</td>
<td>97.8194</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>97.1816</td>
<td>0.6378</td>
</tr>
<tr>
<td>CONNECT</td>
<td>0.004</td>
<td>no</td>
<td>3.7845</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>3.2781</td>
<td>0.5064</td>
</tr>
<tr>
<td>DIVISION</td>
<td>0.003</td>
<td>no</td>
<td>0.5959</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>yes</td>
<td>0.7147</td>
<td>-0.1188</td>
</tr>
</tbody>
</table>
For most metrics, the mean value of the metrics was higher for sub-landscapes in which grizzlies were present. Grizzly presence is indicated by the mean differences being a negative value. Positive mean difference values indicates that the mean value was higher for the metric in sub-landscapes where grizzlies were not present.

The landscape metrics included in the logistic regression model by the conditional forward stepwise regression procedure are the coefficient of variation of the Shape Index (SHAPE_CV), the median of the Contiguity Index (CONTIG_MD), and the mean and area-weighted mean of the Euclidean Nearest Neighbor distance measure (ENN_MN and ENN_AM). Because of differences between what logistic regression and linear regression are predicting, there is no specific $R^2$ value that explains the percentage of variance explained, like there is for linear regression. There is, however, an ‘R-Square’ measure that approximates a normal $R^2$ value, based on likelihood estimates, called Nagelkerke’s R-Square, which was 0.312 for this model. Nagelkerke’s R-Square does not measure goodness-of-fit, but strength of association. From the coefficients for the logistic model, it would appear that grizzly bear presence is associated with an increase in the variation of the patch Shape Index (SHAPE_CV), a higher median Contiguity Index (CONTIG_MD), a decrease in the mean Euclidean Nearest Neighbor distance between patches of the same class (ENN_MN), and an increase in the area-weighted mean Euclidean Nearest Neighbor distance between patches of the same class (ENN_AM).

The formula for this model is:

$$P_a = \frac{1}{1 + e^{(-39.704 + 0.065 \times SHAPE_{CV} + 41.954 \times CONTIG_{MD} - 0.009 \times ENN_{MN} + 0.003 \times ENN_{AM})}}$$
Table 3.5 shows the predicted values for the sub-landscapes based on the logistic regression model. Grizzly bear presence was predicted with 87% accuracy, and the overall prediction accuracy, including both presence and absence prediction, was 71%. The prediction accuracy is based on the number of correctly predicted presence or absence values (using the regression equation) for each sub-landscape when compared to the observed values (the GPS locations).

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Percentage Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absent</td>
<td>Present</td>
</tr>
<tr>
<td>Observed</td>
<td></td>
</tr>
<tr>
<td>Absent</td>
<td>14</td>
</tr>
<tr>
<td>Present</td>
<td>9</td>
</tr>
<tr>
<td>Overall Percentage</td>
<td></td>
</tr>
</tbody>
</table>

3.4.3 Metric Calculation

The results of the metric calculation differences between different spatial and thematic resolutions can be seen in tables 3.6 and 3.7. The metric with the greatest differences between the different spatial and thematic resolutions was the Euclidean Nearest Neighbor distance distributions (ENN_MN, ENN_AM, ENN_MD, ENN_RA, ENN_SV, ENN_CV). There was a greater average % difference between the metrics calculated at different spatial resolutions (IRS metrics versus FMF metrics) compared to those calculated at different thematic resolutions (FMF metrics versus SSM metrics).
Table 3.6: Differences in metric values when calculated from images with different thematic resolution (4 class vs. 15 class).

<table>
<thead>
<tr>
<th>Landscape Metric</th>
<th>Difference (FMF metric – SSM metric)</th>
<th>% difference from FMF value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>PD</td>
<td>0.28</td>
<td>-1.15</td>
</tr>
<tr>
<td>ED</td>
<td>2.51</td>
<td>-31.07</td>
</tr>
<tr>
<td>LSI</td>
<td>0.41</td>
<td>-5.05</td>
</tr>
<tr>
<td>SHAPE_MN</td>
<td>-0.05</td>
<td>-0.61</td>
</tr>
<tr>
<td>SHAPE_AM</td>
<td>0.72</td>
<td>-2.02</td>
</tr>
<tr>
<td>SHAPE_MD</td>
<td>-0.03</td>
<td>-0.33</td>
</tr>
<tr>
<td>SHAPE_RA</td>
<td>0.12</td>
<td>-5.60</td>
</tr>
<tr>
<td>SHAPE_SD</td>
<td>0.00</td>
<td>-0.81</td>
</tr>
<tr>
<td>SHAPE_CV</td>
<td>1.39</td>
<td>-38.22</td>
</tr>
<tr>
<td>CONTIG_MN</td>
<td>-0.04</td>
<td>-0.34</td>
</tr>
<tr>
<td>CONTIG_AM</td>
<td>0.00</td>
<td>-0.07</td>
</tr>
<tr>
<td>CONTIG_MD</td>
<td>-0.04</td>
<td>-0.45</td>
</tr>
<tr>
<td>CONTIG_RA</td>
<td>0.01</td>
<td>-0.22</td>
</tr>
<tr>
<td>CONTIG_SD</td>
<td>0.00</td>
<td>-0.07</td>
</tr>
<tr>
<td>CONTIG_CV</td>
<td>2.48</td>
<td>-22.68</td>
</tr>
<tr>
<td>ENN_MN</td>
<td>-97.97</td>
<td>-700.05</td>
</tr>
<tr>
<td>ENN_AM</td>
<td>-75.31</td>
<td>-582.14</td>
</tr>
<tr>
<td>ENN_MD</td>
<td>-76.21</td>
<td>-774.59</td>
</tr>
<tr>
<td>ENN_RA</td>
<td>-786.45</td>
<td>-3092.07</td>
</tr>
<tr>
<td>ENN_SD</td>
<td>-139.34</td>
<td>-679.08</td>
</tr>
<tr>
<td>ENN_CV</td>
<td>-6.68</td>
<td>-102.36</td>
</tr>
<tr>
<td>PLADJ</td>
<td>-0.38</td>
<td>-5.94</td>
</tr>
<tr>
<td>CONNECT</td>
<td>-0.01</td>
<td>-2.86</td>
</tr>
<tr>
<td>DIVISION</td>
<td>-0.08</td>
<td>-0.73</td>
</tr>
<tr>
<td>SIEI</td>
<td>0.14</td>
<td>-0.13</td>
</tr>
</tbody>
</table>
Table 3.7: Differences in metric values when calculated from images at different spatial resolutions (5m and 30m).

<table>
<thead>
<tr>
<th>Landscape Metric</th>
<th>Difference (IRS metric – FMF metric)</th>
<th>% difference from IRS value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>0.39 -1.35 2.79 4.14</td>
<td>12.5%</td>
</tr>
<tr>
<td>ED</td>
<td>62.18 -17.88 130.42 148.31</td>
<td>57.3%</td>
</tr>
<tr>
<td>LSI</td>
<td>10.06 -2.92 21.19 24.11</td>
<td>54.1%</td>
</tr>
<tr>
<td>SHAPE_MN</td>
<td>1.33 0.79 1.83 1.04</td>
<td>43.1%</td>
</tr>
<tr>
<td>SHAPE_AM</td>
<td>6.55 -2.61 14.74 17.35</td>
<td>54.3%</td>
</tr>
<tr>
<td>SHAPE_MD</td>
<td>0.83 0.15 1.48 1.33</td>
<td>36.2%</td>
</tr>
<tr>
<td>SHAPE_RA</td>
<td>10.97 1.37 26.91 25.54</td>
<td>60.6%</td>
</tr>
<tr>
<td>SHAPE_SD</td>
<td>1.62 0.50 2.94 2.44</td>
<td>61.3%</td>
</tr>
<tr>
<td>SHAPE_CV</td>
<td>27.45 -3.20 67.71 70.91</td>
<td>32.2%</td>
</tr>
<tr>
<td>CONTIG_MN</td>
<td>0.13 0.04 0.35 0.31</td>
<td>16.5%</td>
</tr>
<tr>
<td>CONTIG_AM</td>
<td>0.05 -0.01 0.10 0.11</td>
<td>5.6%</td>
</tr>
<tr>
<td>CONTIG_MD</td>
<td>0.18 0.09 0.51 0.41</td>
<td>20.9%</td>
</tr>
<tr>
<td>CONTIG_RA</td>
<td>0.05 0.00 0.24 0.25</td>
<td>5.5%</td>
</tr>
<tr>
<td>CONTIG_SD</td>
<td>0.04 -0.06 0.14 0.20</td>
<td>17.6%</td>
</tr>
<tr>
<td>CONTIG_CV</td>
<td>0.27 -32.95 19.15 52.10</td>
<td>0.8%</td>
</tr>
<tr>
<td>ENN_MN</td>
<td>-102.01 -1703.50 430.01 2133.50</td>
<td>-58.7%</td>
</tr>
<tr>
<td>ENN_AM</td>
<td>126.39 -73.25 457.77 531.01</td>
<td>62.0%</td>
</tr>
<tr>
<td>ENN_MD</td>
<td>-81.79 -233.35 273.47 506.82</td>
<td>-274.7%</td>
</tr>
<tr>
<td>ENN_RA</td>
<td>2322.65 -2493.03 6095.79 8588.82</td>
<td>48.8%</td>
</tr>
<tr>
<td>ENN_SD</td>
<td>196.84 -924.30 883.05 1807.36</td>
<td>32.7%</td>
</tr>
<tr>
<td>ENN_CV</td>
<td>237.66 -81.12 514.27 595.39</td>
<td>62.2%</td>
</tr>
<tr>
<td>PLADJ</td>
<td>4.63 -1.06 8.28 9.34</td>
<td>4.8%</td>
</tr>
<tr>
<td>CONNECT</td>
<td>1.78 -5.53 5.02 10.54</td>
<td>48.0%</td>
</tr>
<tr>
<td>DIVISION</td>
<td>0.16 -0.46 0.82 1.28</td>
<td>22.7%</td>
</tr>
<tr>
<td>SIEI</td>
<td>0.01 -0.25 0.25 0.50</td>
<td>0.4%</td>
</tr>
</tbody>
</table>

3.5 Discussion

The results of the analysis were separated into those that deal with presence / absence of grizzly bears from the sub-landscapes, and those that deal with grizzly abundance in the sub-landscapes.
3.5.1 Abundance Data

In the correlation analysis, Patch Density (PD) had a high positive correlation with bear abundance, which means that sub-landscapes with more patches of any type were more likely to have bears. The mean Shape Index (SHAPE_MN) and the Connectance Index (CONNECT) (100m) were both negatively correlated with bear abundance, so areas that had a more geometric / regular shaped patches (often associated with anthropogenic activities such as agriculture) and low connectance (larger distance between patches of same type) were more likely to have bears (see Figure 3.3). Also, a larger variation in the Euclidean Nearest Neighbor distance between similar patches (ENN_CV) was strongly (p < 0.01) indicative of grizzly bear abundance in the sub-landscape. Roads were also significantly (p < 0.05) negatively correlated with bear abundance, which is supported by most of the literature; high road densities are associated with increased fragmentation, which leads to loss of overall habitat and increased access and use by humans, all of which have been shown to have impacts on grizzly bear use and selection of an area (McLellan and Shackleton, 1988; Mace et al., 1996; Wielgus et al., 2002; Chruszcz et al, 2003; Waller and Servheen, 2005). Road density is quite high in agricultural areas, so this could relate to avoidance of anthropogenic landscape use. Traffic volume and speed can also play a role in bear reactions to road density (Chruszcz et al, 2003; Waller and Servheen, 2005).

A positive correlation was also seen with Patch Density and the coefficient of variation of the Euclidean Nearest Neighbor distance (ENN_CV) in the linear regression model, in addition to a high explanation of variance by the area-weighted mean of the Contiguity Index (CONTIG_AM), which measures patch cohesion and shape. A high
contiguity is analogous to low fragmentation, so again the pattern emerges that the bears are selecting for more natural, less anthropogenically fragmented landscapes. Patch Density, variance of the Euclidean Nearest Neighbor distance, and the area-weighted mean of the Contiguity Index represented about 35% of the variation seen in the abundance data. Though the data were not strictly normally distributed, the results of the linear regression are still statistically valid, and the results seem to match with the other abundance data.

3.5.2 Presence/Absence Data

In the MANOVA test, bear presence resulted in higher mean values of % forest, so bears are more likely to be present when there is more forested area. Conversely, because of the small number of classes examined, an increase in forest area results in a decrease in agricultural area (forest and agriculture are the two dominant classes in the analysis; as one increases, the other generally decreases), which means that bear presence would be more likely in areas with a low % agriculture. Bear presence also resulted in higher mean values for patch area/edge metrics like Patch Density (PD), Edge Density (ED), and the Landscape Shape Index (LSI), which means that there were more patches, and they had more irregular shapes, with more edge (i.e., more natural areas), in sub-landscapes where bears were present. The Shape Index distributions of area-weighted mean, range, standard deviation, and coefficient of variation (SHAPE_AM, SHAPE_RA, SHAPE_SD, SHAPE.CV) were also larger on average in areas of bear presence, suggesting that bear presence corresponds to more complex shaped patches, with high variety among them. Complex shaped patches can be analogous to more natural, undisturbed areas, as a lower Shape Index is associated with more regular, geometric
shapes, a characteristic of anthropogenic landscapes such as agricultural areas (Forman, 1995). A comparison between natural and anthropogenic landscapes can be seen in Figure 3.3. Complex patch shapes being related to grizzly presence is a different relationship from that of the abundance data, where the Shape Index (and therefore patch shape complexity) was lower in areas of high bear abundance. This difference could be caused by the effects of coding the response variable differently, as presence / absence in this case, versus abundance in the previous case. The mean and standard deviation of the Euclidean Nearest Neighbor distance (ENN_MN and ENN_SD) were both lower in the presence of bears, and the variation in the Euclidean Nearest Neighbor distance

Figure 3.3: Comparison of natural (A) versus agricultural (B) sub-landscapes. Natural areas have high Shape Index mean and variation distributions (complex shapes), low mean nearest neighbor distances (but high variation in nearest neighbor distances) and high contiguity. Agricultural areas have opposite values for these metrics.
(ENN_CV) was higher. An analysis of this Euclidean Nearest Neighbor data would suggest that while the average distance between nearest similar patches was lower, there was a higher overall variation at this smaller distance in areas of bear presence. A higher variation of patch distance is what would be expected in a natural as opposed to an agricultural landscape, as distances between patches in agricultural land can be very far (Figure 3.3). The Percentage of Like Adjacencies (PLADJ) metric supports this, as it is lower in areas of bear presence, and lower values mean that the landscape is more disaggregated, or more natural.

The area-weighted mean of the Contiguity Index (CONTIG_AM) was significantly (p < 0.05) lower in sub-landscapes where bears were present. This Contiguity result is different from the results of the abundance measures, where the area-weighted mean of the Contiguity Index (CONTIG_AM) was found to be positively associated with bear abundance. One reason for this difference could be the different coding between the data, as mentioned earlier. The median Contiguity Index (CONTIG_MD), however, was higher in the bear presence areas; when considering the opposite effect for the area-weighted mean of the Contiguity Index (CONTIG_AM), this would suggest more contiguous but smaller patches in areas of bear presence, which again leads to spatial parameters that are characteristic of natural landscapes. The Landscape Division Index (DIVISION), a measure of the sub-division of the landscape, was also higher in areas of bear presence. However, the Connectance Index (CONNECT) was lower, which means that fewer patches in the landscapes that bears were present in were connected at a range of 100 meters or less. Bear presence being related to a low Connectance Index is not surprising, as grizzly bears have large home
ranges and can move many kilometers throughout the course of a day (Kansas, 2002). Patches on the landscape do not necessarily have to be connected for the bears to use them.

The results of the logistic regression indicate that grizzly bear presence is associated with an increase in the variation of the patch Shape Index (SHAPE_CV), a higher median patch Contiguity Index (CONTIG_MD), a decrease in the mean distance between patches of the same class (mean Euclidean Nearest Neighbor distance, ENN_MN), and an increase in the area-weighted mean of the Euclidean Nearest Neighbor distance between patches of the same class (ENN_AM). These metrics, with the exception of the area-weighted mean of the Euclidean Nearest Neighbor, were also found to be significant in the MANOVA test, with the variable responses also being in the same direction. All of these metrics are associated with natural areas, or at least agricultural areas that have some characteristics of more natural areas. The predictions of bear presence or absence from Table 3.5 are also interesting. From a landscape management perspective, it is much more important to have accurate information on bear presence than it is to have information on bear absence. Grizzly bear presence was predicted with 87% accuracy, which is a good result considering the logistic regression model only explained about 31% of the strength of the associations between the chosen metrics and bear presence in a given sub-landscape.

3.5.3 Metric calculation

The differences in the values of the landscape metrics when calculated from different spatial resolutions are quite striking. There are differences of more than 50% for distributions of the Shape Index (SHAPE) and Euclidean Nearest Neighbor distance.
(ENN) metrics that were found to be important in the regression models. Large differences can also be seen in the metric values between different thematic resolutions. The Euclidean Nearest Neighbor distributions again have very large differences in their values. These differences in landscape metric values for both thematic and spatial comparisons show that the type of sensor used, as well as the classification method, both have an impact on the landscape metric calculations. By changing the spatial resolution of the input imagery, patches have different shapes and sizes due to smaller pixel sizes being able to better represent complex patch boundaries. These different shapes and sizes in turn will have an effect on the calculated distances between the patches. Different thematic resolutions result in different metric values due to more patches being present with a greater thematic resolution. For example, a patch that may be classified as “agriculture” in a low thematic resolution could be made up of 3 different patches classified as “Canola”, “Legumes”, and “Bare Soil / Fallow” in a higher thematic resolution. The differences in metric values between different spatial and thematic resolutions could be a factor when examining the metrics for relationships to grizzly bear location data.

### 3.6 Significance

While this study did not find a direct link between grizzly bear abundance or presence and the amount of agricultural land present, it did find links with spatial attributes that correspond to reduced agricultural activity and human-caused fragmentation. Size, shape, and position of land cover patches in areas of grizzly habitat had a measureable relationship with the presence/absence and abundance of the bears.
There was a link between decreased grizzly bear landscape use and agricultural activity. Nielsen and Boyce (2002) suggested that grizzly bears tend to select habitat that is highly variable, which suggests natural, patchy landscapes, like those to which bear presence was correlated with in this study. Natural, patchy landscapes are different from human-fragmented landscapes, which are characterized by patch isolation, geometric patterns, and increased human presence. Relationships between landscape metrics that were representative of human fragmented landscapes and bears were negative, in that bears were less likely to be present in this type of landscape. It may be important to know for future work which landscape metrics are important for analyzing grizzly habitat, as well as what spatial and thematic resolution these metrics should be calculated at; this research is a step towards these goals.

3.7 Limitations

Although habitat spatial structure and composition had a significant, measurable effect, much of the variance in the bear presence and abundance in each sub-landscape was not explained. The landscape configurational and compositional metrics that were found to be significant could simply be reflections of human presence and use of the landscape, especially in this agricultural setting. Grizzly bears respond to a range of variables that were not included in this study, such as food supply and human presence (Munro et al., 2006). The bears may be reacting more directly to these variables than to the landscape metrics associated with them. Also, the low number of bears sampled (8) means that if some of the bears were habituated to human presence, or their movement was affected by mating or other behavior, then the results could be misleading.
Research in the area of accuracy assessment for landscape metrics is lacking (Gergel, 2007). Unlike classification accuracy assessment, there exists no standard, well-defined method or concept that can accurately predict the accuracy of spatial landscape metrics. Traditional methods of classification accuracy assessment are generally non-spatial in nature, and therefore of limited value for assessing the accuracy of spatial pattern (Gergel, 2007). Even the classification accuracy of the map(s) upon which the landscape metric analysis is based may not be a good indicator of landscape metric accuracy. Langford et al. (2006) showed that high map classification accuracies do not result in more accurate spatial fragmentation indices. The lack of spatial metric accuracy assessment could have potentially large consequences on research, management, and policy where spatial metrics are used (Gergel, 2007), and there is likely unknown error associated with every spatial pattern study ever conducted (Langford et al., 2006). With no solution to this problem in sight, possible unknown error must be taken into consideration when analyzing the results of this study.

Other possible introduction of error could have occurred by means other than spatial metric error. The results of the abundance data versus the presence / absence data were similar, but there were some differences that may have been a product of GPS collar bias. While collar bias is normally predictable (Frair et al., 2004), problems may arise in an agricultural setting because there is likely to be much more loss of collar data in forested areas than in open agricultural areas, as the forest canopy could block the signal. Blocked GPS signals could skew the abundance data to show more location points in open agricultural areas, as there would be very minimal data loss in these areas. Biased data would therefore have affected the relationship between abundance and landscape
metrics that are associated with agricultural areas, such as low patch density and geometric patch shapes.

3.8 Conclusion

Knowledge about grizzly bear selection of habitat in agricultural areas is very limited. While it is known that grizzly bears tend to avoid anthropogenic disturbance, this research presents the first evidence that the physical structure and composition of agricultural areas may play a part in this behavior. There were significant differences among landscapes that grizzly bears did use versus those they did not use. Landscape spatial structure seems to have at least some role in determining whether or not bears will use an area in an agricultural landscape. The results of this research, while not definite, could be helpful in informing other grizzly bear resource selection models.

While the results of this research do not completely explain grizzly bear use and movement in agricultural areas, they are a good starting point for further research. Future analysis should include the effects of food selection, crop preferences, and human avoidance on grizzly bear selection of habitat in these areas.

3.9 References


McGarigal, K., Cushman, S. A., Neel, M. C., and Ene, E., 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at the following web site: www.umass.edu/landeco/research/fragstats/fragstats.html


4. Integration and Synthesis

This chapter will revisit the main findings and contributions of the research manuscripts, relating them back to the broader context of the literature introduced in Chapter 1. Limitations of the research, as well as directions for possible future research are also identified.

4.1 Significance and contributions

The first manuscript concluded that a supervised classification technique, the SSM method, was the best overall choice of the methods tested for this particular large-scale habitat mapping objective. The SSM classification, gave a high classification accuracy (88%), and was easily implemented over a regional image mosaic comprising multiple biomes. The level of accuracy exceeds the best results (81.3% accuracy) of Turker and Arikan (2005), who also used an object-based classification of agricultural fields; their study, however, used multi-temporal imagery (which increased their overall accuracies), while this research only used single-date images. Not requiring multi-date imagery while at the same time getting very good accuracy results from the classification shows the potential for the SSM technique to be an effective mapping and classification tool. The research presented is also a step towards overcoming the issue of availability of multi-temporal imagery (Franklin and Wulder, 2002). The results of the classification analysis were applied to the larger FMFGBRP study area in Alberta, resulting in land cover maps that have an increased thematic accuracy in the agricultural regions. A larger classification also allowed for the analysis of the bear location data across all of the agricultural regions in the western half of the province.
The second manuscript expands on this analysis of the effects of agricultural areas on grizzly bears by examining the relationship between the spatial configuration and composition of the agricultural landscapes and bear use or abundance in these areas. Apps et al. (2004) used a variety of compositional and environmental variables to predict grizzly bear abundance and distribution in British Columbia, but configurational landscape metrics were not used. Linke et al. (2005) did use both configurational and compositional metrics to examine the effect of seismic exploration lines on grizzlies in Alberta, but agricultural areas were not included in the study. Popplewell et al. (2003) used landscape metrics to classify grizzly bear location density in different bear management units in Alberta, but again, agricultural areas were not examined. Wilson et al. (2005, 2006) did examine the influences of an agricultural setting on grizzly bears, but they focused on human-caused attractants, not the spatial pattern of the landscape.

The direct and indirect influences of agriculture on grizzly bear movement and use of habitat have not been closely examined until now. The second manuscript presents a landscape ecology perspective on the issue by using landscape metrics to analyze the effect of the physical structure of this environment on grizzly abundance / use. This research offers the first evidence that the physical structure and composition of agricultural areas may play a part in bear habitat use in agricultural landscapes. Bear presence was predicted with 87% accuracy using a logistic regression equation, and it was discovered that there were significant differences among landscapes that grizzly bears did use versus those they did not use. A pattern emerged showing that the bears were more abundant in more natural, less anthropogenically fragmented landscapes. These results show that landscape metrics can contribute to explanations of bear presence.
and abundance, which accords well with results from other studies (e.g., McGarigal and McComb, 1995; Linke et al., 2005) that have also linked landscape configurational and compositional metrics to species use of a landscape.

Together, these manuscripts show the importance of agricultural land cover on the grizzly bear populations of Alberta. The results from these manuscripts support each other in that the Grass / Forage class is the most predominant land-cover type that the bears have been present in (Chapter 2 results); the Grass / Forage class is analogous to natural grassland and shrubby pastures, which are more ‘natural’ landscapes like those shown in Chapter 3 that are closer to the western margins of the agricultural area. Bears were not located as often (or at all) in classes such as Small Grains and Canola, which are more often planted in the center of agricultural areas, away from the marginal land dominated by grass and pastures. The more central agricultural areas are the areas that are the most fragmented and the most frequented by humans, with landscape structural and compositional elements that are not conducive to bear presence or abundance.

The results from Chapter 3 that show the differences between landscape metrics when calculated with different spatial and thematic resolutions show how important an increased thematic resolution can be for further analysis of landscape metrics. The SSM classification is a way of getting this increased thematic resolution across a large region.

The results of this thesis will be very useful in examining the relationships between the grizzly bears and their use of agricultural areas. The updated land-cover maps are also important from a planning and management perspective. The methods used for this research are not just significant for current grizzly habitat mapping and
planning needs, but could also be applied to other species and land-cover types, such as woodland caribou (e.g., Johnson et al., 2002).

4.2 Limitations

One limitation of the classification and spectral analysis of agricultural land is the possibility of large differences between fields of the same class. Planting dates, crop health, and crop and soil moisture levels can vary by a large amount, even between adjacent fields, which can lead to differences in the spectral responses and classification error.

A similar phenological concern exists for the results of the additional 6 Landsat scene classification, for which no ground data was available. Most of these images are taken later in the season than the two test images, with a corresponding difference in phenology. In many cases, the fields had already been harvested. Harvested fields obviously would be very different in their spectral response when compared to fields of the same crop that have not been harvested, which makes it much more difficult to correctly identify classes.

Although habitat spatial structure and composition had a significant, measurable relationship with grizzly presence/absence and abundance in agricultural areas, much of the variance in each sub-landscape was not explained, nor was it expected to be. The landscape configurational and compositional metrics that were found to be significant could simply be reflections of human presence and use of the landscape, especially in this agricultural setting.
4.3 Future research

Future remote sensing research could be done to incorporate texture measures or multi-temporal imagery into the SSM classification method, to increase classification accuracy, or to increase the number of land cover classes. Other remote sensing platforms, such as SPOT or ASTER, could be examined to determine if they are capable of producing results similar to those of the Landsat sensors when doing a land-cover classification of a large region.

Landscape metrics could also be further examined. Research could include examining possible relationships or correlations between metrics to determine which ones are the most useful for habitat analysis. Also, there is currently no way to accurately test the accuracy of the metrics themselves, so this could be a further area of research in this field. The most useful spatial and thematic resolution of the images used to generate the landscape metrics could also be examined.

While the results of this research do not completely explain grizzly bear use and movement in agricultural areas, they are a good starting point for further research. Future analysis should include the effects of food selection, crop preferences, and human avoidance on grizzly bear selection of habitat in these areas. The analysis could include resource selection functions (Nielsen et al., 2002) to further examine these other influences.

The results from the analysis of the grizzly location data show that food availability may play a part in the bears’ use of the agricultural areas of Alberta, so the
updated grizzly habitat maps may be useful for resource selection and food availability models that could help with grizzly bear management in the agricultural areas.

4.4 References


Appendix A: Confusion Matrices

Confusion matrices for the three tested classification methods of Chapter 2. The data are from validation points only, not training data. The column totals are derived from the number of pixels in the reference data, while the row totals represent pixels that were actually classified in that category. Overall accuracy is determined by dividing the total number of correctly classified pixels (the sum of the major diagonal) by the total number of pixels in the error matrix. If the total number of correctly classified pixels in a category (class) is divided by that class column total, then the result is a measure of omission error (producer’s accuracy). If the total number of correctly classified pixels in a category is divided by that class row total, then the result is a measure of commission error (user’s accuracy).

Table A1: South study area Unsupervised classification confusion matrix

<table>
<thead>
<tr>
<th>User \ Reference Class</th>
<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grasses / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare Soil / Fallow</td>
<td>531</td>
<td>27</td>
<td>4395</td>
<td>0</td>
<td>551</td>
<td>5504</td>
</tr>
<tr>
<td>Canola</td>
<td>0</td>
<td>2921</td>
<td>5</td>
<td>2153</td>
<td>530</td>
<td>5609</td>
</tr>
<tr>
<td>Grasses / Forage</td>
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<td>332</td>
<td>9852</td>
<td>843</td>
<td>7163</td>
<td>18220</td>
</tr>
<tr>
<td>Legumes</td>
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<td>5962</td>
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<td>445</td>
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<td>6989</td>
</tr>
<tr>
<td>Small Grains</td>
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<td>Total</td>
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<td>9575</td>
<td>15492</td>
<td>3482</td>
<td>23626</td>
<td>52736</td>
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</table>

Table A2: North study area Unsupervised classification confusion matrix

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<th>User \ Reference Class</th>
<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grasses / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare Soil / Fallow</td>
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<tr>
<td>Grasses / Forage</td>
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<td>0</td>
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<td>349</td>
<td>1956</td>
<td>5926</td>
</tr>
<tr>
<td>Legumes</td>
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<td>0</td>
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<td>Small Grains</td>
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<td>12049</td>
<td>1118</td>
<td>8858</td>
<td>35637</td>
</tr>
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</table>
Table A3: North study area Nearest Neighbor classification confusion matrix

<table>
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<th>User \ Reference Class</th>
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<th>Canola</th>
<th>Grasses / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
<th>Total</th>
</tr>
</thead>
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<td>12049</td>
<td>1118</td>
<td>8858</td>
<td>35637</td>
</tr>
</tbody>
</table>

Table A4: South study area Nearest Neighbor classification confusion matrix

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<tr>
<th>User \ Reference Class</th>
<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grasses / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
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<td>15492</td>
<td>3482</td>
<td>23626</td>
<td>52736</td>
</tr>
</tbody>
</table>

Table A5: North study area Supervised Sequential Masking (SSM) classification confusion matrix

<table>
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<tr>
<th>User \ Reference Class</th>
<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grasses / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
<th>Total</th>
</tr>
</thead>
<tbody>
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<td>12049</td>
<td>1118</td>
<td>8858</td>
<td>35637</td>
</tr>
</tbody>
</table>

Table A6: South study area Supervised Sequential Masking (SSM) classification confusion matrix

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<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grasses / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare Soil / Fallow</td>
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<td>724</td>
<td>0</td>
<td>0</td>
<td>1285</td>
</tr>
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<td>163</td>
<td>604</td>
<td>10342</td>
</tr>
<tr>
<td>Hay / Pasture</td>
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<td>0</td>
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</tr>
<tr>
<td>Peas</td>
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<td>9575</td>
<td>15492</td>
<td>3482</td>
<td>23626</td>
<td>52736</td>
</tr>
</tbody>
</table>
Appendix B: Field Form

The form used for field data collection purposes.

Field Data
Crops and Pastures

Date/Time______________/_______________ Site ID/Photo Reference_____________/______________

Coordinates (UTM 11, Nad 83) of point: E:_________________________ N:_________________________
for samples of opportunity
Observer location: E:_________________________ N:_________________________
Direction of field from Observer: __________

Description:

Cover Type: Crop (name)_______________ Grass: Planted/Natural/Fenced Current Grazing: Yes/No
Stubble/ Bare Soil/ Weeds/ Other: ________________________________
Condition: Good/ Poor/ Other: ________________________________

Landscape: flat/ rolling/ steep Water: Irrigated/ Standing Water/ Other: __________________________
Other Description: ______________________________________________
__________________________________________________________________
__________________________________________________________________
__________________________________________________________________

__________________________________________________________________
Appendix C: Process Trees

The process tree used for the SSM classification of Chapter 2.

![Process Tree Diagram]

Figure C1: North study area process tree
Figure C2: South study area process tree
Figure C3: Landsat image 41/26 process tree

Figure C4: Landsat image 43/24 process tree
Figure C5: Landsat scene 44/22 process tree

Figure C6: Landsat image 44/23 process tree
Figure C7: Landsat image 45/21 process tree

Figure C8: Landsat image 46/21 process tree
Appendix D: Class Specific Bear Locations

Shows the distribution of grizzly GPS location points in different land cover types by month. Months represented by shades of green are the months in which the most location points are located.

Figure D1: Data represents 18 bears (10 male, 8 female) with 1035 location points.
Figure D2: Data represents 12 bears (7 male, 5 female) with 237 location points.

Figure D3: Data represents 7 bears (2 male, 5 female) with 52 location points.
Appendix E: Tables of Accuracy Results

Detailed class and overall accuracy results for the three classifications that were examined in Chapter 2. Values for the North and South study areas are given separately, as well as averaged. Values are derived from the confusion matrices for these classifications (Appendix A).

Table E1: Unsupervised classification details

<table>
<thead>
<tr>
<th></th>
<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grass / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Producer</td>
<td>97.30%</td>
<td>59.86%</td>
<td>46.82%</td>
<td>40.78%</td>
<td>65.62%</td>
</tr>
<tr>
<td>Average User</td>
<td>26.52%</td>
<td>72.14%</td>
<td>57.59%</td>
<td>53.18%</td>
<td>89.31%</td>
</tr>
<tr>
<td>Average KIA* Per Class</td>
<td>96.97%</td>
<td>54.21%</td>
<td>30.24%</td>
<td>33.78%</td>
<td>53.63%</td>
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<tr>
<td>South Producer</td>
<td>94.65%</td>
<td>30.51%</td>
<td>63.59%</td>
<td>12.78%</td>
<td>60.31%</td>
</tr>
<tr>
<td>South User</td>
<td>9.65%</td>
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<td>54.07%</td>
<td>6.37%</td>
<td>91.57%</td>
</tr>
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<td>South KIA Per Class</td>
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<td>-0.55%</td>
<td>43.69%</td>
</tr>
<tr>
<td>North Producer</td>
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<td>30.05%</td>
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<td>70.94%</td>
</tr>
<tr>
<td>North User</td>
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<td>92.20%</td>
<td>61.10%</td>
<td>100.00%</td>
<td>87.06%</td>
</tr>
<tr>
<td>North KIA Per Class</td>
<td>99.92%</td>
<td>86.19%</td>
<td>16.10%</td>
<td>68.10%</td>
<td>63.56%</td>
</tr>
<tr>
<td>Average Overall Accuracy</td>
<td>59.39%</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Average KIA</td>
<td>46.40%</td>
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</tr>
</tbody>
</table>

*KIA = Kappa Index of Agreement
### Table E2: Supervised Nearest Neighbor classification details

<table>
<thead>
<tr>
<th></th>
<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grass / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Producer</td>
<td>94.62%</td>
<td>95.40%</td>
<td>80.46%</td>
<td>80.01%</td>
<td>79.96%</td>
</tr>
<tr>
<td>Average User</td>
<td>55.45%</td>
<td>95.65%</td>
<td>86.07%</td>
<td>68.46%</td>
<td>84.58%</td>
</tr>
<tr>
<td>Average KIA Per Class</td>
<td>94.44%</td>
<td>94.39%</td>
<td>72.29%</td>
<td>79.03%</td>
<td>70.60%</td>
</tr>
<tr>
<td>South Producer</td>
<td>89.48%</td>
<td>90.88%</td>
<td>78.72%</td>
<td>91.24%</td>
<td>85.23%</td>
</tr>
<tr>
<td>South User</td>
<td>33.40%</td>
<td>91.35%</td>
<td>80.48%</td>
<td>80.98%</td>
<td>89.00%</td>
</tr>
<tr>
<td>South KIA Per Class</td>
<td>89.17%</td>
<td>88.87%</td>
<td>70.14%</td>
<td>90.54%</td>
<td>74.13%</td>
</tr>
<tr>
<td>North Producer</td>
<td>99.76%</td>
<td>99.93%</td>
<td>82.20%</td>
<td>68.78%</td>
<td>74.69%</td>
</tr>
<tr>
<td>North User</td>
<td>77.50%</td>
<td>99.95%</td>
<td>91.66%</td>
<td>55.93%</td>
<td>80.16%</td>
</tr>
<tr>
<td>North KIA Per Class</td>
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<td>99.90%</td>
<td>74.45%</td>
<td>67.53%</td>
<td>67.06%</td>
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<td>Average Overall Accuracy</td>
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<td>Average KIA</td>
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<tr>
<td>South KIA</td>
<td>77.80%</td>
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<tr>
<td>North Overall Accuracy</td>
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<td>North KIA</td>
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### Table E3: Supervised Sequential Masking (SSM) classification details

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<th>Bare Soil / Fallow</th>
<th>Canola</th>
<th>Grass / Forage</th>
<th>Legumes</th>
<th>Small Grains</th>
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</thead>
<tbody>
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<td>Average Producer</td>
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<td>100.00%</td>
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<td>97.66%</td>
<td>80.93%</td>
</tr>
<tr>
<td>Average User</td>
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<td>92.71%</td>
<td>87.31%</td>
<td>85.64%</td>
<td>83.98%</td>
</tr>
<tr>
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<td>86.71%</td>
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<td>91.86%</td>
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<td>100.00%</td>
<td>82.56%</td>
<td>94.87%</td>
<td>77.40%</td>
</tr>
<tr>
<td>North Producer</td>
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<tr>
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<td>82.76%</td>
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</tr>
<tr>
<td>North KIA Per Class</td>
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<td>100.00%</td>
<td>70.51%</td>
<td>100.00%</td>
<td>66.70%</td>
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<tr>
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<tr>
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<tr>
<td>South KIA</td>
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<tr>
<td>North Overall Accuracy</td>
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</tr>
<tr>
<td>North KIA</td>
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</tbody>
</table>