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

PERMISSION TO USE

In presenting this thesis in partial fulfillment of the requirements for a Postgraduate degree from the University of Saskatchewan, I agree that the Libraries of this University may make it freely available for inspection. I further agree that permission for copying of this thesis in any manner, in whole or in part, for scholarly purposes may be granted by the professor or professors who supervised my thesis work or, in their absence, by the Head of the Department or the Dean of the College in which my thesis work was done. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the University of Saskatchewan in any scholarly use which may be made of any material in my thesis.

DISCLAIMER

The software packages mentioned in this thesis were exclusively used to meet the thesis and/or exhibition requirements for the degree of Master of Science at the University of Saskatchewan. Reference in this thesis to any specific commercial products, process, or service by trade name, trademark, manufacturer, or otherwise, does not constitute or imply its endorsement, recommendation, or favoring by the University of Saskatchewan. The views and opinions of the author expressed herein do not state or reflect those of the University of Saskatchewan, and shall not be used for advertising or product endorsement purposes.

Requests for permission to copy or to make other uses of materials in this thesis/dissertation in whole or part should be addressed to:

Head of the Department of Geography
University of Saskatchewan
Saskatoon, Saskatchewan S7N 5A5
Canada

OR

Dean
College of Graduate Studies and Research
University of Saskatchewan
107 Administration Place
Saskatoon, Saskatchewan S7N 5A2
Canada

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 km^2 study area was divided into 107 sub-landscapes of 42 km^2. 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.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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

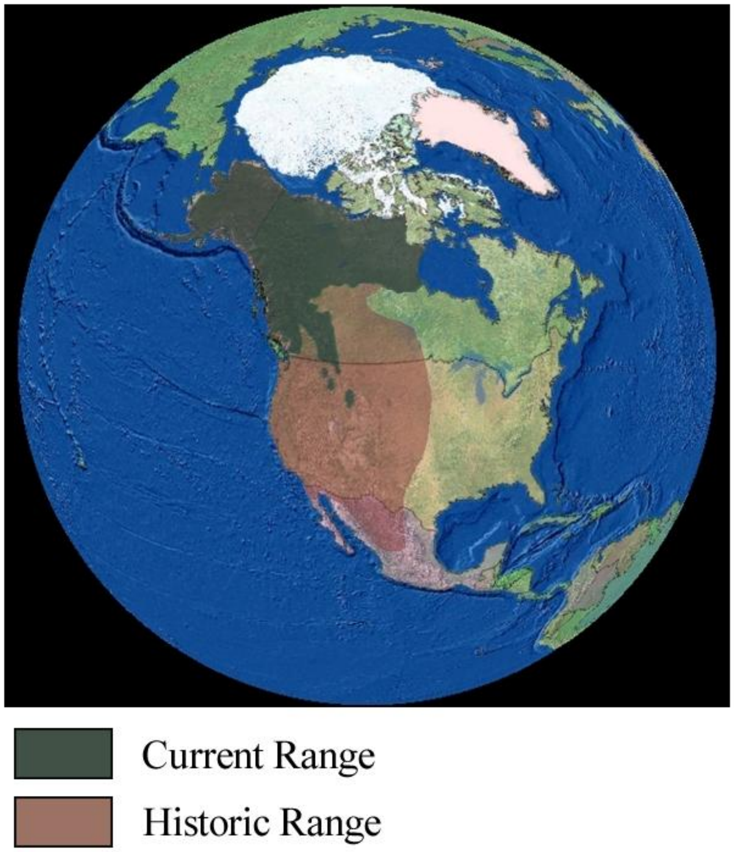

Figure 1.1: Current and historic (last 200 years) range of the grizzly bear in North America. Adapted from Kansas, 2002.

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

5 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

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

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 1.2: Landsat and IRS satellite characteristics. Adapted from Jensen (2000).

Landsat 5 TM			Landsat 7 ETM+			IRS-1C and 1D		
Band	Spectral Wavelength (µm)	Spatial Resolution (m) at Nadir	Band	Spectral Wavelength (µm)	Spatial Resolution (m) at Nadir	Band	Spectral Wavelength (µm)	Spatial Resolution (m) at Nadir
1	0.45-0.52	30x30	1	0.45-0.52	30x30	1	-	-
2	0.52-0.60	30x30	2	0.52-0.60	30x30	2	0.52-0.59	23x23
3	0.63-0.69	30x30	3	0.63-0.69	30x30	3	0.62-0.68	23x23
4	0.76-0.90	30x30	4	0.76-0.90	30x30	4	0.77-0.86	23x23
5	1.55-1.75	30x30	5	1.55-1.75	30x30	5	1.55-1.70	70x70
6	10.4-12.5	120x120	6	10.4-12.5	60x60	Pan	0.50-0.75	5x5
7	2.08-2.35	30x30	7	2.08-2.35	30x30	WiFS 1	0.62-0.68	188x188
-			Pan	0.52-0.90	15x15	WiFS 2	0.77-0.86	188x188
Swath Width	185 km		185 km			142 km for bands 2,3,4; 148 km for band 5; Pan = 70km; 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

Agrawal, S., Joshi, P.K., Shukla, Y., and Roy, P.S., 2003. SPOT VEGETATION multi temporal data for classifying vegetation in south central Asia. *Current Science* 84 (11), 1440 – 1448.

Aplin, P., and Atkinson, P.M., 2001. Sub-pixel land cover mapping for per-field classification. *International Journal of Remote Sensing* 22 (14), 2853 – 2858.

Apps, C.D., McLellan, B.N., Woods, J.G., and Proctor, M.F., 2004. Estimating Grizzly Bear Distribution and Abundance Relative to Habitat and Human Influence. *Journal of Wildlife Management* 68 (1), 138 – 152.

Baldi, G., Guerschman, J.P., and Paruelo, J.M., 2006. Characterizing fragmentation in temperate South America grasslands. *Agriculture, Ecosystems, and Environment* 116, 197–208.

Ban, Y., 2003. Synergy of multitemporal ERS-1 SAR and Landsat TM data for classification of agricultural crops. *Canadian Journal of Remote Sensing* 29 (4), 518 – 526.

Berger, J., Stacey, P.B., Bellis, L., and Johnson, M.P., 2001. A Mammalian Predator-Prey Imbalance: Grizzly Bear and Wolf Extinction Affect Avian Neotropical Migrants. *Ecological Applications* 11 (4), 947 – 960.

Blaes, X., Vanhalle, L., and Defourny, P., 2005. Efficiency of crop identification based on optical and SAR image time series. *Remote Sensing of Environment* 96, 352 – 365.

Bock, M., Xofis, P., Mitchley, J., Rossner, G., Wissen, M., 2005. Object-oriented methods for habitat mapping at multiple scales – Case studies from Northern Germany and Wye Downs, UK. *Journal for Nature Conservation* 13, 75 – 89.

Boegh, E., Soegaard, H., Broge, N., Hasager, C.B., Jensen, N.O., Schelde, K., and Thomsen, A., 2002. Airborne multispectral data for quantifying leaf area index, nitrogen concentration, and photosynthetic efficiency in agriculture. *Remote Sensing of Environment* 81, 179 – 193.

Bolstad, P.V. and Lillesand, T.M., 1991. Rapid maximum likelihood classification. *Photogrammetric Engineering and Remote Sensing* 57, 67–74.

Boyce, M.S., Vernier, P.R., Nielsen, S.E., and Schmiegelow, F.K.A., 2002. Evaluating resource selection functions. *Ecological Modelling* 157, 281 – 300.

Brook, R.K., and Kenkel, N.C., 2002. A multivariate approach to vegetation mapping of Manitoba's Hudson Bay Lowlands. *International Journal of Remote Sensing* 23 (21), 4761 – 4776.

Brown de Colstoun, E.C., Story, M.H., Thompson, C., Commisso, K., Smith, T.G., and Irons, J.R., 2003. National Park vegetation mapping using multitemporal Landsat 7 data and a decision tree classifier. *Remote Sensing of Environment* 85, 316 – 327.

Camacho-De Coca, F.C., Garcia-Haro, F.J., Gilabert, M.A., and Melia, J., 2004. Vegetation cover seasonal changes assessment from TM imagery in a semi-arid landscape. *International Journal of Remote Sensing* 25 (17), 3451-3476.

Chruszcz, B., Clevenger, A.P., Gunson, K.E., and Gibeau, M.L., 2003. Relationships among grizzly bears, highways, and habitat in the Banff-Bow Valley, Alberta, Canada. *Canadian Journal of Zoology* 81, 1378 – 1391.

Chubey, M.S., Franklin, S.E., and Wulder, M.A., 2006. Object-based Analysis of Ikonos-2 Imagery for Extraction of Forest Inventory Parameters. *Photogrammetric Engineering & Remote Sensing* 72 (4), 383-394.

Cihlar, J., 2000. Land cover mapping of large areas from satellites: status and research priorities. *International Journal of Remote Sensing* 21 (6 & 7), 1093 – 1114.

Cihlar, J., Guindon, B., Beaubien, J., Latifovic, R., Peddle, D., Wulder, M., Fernandes, R., and Kerr, J., 2003. From need to product: a methodology for completing a land cover map of Canada with Landsat data. *Canadian Journal of Remote Sensing* 29 (2), 171 – 186.

Cihlar, J., Latifovic, R., Beaubien, J., 2000. A comparison of clustering strategies for unsupervised classification. *Canadian Journal of Remote Sensing* 26 (5), 446 – 454.

Cihlar, J., Xiao, Q., Chen, J., Beaubien, J., Fung, K., and Latifovic, R., 1998. Classification by progressive generalization: a new automated methodology for remote sensing multichannel data. *International Journal of Remote Sensing* 19 (14), 2685 – 2704.

Cohen, Y., and Shoshany, M., 2002. A national knowledge-based crop recognition in Mediterranean environment. *International Journal of Applied Earth Observation and Geoinformation* 4, 75 – 87.

De Wit, A.J.W., and Clevers, J.G.P.W., 2004. Efficiency and accuracy of per-field classification for operational crop mapping. *International Journal of Remote Sensing* 25 (20), 4091 – 4112.

El-Magd, I.A., and Tanton, T.W., 2003. Improvements in land use mapping for irrigated agriculture from satellite sensor data using a multi-stage maximum likelihood classification. *International Journal of Remote Sensing* 24 (21), 4197 – 4206.

Estep, L., Terrie, G., and Davis, B., 2004. Technical Note: Crop stress detection using AVIRIS hyperspectral imagery and artificial neural networks. *International Journal of Remote Sensing* 25 (22), 4999 – 5004.

Fahrig, L., and Merriam, G., 1994. Conservation of Fragmented Populations. *Conservation Biology* 8 (1), 50 – 59.

Ferencz, C., Bognar, P., Lichtenberger, J., Hamar, D., Tarcsai, G., Timar, G., Molnar, G., Pasztor, S., Steinbach, P., Szekely, B., Ferencz, O.E., and Ferencz-Arkos, I., 2004. Crop yield estimation by satellite remote sensing. *International Journal of Remote Sensing* 25, (20), 4113 – 4149.

Foody, G.M., 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* 80, 185 – 201.

Forman, R.T.T., 1995. *Land Mosaics: The Ecology of Landscapes and Regions*. Cambridge University Press: Cambridge, UK.

Franklin, S.E., and Wulder, M.A., 2002. Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. *Progress in Physical Geography* 26 (2), 173-205.

Franklin, S.E., Hansen, M.J., and Stenhouse, G.B., 2002. Quantifying landscape structure with vegetation inventory maps and remote sensing. *The Forestry Chronicle* 78 (6), 866 – 875.

Friedl, M.A., Brodley, C.E., and Strahler, A.H., 1999. Maximizing land cover classification accuracies produced by decision trees at continental to global scales. *IEEE Transactions on Geoscience and Remote Sensing* 37 (2), 969 – 977.

Garshelis, D.L., Gibeau, M.L., and Herrero, S., 2005. Grizzly Bear Demographics in and Around Banff National Park and Kananaskis Country, Alberta. *Journal of Wildlife Management* 69, 277 – 297.

Gibeau, M.L., Clevenger, A.P., Herrero, S., and Wierzchowski, J., 2002. Grizzly bear response to human development and activities in the Bow River Watershed, Alberta, Canada.

Guerschman, J.P., Paruelo, J.M., Di Bella, C., Giallorenzi, M.C., and Pacin, F., 2003. Land cover classification in the Argentine Pampas using multi-temporal Landsat TM data. *International Journal of Remote Sensing* 24 (17), 3381 – 3402.

Hilderbrand, G.V., Hanley, T.A., Robbins, C.T., and Schwartz, C.C., 1999. Role of brown bears (*Ursus arctos*) in the flow of marine nitrogen into a terrestrial ecosystem. *Oecologia* 121, 546 – 550.

Hoffmeister, T.S., Vet, L.E, Biere, A., Holsinger, K., and Filser, J., 2005. Ecological and Evolutionary Consequences of Biological Invasion and Habitat Fragmentation. *Ecosystems* 8, 657 – 667.

Hunter, E.L., and Power, C.H., 2002. An assessment of two classification methods for mapping Thames Estuary intertidal habitats using CASI data. *International Journal of Remote Sensing* 23 (15), 2989 – 3008.

Jensen, J.R., 2000. *Remote Sensing of the Environment: An Earth Resource Perspective*. Upper Saddle River: Prentice Hall.

Joshi, P.K.K., Roy, P.S., Singh, S., Agrawal, S., and Yadav, D., 2006. Vegetation cover mapping in India using multi-temporal IRS Wide Field Sensor (WiFS) data. *Remote Sensing of Environment* 103, 190-202.

Kansas, J., 2002. Status of the Grizzly Bear (*Ursus arctos*) in Alberta. Alberta Sustainable Resource Development, Fish and Wildlife Division, and Alberta Conservation Association. Wildlife Status Report No. 37, Edmonton, AB. 43 pp.

Kerr, J.T., and Cihlar, J., 2003. Land use and cover with intensity of agriculture for Canada from satellite and census data. *Global Ecology and Biogeography* 12, 161 – 172.

Keuchel, J., Naumann, S., Heiler, M., and Siegmund, A., 2003. Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data. *Remote Sensing of Environment* 86, 530 – 541.

Langley, S.K., Cheshire, H.M., and Humes, K.S., 2001. A comparison of single date and multitemporal satellite image classifications in a semi-arid grassland. *Journal of Arid Environments* 49, 401 – 411.

Latifovic, R., Cihlar, J., and Beaubien, J., 1999. Clustering methods for unsupervised classification. Presented at the Fourth International Airborne Remote Sensing Conference and Exhibition / 21st Canadian Symposium on Remote Sensing, Ottawa, Ontario, Canada, 21 – 24 June, 1999.

Leach, M.K., and Givnish, T.J., 1996. Ecological Determinants of Species Loss in Remnant Prairies. *Science* 273, 1555 – 1558.

Linke, J., Franklin, S.E., Huettmann, F., and Stenhouse, G.B., 2005. Seismic cutlines, changing landscape metrics and grizzly bear landscape use in Alberta. *Landscape Ecology* 20, 811 – 826.

Lloyd, C.D., Berberoglu, S., Curran, P.J., and Atkinson, P.M., 2004. A comparison of texture measures for the per-field classification of Mediterranean land cover. *International Journal of Remote Sensing* 25 (19), 3943 – 3965.

Lobell, D.B., and Asner, G.P., 2003. Comparison of Earth Observing-1 ALI and Landsat ETM+ for Crop Identification and Yield Prediction in Mexico. *IEEE Transactions on Geoscience and Remote Sensing* 41 (6), 1277 – 1282.

Mace, R.D., Waller, J.S., Manley, T.L., Lyon, L.J., and Zuuring, H., 1996. Relationships Among Grizzly Bears, Roads and Habitat in the Swan Mountains Montana. *The Journal of Applied Ecology* 33 (6), 1395 – 1404.

Mattson, D.J., and Reid, M.M., 1991. Conservation of the Yellowstone Grizzly Bear. *Conservation Biology* 5 (3), 364 – 372.

McDermid, G.J., Franklin, S.E., and LeDrew, E.F., 2005. Remote sensing for large-area habitat mapping. *Progress in Physical Geography* 29 (4), 449 – 474.

McGarigal, K., 2002. *Landscape pattern metrics*. Pages 1135-1142 in A. H. El-Shaarawi and W. W. Piegorsch, eds. Encyclopedia of Environmentrics Volume 2: 1135-1142. John Wiley & Sons: Sussex, England.

McIver, D.K., and Friedl, M.A., 2002. Using prior probabilities in decision-tree classification of remotely sensed data. *Remote Sensing of Environment* 81, 253 – 261.

McLellan, B.N., and Shackleton, D.M., 1988. Grizzly Bears and Resource-Extraction Industries: Effects of Roads on Behaviour, Habitat Use and Demography. *Journal of Applied Ecology* 25, 451 – 460.

McLellan, B.N., and Shackleton, D.M., 1989. Grizzly Bears and Resource-Extraction Industries: Habitat Displacement in Response to Seismic Exploration, Timber Harvesting and Road Maintenance. *The Journal of Applied Ecology* 26, 371 – 380.

Michelson, D.B., Liljeberg, B.M., and Pilesjo, P., 2000. Comparison of algorithms for classifying Swedish landcover using Landsat TM and ERS-1 SAR data. *Remote Sensing of Environment* 71, 1 – 15.

Murthy, C.S., Raju, P.V., and Badrinath, K.V.S., 2003. Classification of wheat crop with multi-temporal images: performance of maximum likelihood and artificial neural networks. *International Journal of Remote Sensing* 24 (23), 4871 – 4890.

Narumalani, S., Mishra, D.R., and Rothwell, R.G., 2004. Change detection and landscape metrics for inferring anthropogenic processes in the greater EFMO area. *Remote Sensing of Environment* 91, 478 – 489.

Nielsen, S.E., Boyce, M.S., Stenhouse, G.B., and Munro, R.H.M., 2002. Modeling Grizzly Bear Habitats in the Yellowhead Ecosystem of Alberta: Taking Autocorrelation Seriously. *Ursus* 13, 45 – 56.

Nielsen, S.E., Boyce, M.S., and Stenhouse, G.B., 2004. Grizzly bears and forestry I. Selection of clearcuts by grizzly bears in west-central Alberta, Canada. *Forest Ecology and Management* 199, 51 – 65.

Nielsen, S.E., Stenhouse, G.B., and Boyce, M.S., 2006. A habitat-based framework for grizzly bear conservation in Alberta. *Biological Conservation* 130, 217 – 229.

O'Neill, R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B., DeAngelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H., and Graham, R.L., 1988. Indices of landscape pattern. *Landscape Ecology* 1 (3), 153 – 162.

Peak, J., Beecham, J., Garshelis, D., Messier, F., Miller, S., and Strickland, D., 2003. Management of Grizzly Bears in British Columbia: A Review by an Independent Scientific Panel. Final report, submitted to Minister of Water, Land and Air Protection, Government of British Columbia, March 6, 2003.

Price, K.P., Guo, X., and Stiles, J.M., 2002. Optimal Landsat TM band combinations and vegetation indices for discrimination of six grassland types in eastern Kansas. *International Journal of Remote Sensing* 23 (23), 5031 – 5042.

Raclot, D., Colin, F., and Puech, C., 2005. Updating land cover classification using a rule-based decision system. *International Journal of Remote Sensing* 26 (7), 1309 – 1321.

Reese, H.M., Lillesand, T.M., Nagel, D.E., Stewart, J.S., Goldmann, R.A., Simmons, T.E., Chipman, J.W., and Tessar, P.A., 2002. Statewide land cover derived from multiseasonal Landsat TM data: A retrospective of the WISCLAND project. *Remote Sensing of Environment* 82, 224 – 237.

Rosenberg, D.K., Noon, B.R., and Menslow, E.C., 1997. Biological Corridors: Form, Function, and Efficiency. *Bioscience* 47, 677 – 687.

Saunders, D.A., Hobbs, R.J., and Margules, C.R., 1991. Biological Consequences of Ecosystem Fragmentation: A Review. *Conservation Biology* 5 (1), 18 – 32.

Schowengerdt, R.A., 2006. *Remote Sensing: Models and Methods for Image Processing*. Amsterdam: Academic Press.

Serpico, S.B., Bruzzone, L., and Roli, F., 1996. An experimental comparison of neural and statistical non-parametric algorithms for supervised classification of remote-sensing images. *Pattern Recognition Letters* 17, 1331 – 1341.

Shanmugam, P., Ahn, Y., and Sanjeevi, S., 2006. A comparison of the classification of wetland characteristics by linear spectral mixture modeling and traditional hard classifiers on multispectral remotely sensed imagery in southern India. *Ecological Modelling* 194, 379 – 394.

Singleton, P.H., Gaines, W.L., Lehmkuhl, J.F., 2004. Landscape permeability for grizzly bear movements in Washington and southwestern British Columbia. *Ursus* 15 (1), Workshop Supplement, 90 – 103.

Smith, G.M., and Fuller, R.M., 2001. An integrated approach to land cover classification: an example in the Island of Jersey. *International Journal of Remote Sensing* 22 (16), 3123 – 3142.

Stenhouse, G.B., Boyce, M.S., Boulanger, J., 2003. Report on Alberta Grizzly Bear Assessment of Allocation. Alberta Sustainable Resource Development, Fish and Wildlife Division, Hinton, Alta.

Tateishi, R., Shimazaki, Y., and Gunin, P.D., 2004. Spectral and temporal linear mixing model for vegetation classification. *International Journal of Remote Sensing* 25 (20), 4203 – 4218.

Thompson, A.G., Fuller, R.M., and Eastwood, J.A., 1998. Supervised versus unsupervised methods for classification of coasts and river corridors from airborne remote sensing. *International Journal of Remote Sensing* 19 (17), 3423 – 3431.

Turker, M., and Arikan, M., 2005. Sequential masking classification of multi-temporal Landsat 7 ETM+ images for field-based crop mapping in Karacabey, Turkey. *International Journal of Remote Sensing* 26 (17), 3813 – 3830.

Van Niel, T.G., and McVicar, T.R., 2004. Determining temporal windows for crop discrimination with remote sensing: a case study in south-eastern Australia. *Computers and Electronics in Agriculture* 45, 91–108.

Vescovi, F.D., and Gomarasca, M.A., 1999. Integration of optical and microwave remote sensing data for agricultural land use classification. *Environmental Monitoring and Assessment* 58, 133 – 149.

Waller, J.S., and Servheen, C., 2005. Effects of Transportation Infrastructure on Grizzly Bears in Northwestern Montana. *Journal of Wildlife Management* 69 (3), 985 – 1000.

Walter, V., 2004. Object-based classification of remote sensing data for change detection. *ISPRS Journal of Photogrammetry & Remote Sensing* 58, 225-238.

Wang, L., Sousa, W.P., and Gong, P., 2004. Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. *International Journal of Remote Sensing* 25 (24), 5655 – 5668.

Wielgus, R.B., Vernier, P.R., and Schivatcheva, T., 2002. Grizzly bear use of open, closed, and restricted forestry roads. *Canadian Journal of Forest Research* 32, 1597 – 1606.

Wilson, S.M., Madel, M.J., Mattson, D.J., Graham, J.M., Burchfield, J.A., and Belsky, J.M., 2005. Natural landscape features, human-related attractants, and conflict hotspots: a spatial analysis of human-grizzly bear conflicts. *Ursus* 16 (1), 117 – 129.

Wilson, S.M., Madel, M.J., Mattson, D.J., Graham, J.M., and Merrill, T., 2006. Landscape conditions predisposing grizzly bears to conflicts on private agricultural lands in the western USA. *Biological Conservation* 130, 47 – 59.

Wulder, M.A., Franklin, S.E., and White, J.C., 2004a. Sensitivity of hyperclustering and labeling land cover classes to Landsat image acquisition date. *International Journal of Remote Sensing* 25 (23), 5337 – 5344.

Wulder, M.A., Franklin, S.E., White, J.C., Cranny, M.M., and Dechka, J.A., 2004b. Inclusion of topographic variables in an unsupervised classification of satellite imagery. *Canadian Journal of Remote Sensing* 20 (2), 137 – 149.

Wunderle, A., Guo, X., Crump, S., and Brandt, S..2005. Crop delineation using hybrid classification procedures: a case study in Scott, Saskatchewan. Soils and Crops Conference Proceedings, February 17 in Saskatoon, Saskatchewan.

Xu, M., Watanachaturaporn, P., Varshney, P.K., and Arora, M.K., 2005. Decision tree regression for soft classification of remote sensing data. *Remote Sensing of Environment* 97, 322 – 336.

Yang, C., Prasher, S.O., Enright, P., Madramootoo, C., Burgess, M., Goel, P.K., and Callum, I., 2003. Application of decision tree technology for image classification using remote sensing data. *Agricultural Systems* 76, 1101 – 1117.

Yuan, F., Sawaya, K.E., Loeffelholz, B.C., and Bauer, M.E., 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. *Remote Sensing of Environment* 98, 317 – 328.

Yunhao, C., Peijun, S., Xiaobing, L., Jin, C., and Jing, L., 2006. A combined approach for estimating vegetation cover in urban / suburban environments from remotely sensed data. *Computers and Geosciences* 32, 1299 – 1309.

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 2.1: Medium-resolution agricultural and herbaceous applications

Application	Study
Crop yield prediction	Lobell and Asner, 2003; Ferencz *et al.*, 2004
Crop nitrogen content	Boegh *et al.*, 2002
Crop stress	Estep *et al.*, 2004
Crop classification	Aplin and Atkinson, 2001; Turker and Arikan, 2005
Grassland discrimination / agricultural classification	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

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. 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 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 km^2 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.

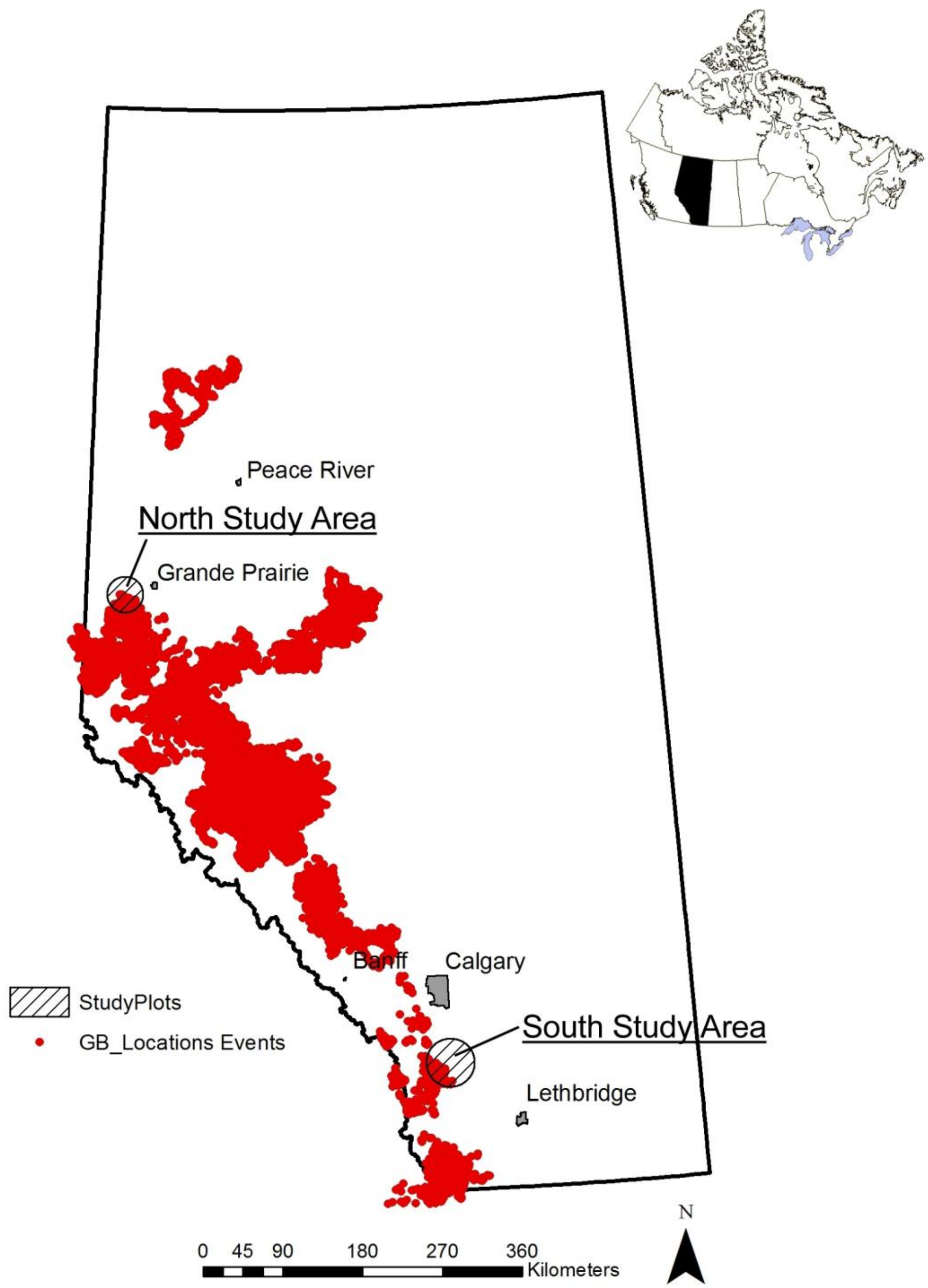

Figure 2.1: Map of Alberta showing collared grizzly GPS locations and the North and South study areas. A description of the GPS location events is given in section 2.3.2.

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 2.2: Landsat scene acquisitions

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

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

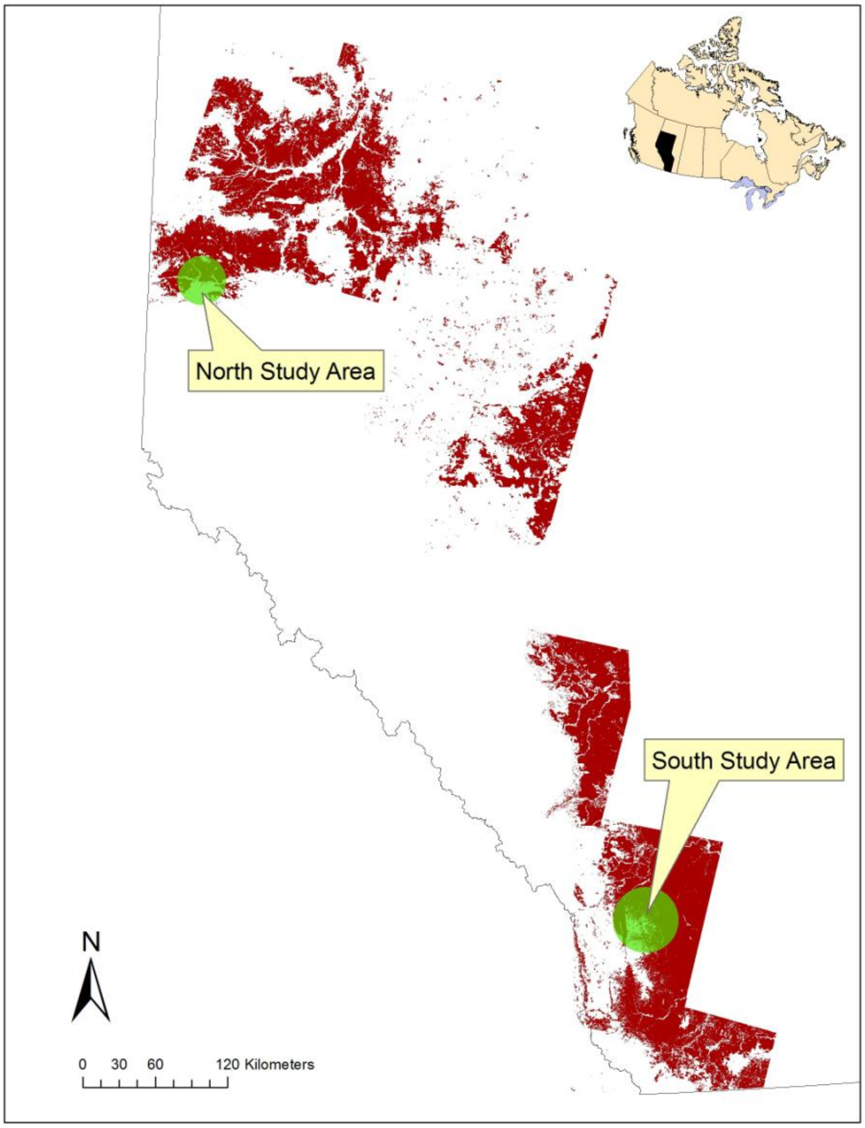

Figure 2.2: Red areas define the mask used to select the areas to classify.

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).

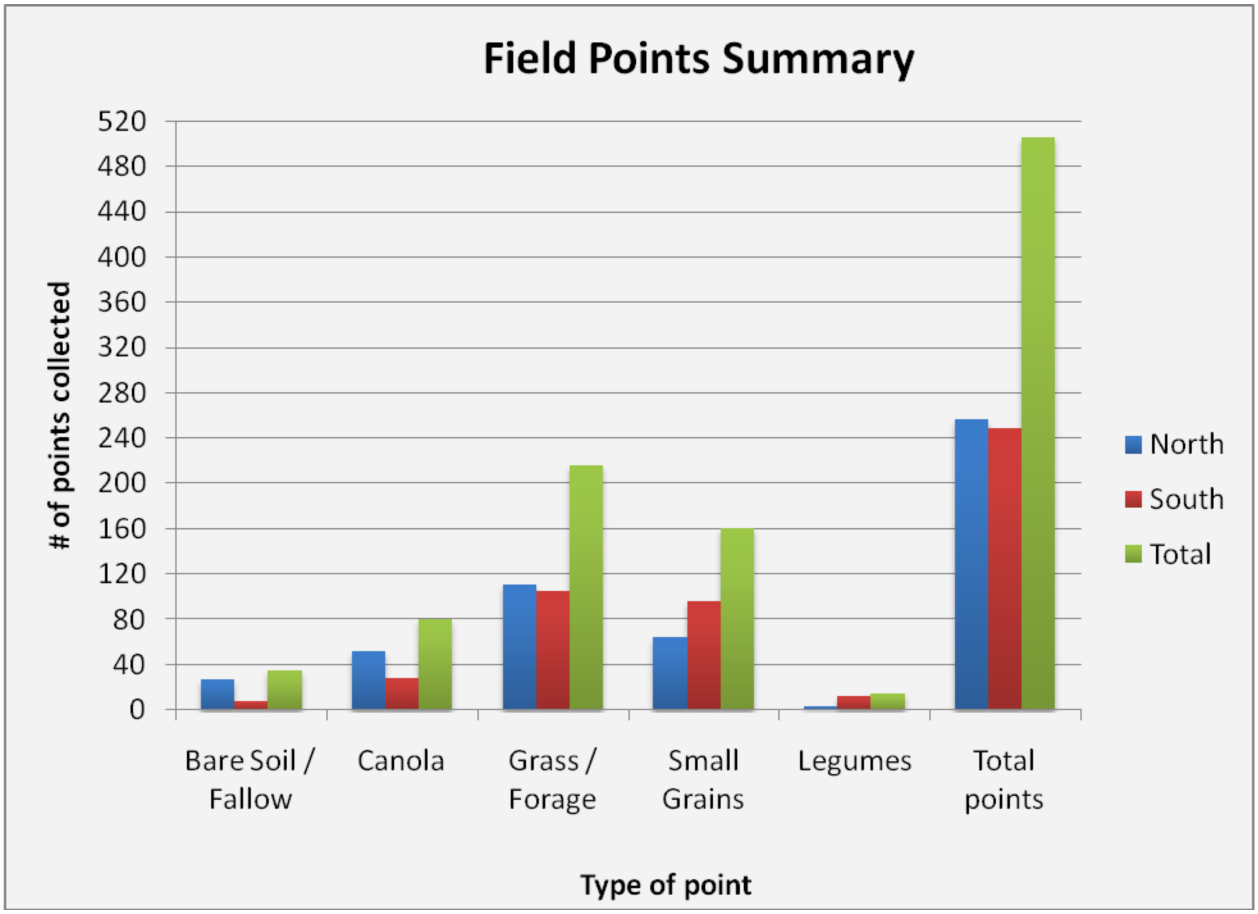

Figure 2.3: Distribution of ground sample points in the North and South study areas

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).

$$\text{NDMI} = \frac{band4 - band5}{band4 + band5} \qquad \text{(eq. 2.1)}$$

band4 = TM or ETM+ band 4
band5 = TM or ETM+ band 5

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.

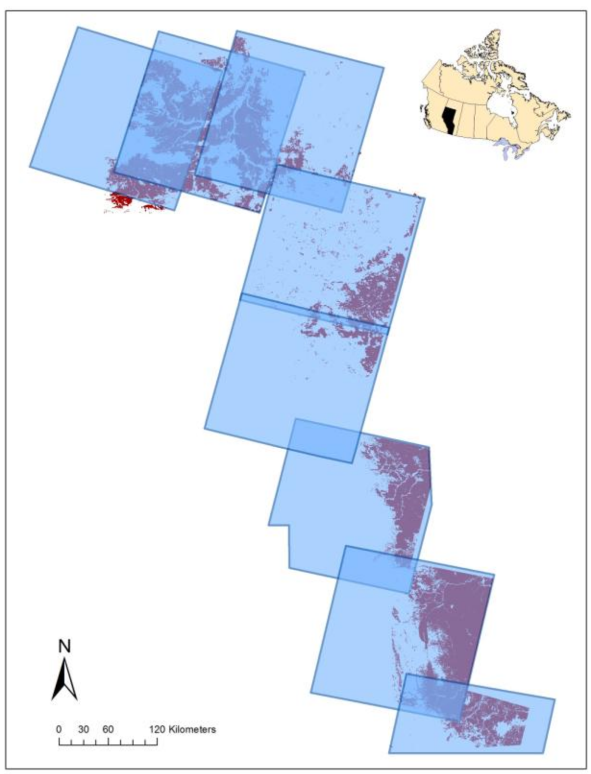

Figure 2.4: Blue areas show outlines of the 8 Landsat scenes used to classify the agricultural area. The red area is the agricultural mask.

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

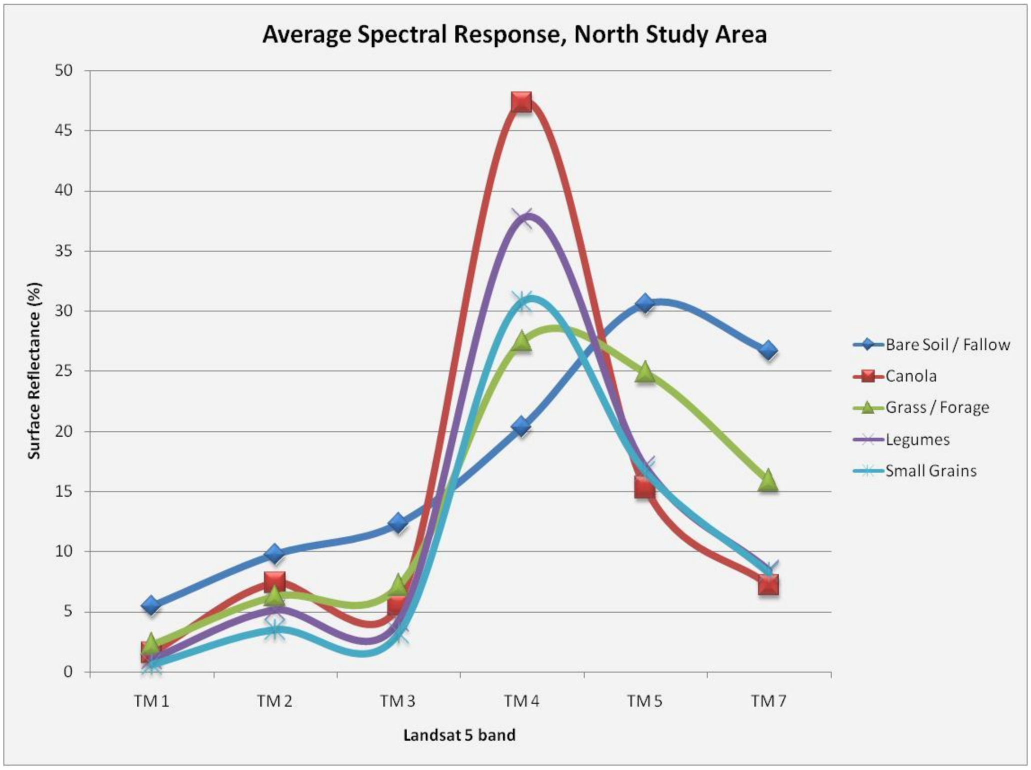

Figure 2.6: Spectral values (in surface reflectance) of the different classes in the main Landsat TM bands for the North study area.

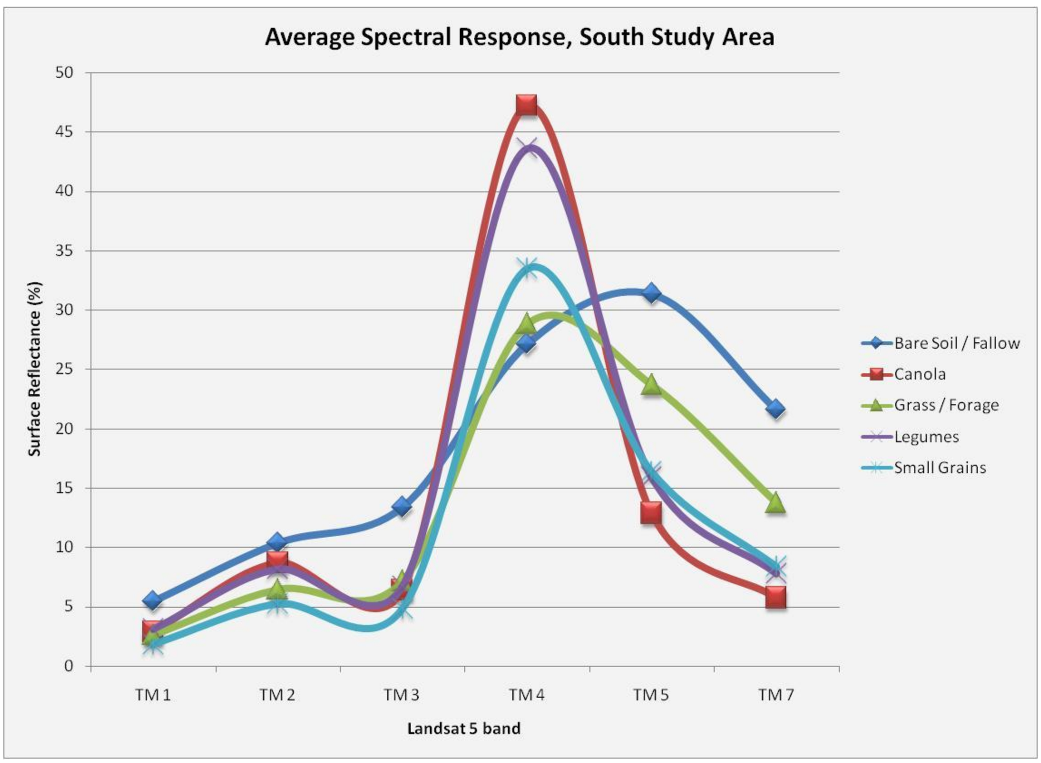

Figure 2.5: Spectral values (in surface reflectance) of the different classes in the main Landsat TM bands for the South study area.

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

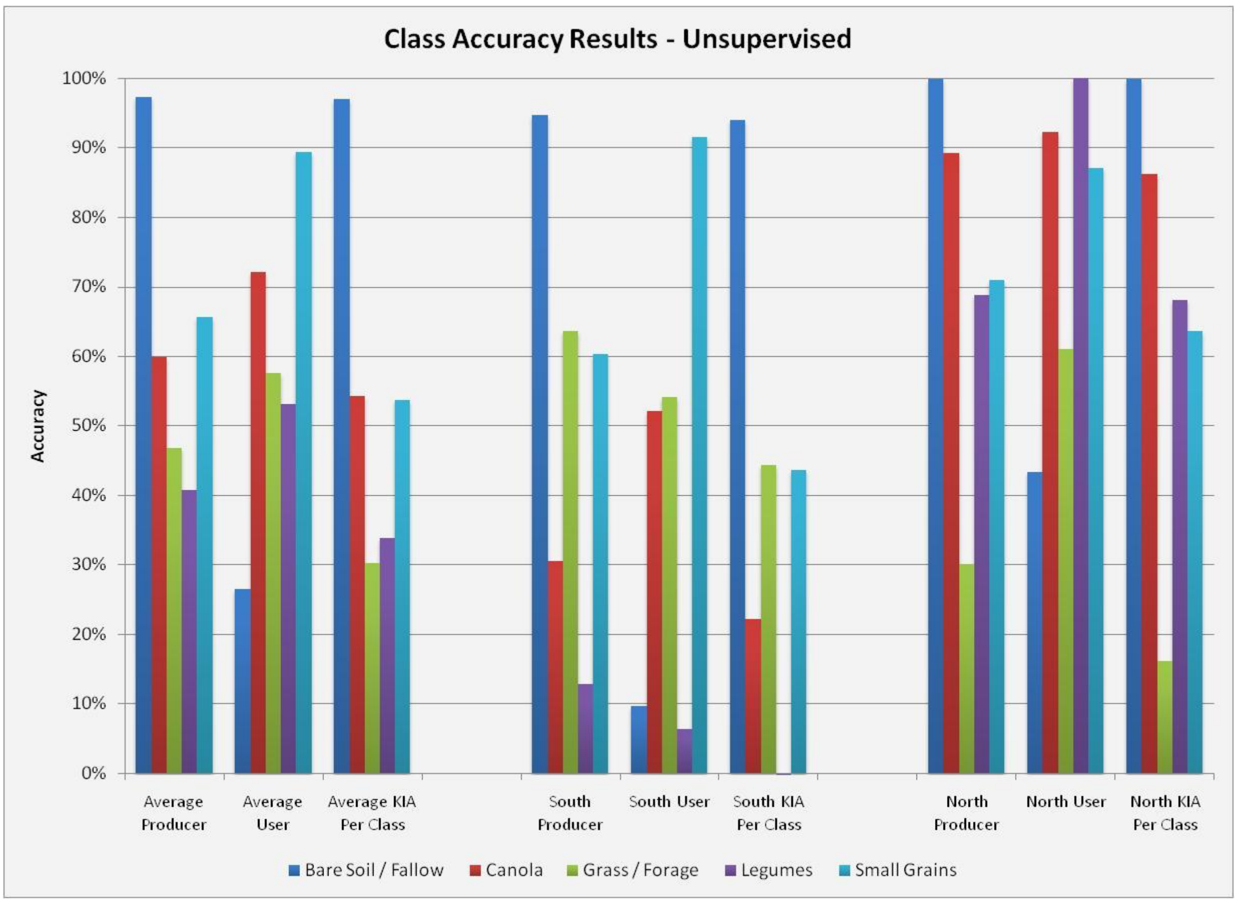

Figure 2.7: Class accuracy results for the unsupervised classification. Overall accuracy was 59.4%.

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

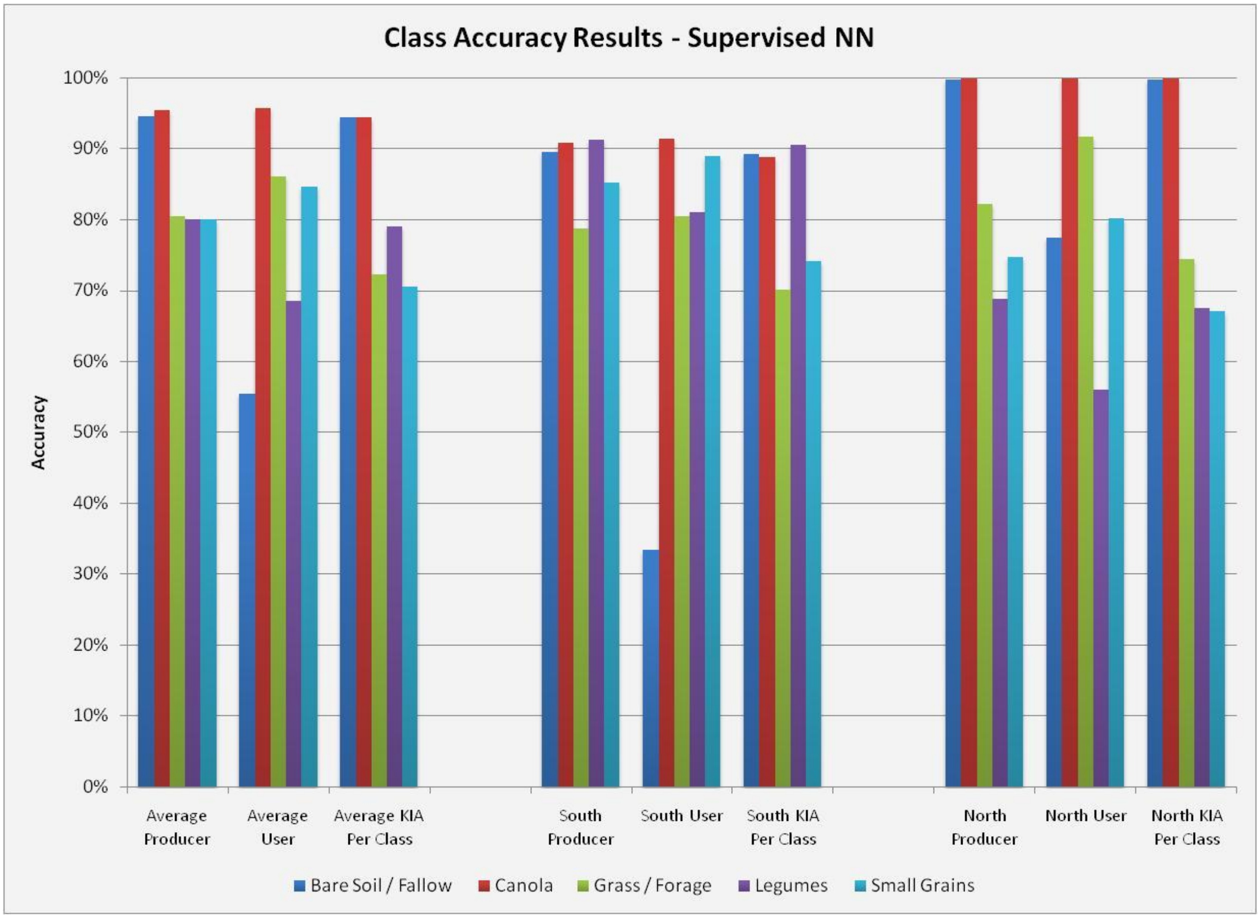

Figure 2.8: Class accuracy results for the supervised NN classification. Overall accuracy was 86.7%.

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.

Standard deviation:	Mean:
Wetness	Wetness
Greenness	TM 2
TM 2	TM 3
TM 3	
TM 4	
Dimension: 8	
Best separation distance: 0.57	

Table 2.4: South NN distance matrix

Class / Class	Bare Soil / Fallow	Canola	Grass / Forage	Legumes	Small Grains
Bare Soil / Fallow	0	8.9	0.7	7.2	2.6
Canola	8.9	0	6.0	0.6	2.9
Grass / Forage	0.7	6.0	0	5.0	0.6
Legumes	7.2	0.6	5.0	0	2.1
Small Grains	2.6	2.9	0.6	2.1	0

Table 2.5: North NN feature space.

Standard deviation:	Mean:
NDMI	NDMI
Brightness	Greenness
Greenness	TM 1
Wetness	TM 2
TM 1	TM 3
TM 2	TM 4
TM 3	TM 5
TM 4	TM 7
TM 5	
TM 7	
Dimension: 18	
Best separation distance: 0.58	

Table 2.6: North NN distance matrix					
Class / Class	Bare Soil / Fallow	Canola	Grass / Forage	Legumes	Small Grains
Bare Soil / Fallow	0	7.9	1.5	10.1	4.3
Canola	7.9	0	3.7	0.9	2.1
Grass / Forage	1.5	3.7	0	4.9	0.6
Legumes	10.1	0.9	4.9	0	1.6
Small Grains	4.3	2.1	0.6	1.6	0

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

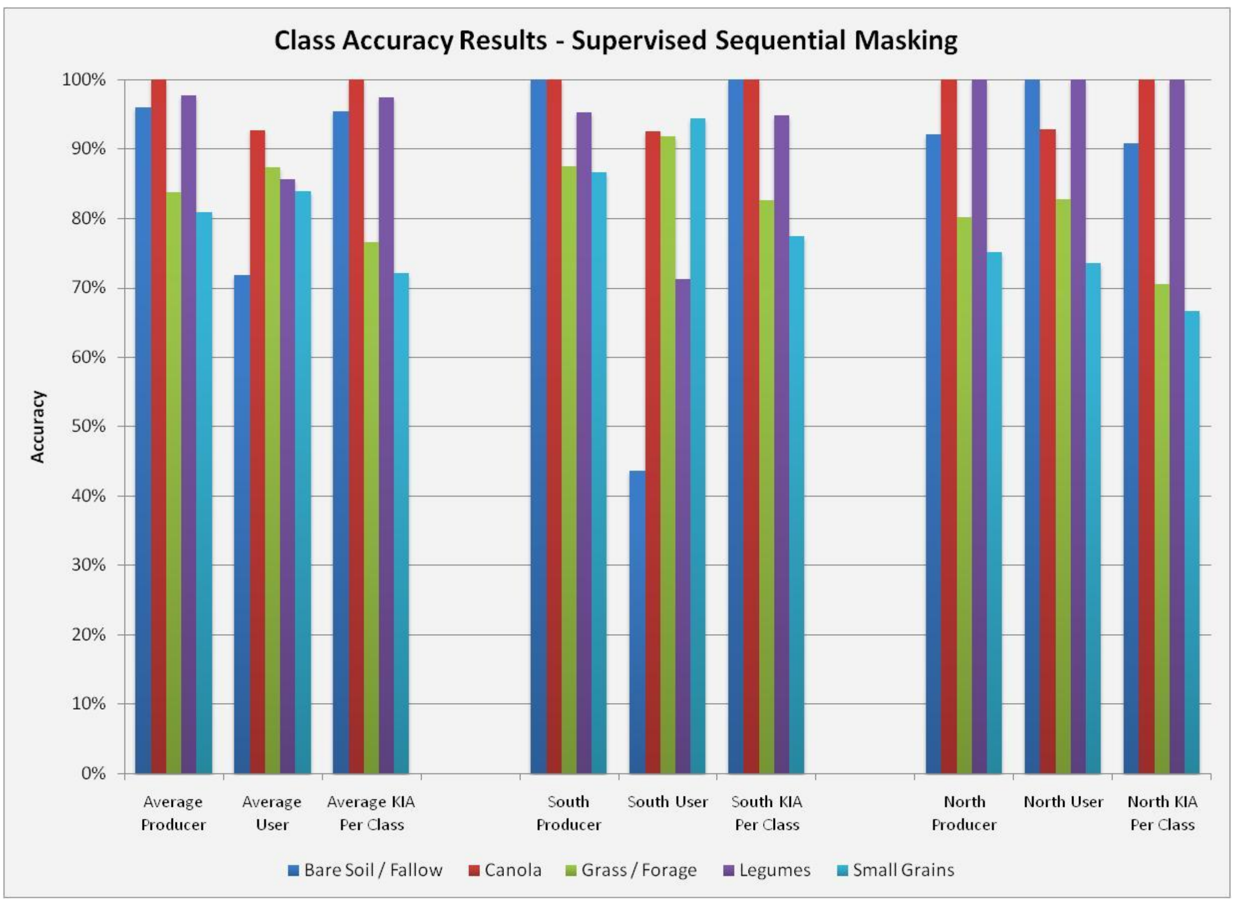

Figure 2.9: Class accuracy results for the SSM classification. Overall accuracy was 88%.

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

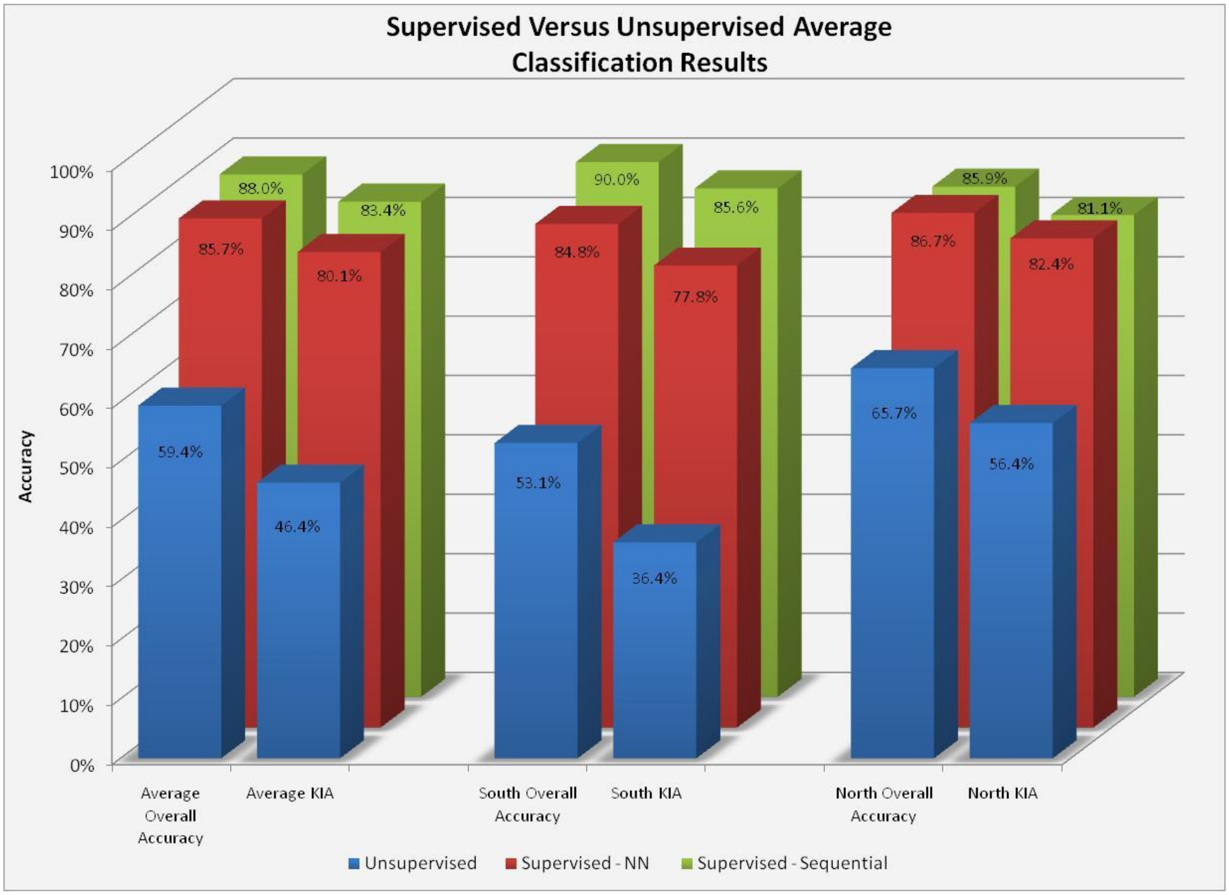

Figure 2.10: Overall accuracy and KIA for all three classification methods

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 yellowy-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.

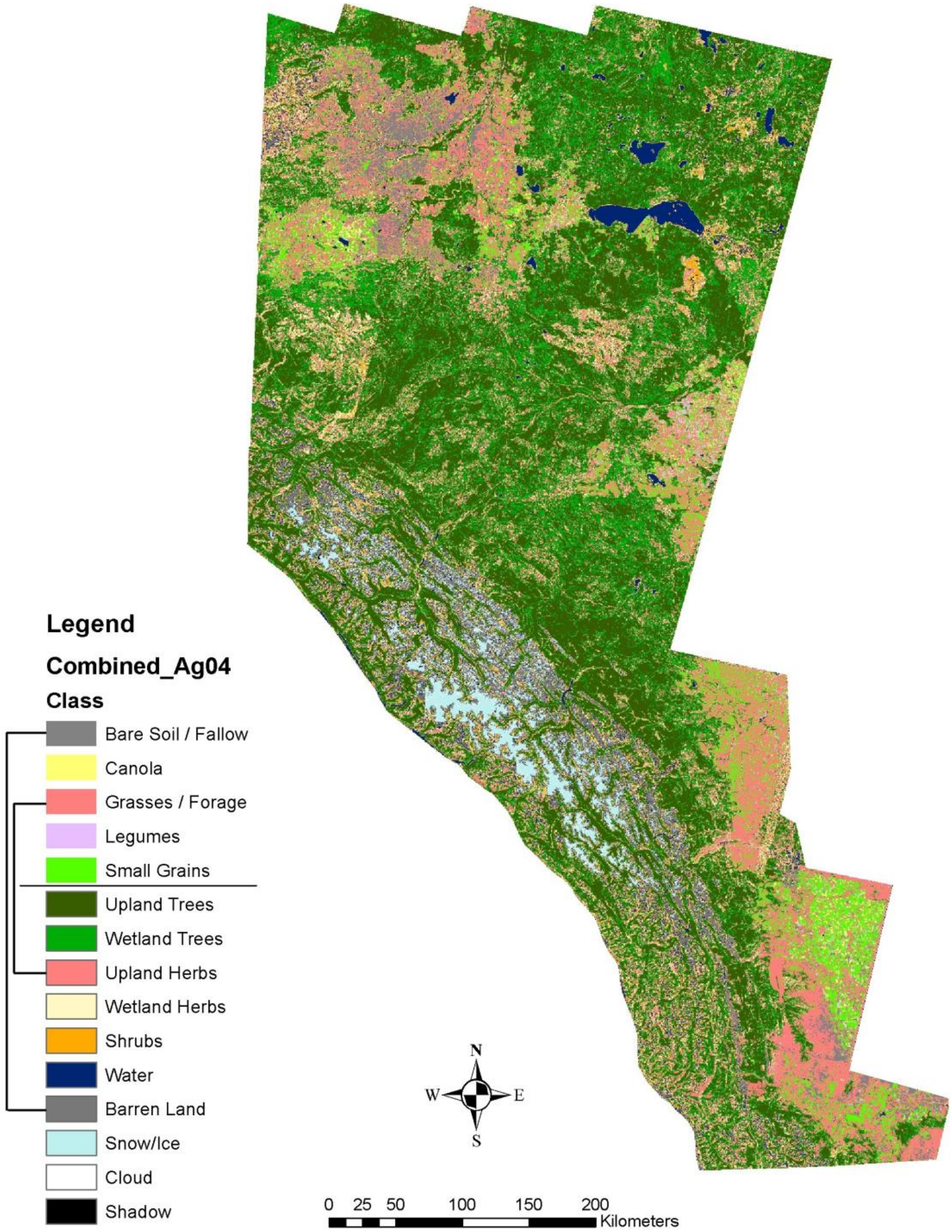

Figure 2.11: Completed mosaic with SSM classification, showing new agricultural classes (top 5 in legend) with those of the FMF land cover map.

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.

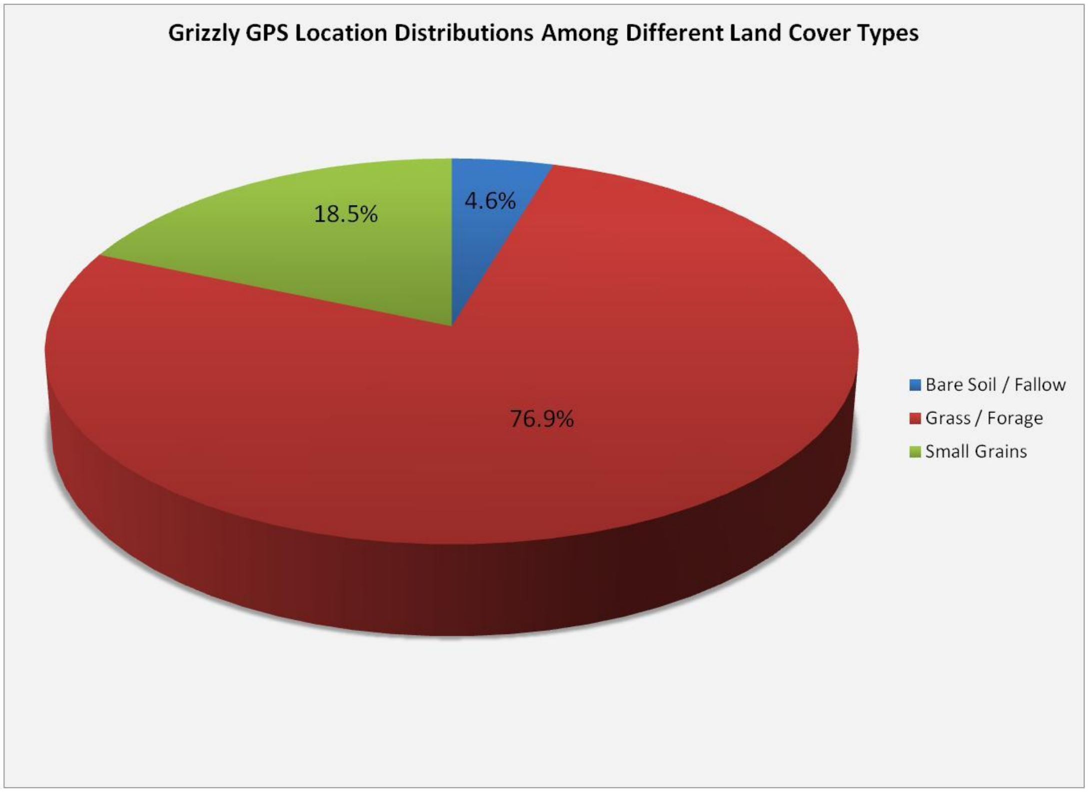

Figure 2.12: Distribution of bear location points within newly classified (SSM) agricultural classes.

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).

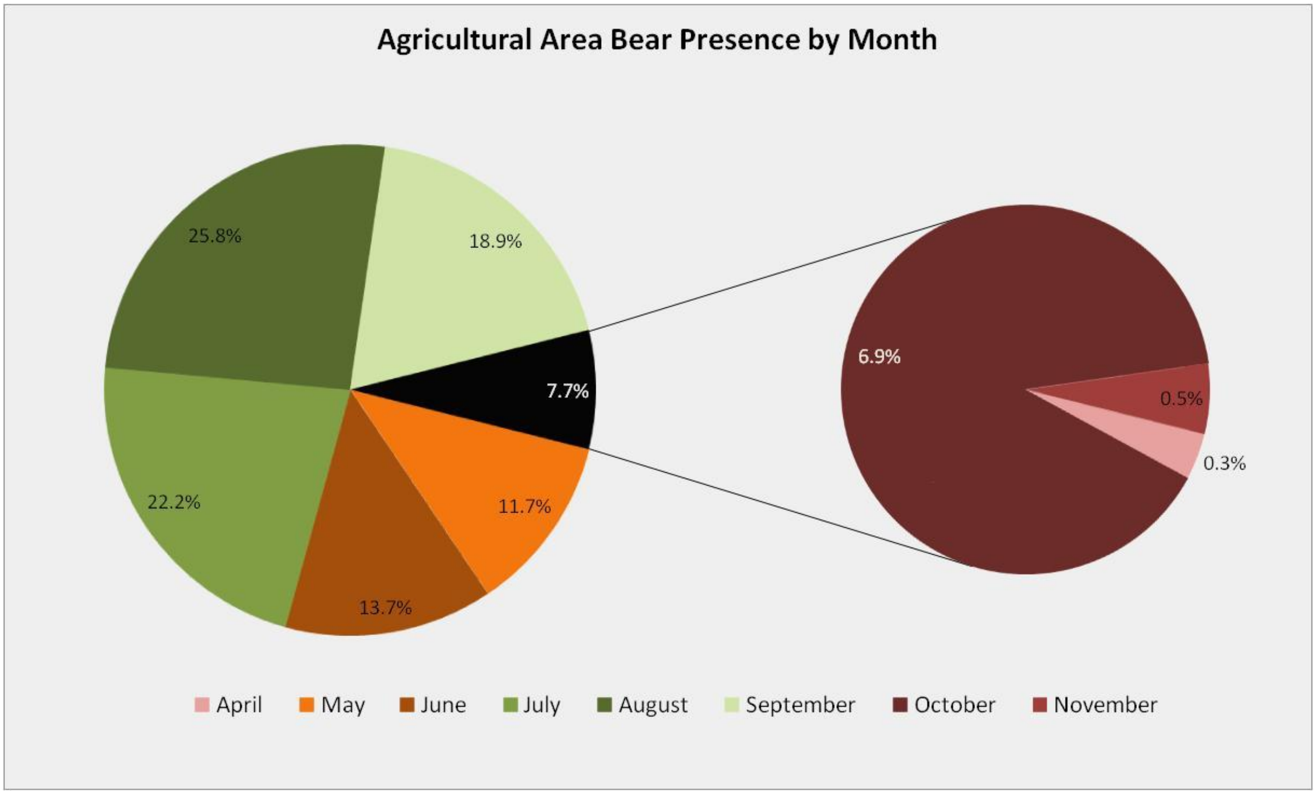

Figure 2.13: Bear presence in agricultural areas, shown by month. Months represented by green slices showed the highest bear presence.

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

Agri-Food Statistics Update, 2007. March Intentions of Principal Field Crops Areas, Alberta, 2007. Alberta Agriculture and Food, Economics and Competitiveness Division, Statistics and Data Development Unit.

Aplin, P., and Atkinson, P.M., 2001. Sub-pixel land cover mapping for per-field classification. *International Journal of Remote Sensing* 22 (14), 2853 – 2858.

Baldi, G., Guerschman, J.P., and Paruelo, J.M., 2006. Characterizing fragmentation in temperate South America grasslands. *Agriculture, Ecosystems, and Environment* 116, 197–208.

Ban, Y., 2003. Synergy of multitemporal ERS-1 SAR and Landsat TM data for classification of agricultural crops. *Canadian Journal of Remote Sensing* 29 (4), 518 – 526.

Bergstrom, K., 2007. "Crop Conditions as of July 24, 2007". Alberta Agriculture and Food, Economics and Competitiveness Division, Statistics and Data Development Unit. July 24, 2007.

Berk, A., Anderson, G.P., Acharya, P.K., Chetwynd, J.H., Bernstein, L.S., Shettle, E.P., Matthew, M.W., and Adler-Golden, S.M., 1999. MODTRAN4 User's Manual. Air Force Research Laboratory, Space Vehicles Directorate. Hanscom AFB, Ma., 01731-3010.

Bezdek, J.C., 1973. Fuzzy Mathematics in Pattern Classification. PhD thesis, Applied Math Center, Cornell University, Ithaca.

Bock, M., Xofis, P., Mitchley, J., Rossner, G., Wissen, M., 2005. Object-oriented methods for habitat mapping at multiple scales – Case studies from Northern Germany and Wye Downs, UK. *Journal for Nature Conservation* 13, 75 – 89.

Boegh, E., Soegaard, H., Broge, N., Hasager, C.B., Jensen, N.O., Schelde, K., and Thomsen, A., 2002. Airborne multispectral data for quantifying leaf area index, nitrogen concentration, and photosynthetic efficiency in agriculture. *Remote Sensing of Environment* 81, 179 – 193.

Boyce, M.S., Vernier, P.R., Nielsen, S.E., and Schmiegelow, F.K.A., 2002. Evaluating resource selection functions. *Ecological Modelling* 157, 281 – 300.

Brown de Colstoun, E.C., Story, M.H., Thompson, C., Commisso, K., Smith, T.G., and Irons, J.R., 2003. National Park vegetation mapping using multitemporal Landsat 7 data and a decision tree classifier. *Remote Sensing of Environment* 85, 316 – 327.

Camacho-De Coca, F.C., Garcia-Haro, F.J., Gilabert, M.A., and Melia, J., 2004. Vegetation cover seasonal changes assessment from TM imagery in a semi-arid landscape. *International Journal of Remote Sensing* 25 (17), 3451-3476.

Chubey, M.S., Franklin, S.E., and Wulder, M.A., 2006. Object-based Analysis of Ikonos-2 Imagery for Extraction of Forest Inventory Parameters. *Photogrammetric Engineering & Remote Sensing* 72 (4), 383-394.

Cihlar, J., Latifovic, R., Beaubien, J., 2000. A comparison of clustering strategies for unsupervised classification. *Canadian Journal of Remote Sensing* 26 (5), 446 – 454.

Cohen, Y., and Shoshany, M., 2002. A national knowledge-based crop recognition in Mediterranean environment. *International Journal of Applied Earth Observation and Geoinformation* 4, 75 – 87.

Crist, E. P., and Cicone, R.C., 1984. A physically based transformation of Thematic Mapper data - The TM Tasseled Cap. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-22 (3), 256 - 263.

De Wit, A.J.W., and Clevers, J.G.P.W., 2004. Efficiency and accuracy of per-field classification for operational crop mapping. *International Journal of Remote Sensing* 25 (20), 4091 – 4112.

Definiens AG, 2006. *Definiens Professional 5 User Guide*. Munchen: Definiens AG.

El-Magd, I.A., and Tanton, T.W., 2003. Improvements in land use mapping for irrigated agriculture from satellite sensor data using a multi-stage maximum likelihood classification. *International Journal of Remote Sensing* 24 (21), 4197 – 4206.

Environment Canada, 2008. "Canadian Climate Normals". National Climate Data and Information Archive. Available online at: http://climate.weatheroffice.ec.gc.ca

Estep, L., Terrie, G., and Davis, B., 2004. Technical Note: Crop stress detection using AVIRIS hyperspectral imagery and artificial neural networks. *International Journal of Remote Sensing* 25 (22), 4999 – 5004.

Ferencz, C., Bognar, P., Lichtenberger, J., Hamar, D., Tarcsai, G., Timar, G., Molnar, G., Pasztor, S., Steinbach, P., Szekely, B., Ferencz, O.E., and Ferencz-Arkos, I., 2004. Crop yield estimation by satellite remote sensing. *International Journal of Remote Sensing* 25, (20), 4113 – 4149.

Foody, G.M., 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* 80, 185 – 201.

Franklin, S.E., and Wulder, M.A., 2002. Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. *Progress in Physical Geography* 26 (2), 173-205.

Franklin, S. E., Stenhouse, G.B., Hansen, M.J., Popplewell, C.C., Dechka, J.A., and Peddle, D.R., 2001. Integrated Decision Tree Approach (IDTA) to classification of landcover in support of grizzly bear habitat analysis in the Alberta Yellowhead Ecosystem. *Canadian Journal of Remote Sensing,* 27(6), 579-593.

Hobson, D., 2005. Bear Capturing and Handling. In Stenhouse, G. and K.Graham (eds). Foothills Model Forest Grizzly Bear Research Program 1999-2003 Final Report. Hinton, Alberta.

Hobson, D., 2006. Summary of 2005 Spring Capture Program. In Stenhouse, G. and K.Graham (eds). Foothills Model Forest Grizzly Bear Research Program 2005 Annual Report. Hinton, Alberta.

Jensen, J.R., 2000. *Remote Sensing of the Environment: An Earth Resource Perspective*. Upper Saddle River: Prentice Hall.

Kansas, J., 2002. Status of the Grizzly Bear (*Ursus arctos*) in Alberta. Alberta Sustainable Resource Development, Fish and Wildlife Division, and Alberta Conservation Association. Wildlife Status Report No. 37, Edmonton, AB. 43 pp.

Langley, S.K., Cheshire, H.M., and Humes, K.S., 2001. A comparison of single date and multitemporal satellite image classifications in a semi-arid grassland. *Journal of Arid Environments* 49, 401 – 411.

Lloyd, C.D., Berberoglu, S., Curran, P.J., and Atkinson, P.M., 2004. A comparison of texture measures for the per-field classification of Mediterranean land cover. *International Journal of Remote Sensing* 25 (19), 3943 – 3965.

Lobell, D.B., and Asner, G.P., 2003. Comparison of Earth Observing-1 ALI and Landsat ETM+ for Crop Identification and Yield Prediction in Mexico. *IEEE Transactions on Geoscience and Remote Sensing* 41 (6), 1277 – 1282.

Martinez-Casanovas, J.A., Martin-Montero, A., and Casterad, M.A., 2005. Mapping multi-year cropping patterns in small irrigation districts from time-series analysis of Landsat TM images. *European Journal of Agronomy* 23, 159 – 169.

McDermid, G.J., Franklin, S.E., and LeDrew, E.F., 2005. Remote sensing for large-area habitat mapping. *Progress in Physical Geography* 29 (4), 449 – 474.

McDermid, G.J., Pape, A., and Laskin, D., 2006. Map Production Update. In Stenhouse, G. and K.Graham (eds). Foothills Model Forest Grizzly Bear Research Program 2005 Annual Report. Hinton, Alberta.

McIver, D.K., and Friedl, M.A., 2002. Using prior probabilities in decision-tree classification of remotely sensed data. *Remote Sensing of Environment* 81, 253 – 261.

McLellan, B.N., and Shackleton, D.M., 1988. Grizzly Bears and Resource-Extraction Industries: Effects of Roads on Behaviour, Habitat Use and Demography. *Journal of Applied Ecology* 25, 451 – 460.

Nielsen, S.E., Boyce, M.S., Stenhouse, G.B., and Munro, R.H.M., 2002. Modeling Grizzly Bear Habitats in the Yellowhead Ecosystem of Alberta: Taking Autocorrelation Seriously. *Ursus* 13, 45 – 56.

Nielsen, S.E., Stenhouse, G.B., and Boyce, M.S., 2006. A habitat-based framework for grizzly bear conservation in Alberta. *Biological Conservation* 130, 217 – 229.

Price, K.P., Guo, X., and Stiles, J.M., 2002. Optimal Landsat TM band combinations and vegetation indices for discrimination of six grassland types in eastern Kansas. *International Journal of Remote Sensing* 23 (23), 5031 – 5042.

Reese, H.M., Lillesand, T.M., Nagel, D.E., Stewart, J.S., Goldmann, R.A., Simmons, T.E., Chipman, J.W., and Tessar, P.A., 2002. Statewide land cover derived from multiseasonal Landsat TM data: A retrospective of the WISCLAND project. *Remote Sensing of Environment* 82, 224 – 237.

Richter, R., 2008. Atmospheric / Topographic Correction for Satellite Imagery: ATCOR-2/3 User Guide, Version 6.4, January 2008. DLR -1B 565-01/08. Wessling, Germany.

Smith, G.M., and Fuller, R.M., 2001. An integrated approach to land cover classification: an example in the Island of Jersey. *International Journal of Remote Sensing* 22 (16), 3123 – 3142.

Song, C., Woodcock, C.E., Seto, K.C., Lenney, M.P., and Macomber, S.A., 2001. Classification and Change Detection Using Landsat TM Data: When and How to Correct Atmospheric Effects. *Remote Sensing of Environment* 75, 230-244.

Stenhouse, G.B., Boyce,M.S., Boulanger, J., 2003. Report on Alberta Grizzly Bear Assessment of Allocation. Alberta Sustainable Resource Development, Fish and Wildlife Division, Hinton, Alta.

Turker, M., and Arikan, M., 2005. Sequential masking classification of multi-temporal Landsat 7 ETM+ images for field-based crop mapping in Karacabey, Turkey. *International Journal of Remote Sensing* 26 (17), 3813 – 3830.

Van Niel, T.G., McVicar, T.R., and Datt, B., 2005. On the relationship between training sample size and data dimensionality: Monte Carlo analysis of broadband multi-temporal classification. *Remote Sensing of Environment* 98, 468 – 480.

Walter, V., 2004. Object-based classification of remote sensing data for change detection. *ISPRS Journal of Photogrammetry & Remote Sensing* 58, 225-238.

Wang, L., Sousa, W.P., and Gong, P., 2004. Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. *International Journal of Remote Sensing* 25 (24), 5655 – 5668.

Wiemker, R., 1997. Unsupervised fuzzy classification of multispectral imagery using spatial-spectral features. In Balderjahn, I., Mathar, R., and Schader, M., eds., *Data Highways and Information Flooding, A Challenge for Classification and Data Analysis*. Springer, 1997.

Wilson, E.H., and Sader, S.A., 2002. Detection of forest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment* 80, 385–396.

Wilson, S.M., Madel, M.J., Mattson, D.J., Graham, J.M., Burchfield, J.A., and Belsky, J.M., 2005. Natural landscape features, human-related attractants, and conflict hotspots: a spatial analysis of human-grizzly bear conflicts. *Ursus* 16 (1), 117 – 129.

Wilson, S.M., Madel, M.J., Mattson, D.J., Graham, J.M., and Merrill, T., 2006. Landscape conditions predisposing grizzly bears to conflicts on private agricultural lands in the western USA. *Biological Conservation* 130, 47 – 59.

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 km^2 study area was divided into 107 sub-landscapes of 42 km^2. 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; Chruszcz *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 km^2, which was made up of 107 square sub-landscapes of 42 km^2 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 km^2. Nams *et al.* (2006)

found a strong selection preference at a scale of 16 - 64 km^2, with a peak preference at 36 km^2, while Linke *et al.* (2005) found a possible range from 31 – 49 km^2, and used a

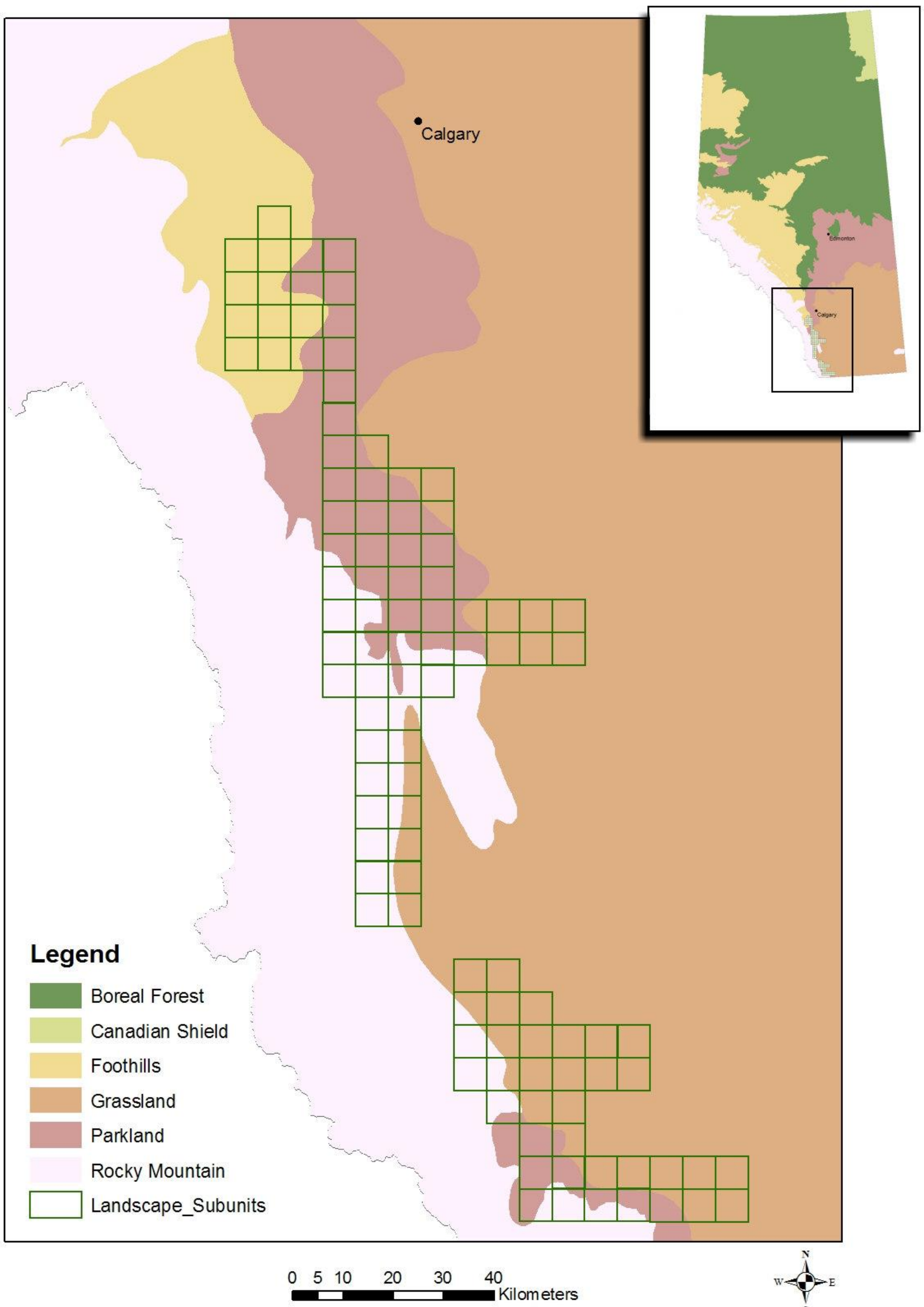

Figure 3.1: Study area map showing the distribution of the 107 sub-landscapes in southern Alberta.

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 3.1: IRS imagery coverage and dates. Images were compiled from as many as 7 dates, acquired between April and October, and may span more than one year. Dates given are those that make up the majority of the image.

NTS map sheet area	Imagery Dates
82I_04	Sept., 2001/2002
82J_01	July, 2001
82J_08	July, 2001
82J_(the rest)	Sept., 2005
82G	Sept., 2005
82H	Sept., 2005

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

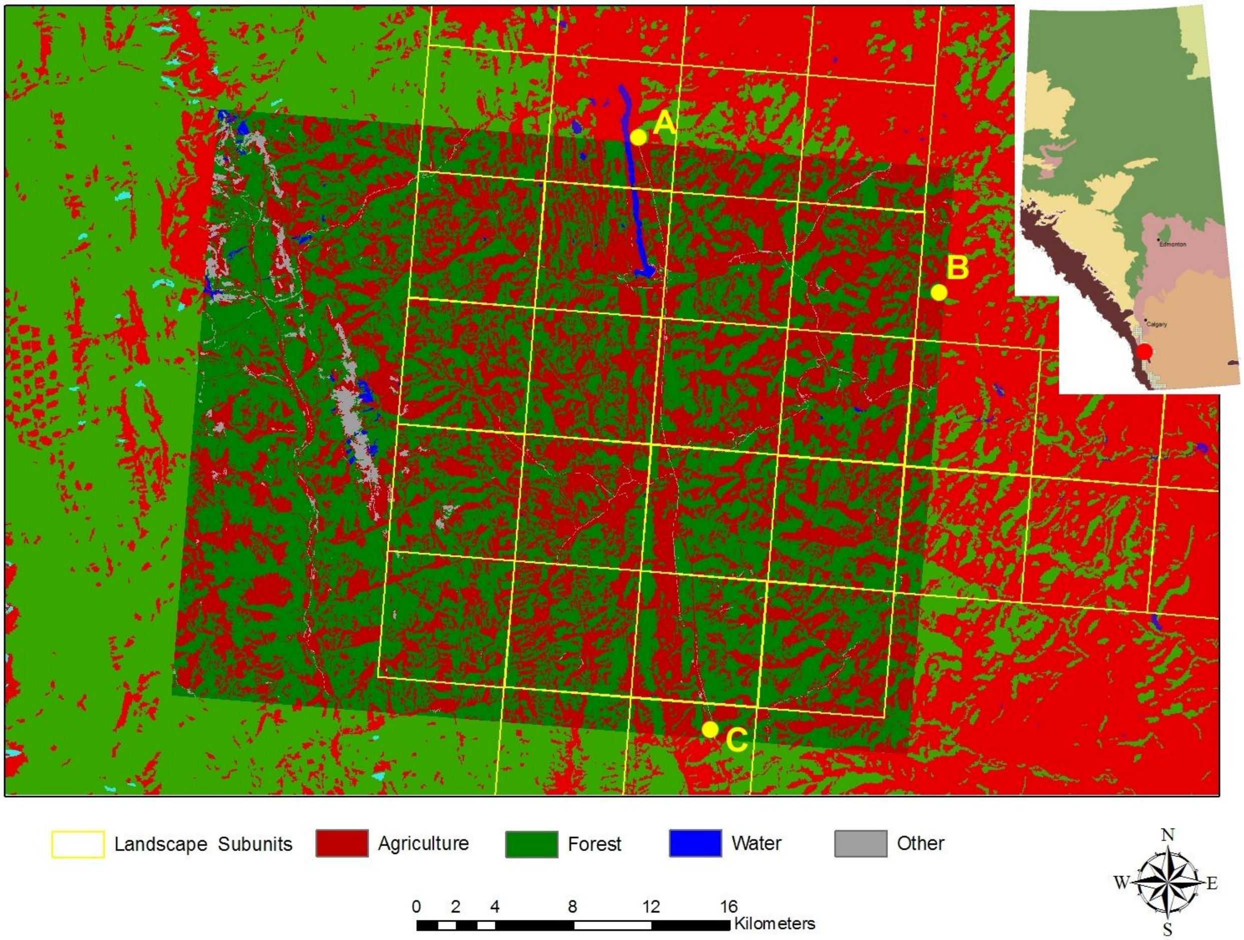

Figure 3.2: Shows correlation between a classified IRS image (darker colored square in center) and the FMF land cover map (lighter colors), after combining the Landsat classes to match those used in the IRS image classification. Points A, B, and C are located at areas that showcase how the two images are in thematic agreement.

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 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.

Table 3.2: Configurational landscape metrics used in the regression analysis. Entries marked as (distribution) are aggregates of that metric across the entire sub-landscape in all classes, and include the following statistical distributions: mean (MN), area-weighted mean (AM), median (MD), range (RA), standard deviation (SD), and coefficient of variation (CV). For more detailed information and formulas, see McGarigal and Marks (1995)

Name	Abbreviation	Measure of	Description
Patch Density	PD	Area/Density/Edge	# of patches per landscape area
Edge Density	ED	Area/Density/Edge	Amount of edge per landscape area
Landscape Shape Index	LSI	Area/Density/Edge	A measure of density that adjusts for the landscape size
Shape Index	SHAPE_ (distributions)	Shape	A measure of overall patch shape complexity
Contiguity Index	CONTIG_ (distributions)	Shape	Assesses the spatial connectedness (contiguity) of cells in a patch to provide an index of patch boundary configuration or shape
Euclidean Nearest Neighbor Distance	ENN_ (distributions)	Isolation/ Proximity	A measure of patch context – the shortest straight line distance between a patch and its nearest neighbor of the same class
Percentage of Like Adjacencies	PLADJ	Contagion / Interspersion	Measures the degree of aggregation of patch types
Landscape Division Index	DIVISION	Contagion / Interspersion	Measures the probability that 2 randomly chosen points in the landscape are not situated in the same patch
Connectance Index (100m)	CONNECT	Connectivity	The number of functional joinings between patches of the same class that are within 100m of each other
Simpson's Evenness Index	SIEI	Diversity	Measures the distribution of area among the different patch classes

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 / km^2).

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 R^2 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:

$$Y = -35.041 + 0.453*PD + 34.245*CONTIG\_AM + 0.002*ENN\_CV. \quad \text{(eq. 3.1)}$$

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.

Metric	Sig. (2-tailed) (p-value)	Bear presence	Mean	Mean Difference
% Forest	0.020	no	20.5887	
		yes	28.4446	-7.8559
PD	0.007	no	3.0369	
		yes	3.8044	-0.7675
ED	0.001	no	84.1313	
		yes	109.6331	-25.5019
LSI	0.001	no	14.6252	
		yes	18.6820	-4.0568
SHAPE_AM	0.003	no	8.7114	
		yes	11.0737	-2.3623
SHAPE_RA	0.001	no	14.3779	
		yes	18.3333	-3.9555
SHAPE_SD	0.023	no	2.2538	
		yes	2.4754	-0.2215
SHAPE_CV	0.006	no	74.9961	
		yes	81.7614	-6.7653
CONTIG_AM	0.001	no	0.9744	
		yes	0.9671	0.0073
CONTIG_MD	0.039	no	0.8607	
		yes	0.8674	-0.0068
ENN_MN	0.000	no	224.5892	
		yes	145.3429	79.2463
ENN_SD	0.018	no	649.3260	
		yes	514.7290	134.5970
ENN_CV	0.011	no	304.9093	
		yes	361.8683	-56.9590
PLADJ	0.001	no	97.8194	
		yes	97.1816	0.6378
CONNECT	0.004	no	3.7845	
		yes	3.2781	0.5064
DIVISION	0.003	no	0.5959	
		yes	0.7147	-0.1188

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:

$$P_a = \frac{1}{1+e^{(-39.704+0.065*SHAPE\_CV+41.954*CONTIG\_MD-0.009*ENN\_MN+0.003*ENN\_AM)}}$$

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 3.5: Predicted grizzly presence / absence based on logistic regression model.

		Predicted		Percentage Correct
		Absent	Present	
Observed	Absent	14	22	38.9
	Present	9	62	87.3
Overall Percentage				71.0

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).

Landscape Metric	Difference (FMF metric – SSM metric)				% difference from FMF value
	Average	Min	Max	Range	
PD	0.28	-1.15	2.52	3.67	10.3%
ED	2.51	-31.07	39.61	70.68	5.4%
LSI	0.41	-5.05	6.45	11.49	4.8%
SHAPE_MN	-0.05	-0.61	0.25	0.86	-2.7%
SHAPE_AM	0.72	-2.02	5.09	7.12	13.1%
SHAPE_MD	-0.03	-0.33	0.18	0.52	-2.3%
SHAPE_RA	0.12	-5.60	4.85	10.45	1.7%
SHAPE_SD	0.00	-0.81	0.69	1.49	0.2%
SHAPE_CV	1.39	-38.22	34.27	72.48	2.4%
CONTIG_MN	-0.04	-0.34	0.11	0.44	-6.5%
CONTIG_AM	0.00	-0.07	0.06	0.12	-0.4%
CONTIG_MD	-0.04	-0.45	0.15	0.60	-6.5%
CONTIG_RA	0.01	-0.22	0.28	0.51	1.0%
CONTIG_SD	0.00	-0.07	0.08	0.15	2.2%
CONTIG_CV	2.48	-22.68	36.10	58.78	7.8%
ENN_MN	-97.97	-700.05	1540.93	2240.98	-35.5%
ENN_AM	-75.31	-582.14	70.26	652.41	-97.4%
ENN_MD	-76.21	-774.59	104.56	879.15	-68.3%
ENN_RA	-786.45	-3092.07	2963.45	6055.52	-32.2%
ENN_SD	-139.34	-679.08	1392.25	2071.33	-34.5%
ENN_CV	-6.68	-102.36	167.43	269.80	-4.6%
PLADJ	-0.38	-5.94	4.66	10.60	-0.4%
CONNECT	-0.01	-2.86	5.17	8.03	-0.4%
DIVISION	-0.08	-0.73	0.46	1.19	-15.3%
SIEI	0.14	-0.13	0.38	0.51	10.6%

Table 3.7: Differences in metric values when calculated from images at different spatial resolutions (5m and 30m).					
Landscape Metric	Difference (IRS metric – FMF metric) Average	Min	Max	Range	% difference from IRS value
PD	0.39	-1.35	2.79	4.14	12.5%
ED	62.18	-17.88	130.42	148.31	57.3%
LSI	10.06	-2.92	21.19	24.11	54.1%
SHAPE_MN	1.33	0.79	1.83	1.04	43.1%
SHAPE_AM	6.55	-2.61	14.74	17.35	54.3%
SHAPE_MD	0.83	0.15	1.48	1.33	36.2%
SHAPE_RA	10.97	1.37	26.91	25.54	60.6%
SHAPE_SD	1.62	0.50	2.94	2.44	61.3%
SHAPE_CV	27.45	-3.20	67.71	70.91	32.2%
CONTIG_MN	0.13	0.04	0.35	0.31	16.5%
CONTIG_AM	0.05	-0.01	0.10	0.11	5.6%
CONTIG_MD	0.18	0.09	0.51	0.41	20.9%
CONTIG_RA	0.05	0.00	0.24	0.25	5.5%
CONTIG_SD	0.04	-0.06	0.14	0.20	17.6%
CONTIG_CV	0.27	-32.95	19.15	52.10	0.8%
ENN_MN	-102.01	-1703.50	430.01	2133.50	-58.7%
ENN_AM	126.39	-73.25	457.77	531.01	62.0%
ENN_MD	-81.79	-233.35	273.47	506.82	-274.7%
ENN_RA	2322.65	-2493.03	6095.79	8588.82	48.8%
ENN_SD	196.84	-924.30	883.05	1807.36	32.7%
ENN_CV	237.66	-81.12	514.27	595.39	62.2%
PLADJ	4.63	-1.06	8.28	9.34	4.8%
CONNECT	1.78	-5.53	5.02	10.54	48.0%
DIVISION	0.16	-0.46	0.82	1.28	22.7%
SIEI	0.01	-0.25	0.25	0.50	0.4%

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

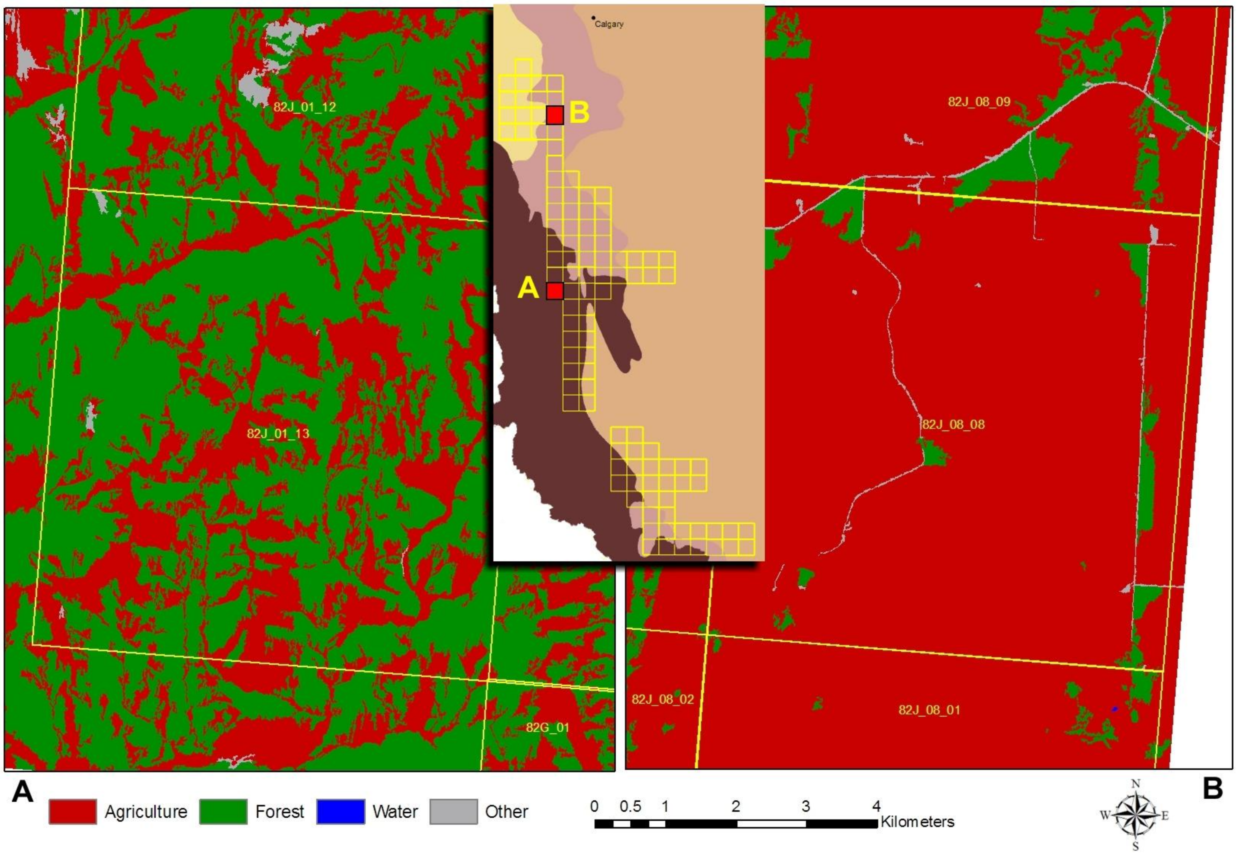

Figure 3.3: Comparison of natural (A) versus agricultural (B) sub-landscapes. Natural areas have high Shape Index mean and variation distributions (complex shapes), low mean nearest neighbor distances (but high variation in nearest neighbor distances) and high contiguity. Agricultural areas have opposite values for these metrics.

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

(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

Apps, C.D., McLellan, B.N., Woods, J.G., and Proctor, M.F., 2004. Estimating Grizzly Bear Distribution and Abundance Relative to Habitat and Human Influence. *Journal of Wildlife Management* 68 (1), 138 – 152.

Bowers, M.A., Gregario, K., Brame, C.J., Matter, S.F., and Dooley, J.L., 1996. Use of space and habitats by meadow voles at the home range, patch and landscape scales. *Oecologia* 105, 107 – 115.

Chruszcz, B., Clevenger, A.P., Gunson, K.E., and Gibeau, M.L., 2003. Relationships among grizzly bears, highways, and habitat in the Banff-Bow Valley, Alberta, Canada. *Canadian Journal of Zoology* 81, 1378 – 1391.

Cushman, S. A. and McGarigal, K., 2004. Patterns in the species - environment relationship depend on both scale and choice of response variables. *Oikos* 105, 117 - 124.

Forman, R.T.T., 1995. *Land Mosaics: The Ecology of Landscapes and Regions*. Cambridge University Press: Cambridge, UK.

Frair, J.L., Nielsen, S.E., Merrill, E.H., Lele, S.R., Boyce, M.S., Munro, R.H., Stenhouse, G.B., and Beyer, H.L., 2004. Removing GPS collar bias in habitat selection studies. *Journal of Applied Ecology* 41, 201 – 212.

Franklin S.E., Stenhouse G.B., Hansen M.J., Popplewell C.C., Dechka J.A., and Peddle, D.R., 2001. An integrated decision tree approach (IDTA) to mapping landcover using satellite remote sensing in support of grizzly bear habitat analysis in the Alberta Yellowhead Ecosystem. *Canadian Journal of Remote Sensing* 27, 579–591.

Garshelis, D.L., Gibeau, M.L., and Herrero, S., 2005. Grizzly Bear Demographics in and Around Banff National Park and Kananaskis Country, Alberta. *Journal of Wildlife Management* 69, 277 – 297.

Gergel, S.E., 2007. New Directions in Landscape Pattern Analysis and Linkages with Remote Sensing. In *Understanding Forest Disturbance and Spatial Pattern: Remote Sensing and GIS Approaches*. Edited by M.A. Wulder and S.E. Franklin. Taylor & Francis, Boca Raton. pp. 173 – 208.

Gibeau, M.L., Clevenger, A.P., Herrero, S., and Wierzchowski, J., 2002. Grizzly bear response to human development and activities in the Bow River Watershed, Alberta, Canada. *Biological Conservation* 103, 227 – 236.

Herzog, F., and Lausch, A., 2001. Supplementing Land-use Statistics With Landscape Metrics: Some Methodological Considerations. *Environmental Monitoring and Assessment* 72, 37 – 50.

Hobson, D., 2005. Bear Capturing and Handling. In Stenhouse, G. and K.Graham (eds). Foothills Model Forest Grizzly Bear Research Program 1999-2003 Final Report. Hinton, Alberta.

Hobson, D., 2006. Summary of 2005 Spring Capture Program. In Stenhouse, G. and K.Graham (eds). Foothills Model Forest Grizzly Bear Research Program 2005 Annual Report. Hinton, Alberta.

Ivits, E., Koch, B., Blaschke, T., and Waser, L., 2002. Landscape connectivity studies on segmentation based classification and manual interpretation of remote sensing data. eCognition User Meeting, October 2002, München, Germany.

Kansas, J., 2002. Status of the Grizzly Bear (*Ursus arctos*) in Alberta. Alberta Sustainable Resource Development, Fish and Wildlife Division, and Alberta Conservation Association. Wildlife Status Report No. 37, Edmonton, AB. 43 pp.

Langford, W.T., Gergel, S.E., Dietterich, T.G., and Cohen, W., 2006. Map Misclassification Can Cause Large Errors in Landscape Pattern Indices: Examples from Habitat Fragmentation. *Ecosystems* 9, 474 – 488.

Linke, J., Franklin, S.E., Huettmann, F., and Stenhouse, G.B., 2005. Seismic cutlines, changing landscape metrics and grizzly bear landscape use in Alberta. *Landscape Ecology* 20, 811 – 826.

Mace, R.D., Waller, J.S., Manley, T.L., Lyon, L.J., and Zuuring, H., 1996. Relationships Among Grizzly Bears, Roads and Habitat in the Swan Mountains Montana. *The Journal of Applied Ecology* 33 (6), 1395 – 1404.

McDermid, G.J., Franklin, S.E., and LeDrew, E.F., 2005. Remote sensing for large-area habitat mapping. *Progress in Physical Geography* 29 (4), 449 – 474.

McDermid, G.J., Pape, A., and Laskin, D., 2006. Map Production Update. In Stenhouse, G. and K.Graham (eds). Foothills Model Forest Grizzly Bear Research Program 2005 Annual Report. Hinton, Alberta.

McGarigal, K., 2002. *Landscape pattern metrics*. Pages 1135-1142 in A. H. El-Shaarawi and W. W. Piegorsch, eds. Encyclopedia of Environmentrics Volume 2: 1135-1142. John Wiley & Sons: Sussex, England.

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

McGarigal, K., and Marks, B.J., 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA For. Serv. Gen. Tech. Rep. PNW-351.

McGarigal, K., and McComb, W. C., 1995. Relationships between landscape structure and breeding birds in the Oregon Coast Range. *Ecological Monographs* 65 (3), 235-260.

McLellan, B.N., and Shackleton, D.M., 1988. Grizzly Bears and Resource-Extraction Industries: Effects of Roads on Behaviour, Habitat Use and Demography. *The Journal of Applied Ecology* 25, 451 – 460.

McLellan, B.N., and Shackleton, D.M., 1989. Grizzly Bears and Resource-Extraction Industries: Habitat Displacement in Response to Seismic Exploration, Timber Harvesting and Road Maintenance. *The Journal of Applied Ecology* 26, 371 – 380.

Munro, R.H.M., Nielsen, S.E., Price, M.H., Stenhouse, G.B., and Boyce, M.S., 2006. Seasonal and Diel Patterns of Grizzly Bear Diet and Activity in West-Central Alberta. *Journal of Mammalogy* 87 (6), 1112 – 1121.

Nams, V.O., Mowat, G., and Panian, M.A., 2006. Determining the spatial scale for conservation purposes – an example with grizzly bears. *Biological Conservation* 128, 109 – 119.

Narumalani, S., Mishra, D.R., and Rothwell, R.G., 2004. Change detection and landscape metrics for inferring anthropogenic processes in the greater EFMO area. *Remote Sensing of Environment* 91, 478 – 489.

Nielsen, S.E., and Boyce, M.S., 2002. Resource selection functions and population viability analyses. In: Stenhouse, G.B. and Munro, R.H. (eds.), Foothills Model Forest Grizzly Bear Research Program. 2001 Annual Report. Hinton, Alberta, pp. 17–42.

Nielsen S.E., Boyce M.S., Stenhouse G.B., and Munro R.H.M., 2002. Modeling grizzly bear habitats in the Yellowhead Ecosystem of Alberta: taking autocorrelation seriously. *Ursus* 13, 153–164.

Nielsen, S.E., Boyce, M.S., and Stenhouse, G.B., 2004. Grizzly bears and forestry I. Selection of clearcuts by grizzly bears in west-central Alberta, Canada. *Forest Ecology and Management* 199, 51 – 65.

Nielsen, S.E., Stenhouse, G.B., and Boyce, M.S., 2006. A habitat-based framework for grizzly bear conservation in Alberta. *Biological Conservation* 130, 217 – 229.

O'Neill, R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B., DeAngelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H., and Graham, R.L., 1988. Indices of landscape pattern. *Landscape Ecology* 1 (3), 153 – 162.

Singleton, P.H., Gaines, W.L., Lehmkuhl, J.F., 2004. Landscape permeability for grizzly bear movements in Washington and southwestern British Columbia. *Ursus* 15 (1), Workshop Supplement, 90 – 103.

Song, C., Woodcock, C.E., Seto, K.C., Lenney, M.P., and Macomber, S.A., 2001. Classification and Change Detection Using Landsat TM Data: When and How to Correct Atmospheric Effects. *Remote Sensing of Environment* 75, 230-244.

Stenhouse, G.B., Boyce, M.S., Boulanger, J., 2003. Report on Alberta Grizzly Bear Assessment of Allocation. Alberta Sustainable Resource Development, Fish and Wildlife Division, Hinton, Alta.

Waller, J.S., and Servheen, C., 2005. Effects of Transportation Infrastructure on Grizzly Bears in Northwestern Montana. *Journal of Wildlife Management* 69 (3), 985 – 1000.

Wielgus, R.B., Vernier, P.R., and Schivatcheva, T., 2002. Grizzly bear use of open, closed, and restricted forestry roads. *Canadian Journal of Forest Research* 32, 1597 – 1606.

Wilson, S.M., Madel, M.J., Mattson, D.J., Graham, J.M., Burchfield, J.A., and Belsky, J.M., 2005. Natural landscape features, human-related attractants, and conflict hotspots: a spatial analysis of human-grizzly bear conflicts. *Ursus* 16 (1), 117 – 129.

Wilson, S.M., Madel, M.J., Mattson, D.J., Graham, J.M., and Merrill, T., 2006. Landscape conditions predisposing grizzly bears to conflicts on private agricultural lands in the western USA. *Biological Conservation* 130, 47 – 59.

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 analagous 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 condusive 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

Apps, C.D., McLellan, B.N., Woods, J.G., and Proctor, M.F., 2004. Estimating Grizzly Bear Distribution and Abundance Relative to Habitat and Human Influence. *Journal of Wildlife Management* 68 (1), 138 – 152.

Franklin, S.E., and Wulder, M.A., 2002. Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. *Progress in Physical Geography* 26 (2), 173-205.

Johnson, C., Parker, K., Heard, D., and Gillingham, M., 2002. A Multiscale Behavioral Approach to Understanding the Movements of Woodland Caribou. *Ecological Applications* 12 (6), 1840 – 1860.

Linke, J., Franklin, S.E., Huettmann, F., and Stenhouse, G.B., 2005. Seismic cutlines, changing landscape metrics and grizzly bear landscape use in Alberta. *Landscape Ecology* 20, 811 – 826.

McGarigal, K., and McComb, W. C., 1995. Relationships between landscape structure and breeding birds in the Oregon Coast Range. *Ecological Monographs* 65 (3), 235-260.

Nielsen S.E., Boyce M.S., Stenhouse G.B., and Munro R.H.M., 2002. Modeling grizzly bear habitats in the Yellowhead Ecosystem of Alberta: taking autocorrelation seriously. *Ursus* 13, 153–164.

Popplewell, C., Franklin, S.E., Stenhouse, G., and Hall-Beyer, M., 2003. Using landscape structure to classify grizzly bear density in Alberta Yellowhead Ecosystem bear management units. *Ursus* 14 (1), 27 – 34.

Turker, M., and Arikan, M., 2005. Sequential masking classification of multi-temporal Landsat 7 ETM+ images for field-based crop mapping in Karacabey, Turkey. *International Journal of Remote Sensing* 26 (17), 3813 – 3830.

Wilson, S.M., Madel, M.J., Mattson, D.J., Graham, J.M., Burchfield, J.A., and Belsky, J.M., 2005. Natural landscape features, human-related attractants, and conflict hotspots: a spatial analysis of human-grizzly bear conflicts. *Ursus* 16 (1), 117 – 129.

Wilson, S.M., Madel, M.J., Mattson, D.J., Graham, J.M., and Merrill, T., 2006. Landscape conditions predisposing grizzly bears to conflicts on private agricultural lands in the western USA. *Biological Conservation* 130, 47 – 59.

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

User \ Reference Class	Bare Soil / Fallow	Canola	Grasses / Forage	Legumes	Small Grains	Total
Bare Soil / Fallow	531	27	4395	0	551	5504
Canola	0	2921	5	2153	530	5609
Grasses / Forage	30	332	9852	843	7163	18220
Legumes	0	5962	0	445	582	6989
Small Grains	0	45	1237	30	14248	15560
unclassified	0	288	3	11	552	854
Total	561	9575	15492	3482	23626	52736

Table A2: North study area Unsupervised classification confusion matrix

User \ Reference Class	Bare Soil / Fallow	Canola	Grasses / Forage	Legumes	Small Grains	Total
Bare Soil / Fallow	5527	0	7205	0	6	12738
Canola	0	7211	0	0	610	7821
Grasses / Forage	0	0	3621	349	1956	5926
Legumes	0	0	0	769	0	769
Small Grains	3	3	928	0	6284	7218
unclassified	0	868	295	0	2	1165
Total	5530	8082	12049	1118	8858	35637

Table A3: North study area Nearest Neighbor classification confusion matrix

User \ Reference Class	Bare Soil / Fallow	Canola	Grasses / Forage	Legumes	Small Grains	Total
Canola	0	8076	0	0	4	8080
Bare Soil / Fallow	5517	0	858	0	744	7119
Grasses / Forage	10	3	9904	0	888	10805
Small Grains	3	0	1285	349	6616	8253
Legumes	0	0	0	769	606	1375
unclassified	0	3	2	0	0	5
Total	5530	8082	12049	1118	8858	35637

Table A4: South study area Nearest Neighbor classification confusion matrix

User \ Reference Class	Bare Soil / Fallow	Canola	Grasses / Forage	Legumes	Small Grains	Total
Bare Soil / Fallow	502	0	1001	0	0	1503
Canola	0	8702	0	194	630	9526
Grasses / Forage	51	75	12195	20	2812	15153
Legumes	0	697	6	3177	43	3923
Small Grains	8	101	2290	91	20137	22627
unclassified	0	0	0	0	4	4
Total	561	9575	15492	3482	23626	52736

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

User \ Reference Class	Bare Soil / Fallow	Canola	Grasses / Forage	Legumes	Small Grains	Total
Bare Soil / Fallow	5094	0	0	0	0	5094
Canola	0	8082	0	0	624	8706
Grasses / Forage	436	0	9660	0	1577	11673
Legumes	0	0	0	1118	0	1118
Small Grains	0	0	2389	0	6657	9046
Total	5530	8082	12049	1118	8858	35637

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

User \ Reference Class	Bare Soil / Fallow	Canola	Grasses / Forage	Legumes	Small Grains	Total
Bare Soil / Fallow	561	0	724	0	0	1285
Canola	0	9575	0	163	604	10342
Hay / Pasture	0	0	13546	0	1200	14746
Peas	0	0	0	3319	1337	4656
Small Grains	0	0	1222	0	20485	21707
Total	561	9575	15492	3482	23626	52736

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 tress used for the SSM classification of Chapter 2.

- Classification
  - Clear Classification
  - Canola (*)
    - unclassified at Level 1: Canola
    - Canola with Mean TM 4 < 37 at Level 1: unclassified
    - Canola with Mean TBrightness < 35 at Level 1: unclassified
    - Canola with Mean TGreeness < 18 at Level 1: unclassified
    - Canola with Mean TWetness < 1 at Level 1: unclassified
    - Canola with Mean NDMI < 0.35 at Level 1: unclassified
  - Bare Soil
    - unclassified at Level 1: Bare Soil / Fallow
    - Bare Soil / Fallow with Mean TWetness > 0.01 at Level 1: unclassified
    - Bare Soil / Fallow with Mean TM 3 < 5 at Level 1: unclassified
    - Bare Soil / Fallow with Mean TBrightness < 25 at Level 1: unclassified
    - Bare Soil / Fallow with Mean TGreeness > 5 at Level 1: unclassified
  - Legumes
    - unclassified at Level 1: Legumes
    - Legumes with Mean TBrightness < 25 at Level 1: unclassified
    - Legumes with Mean TM 2 < 4 at Level 1: unclassified
    - Legumes with Mean TGreeness < 20 at Level 1: unclassified
    - Legumes with Mean NDMI < 0.3 at Level 1: unclassified
    - Legumes with Mean TM 2 > 7 at Level 1: unclassified
  - Grasses / Forage
    - unclassified at Level 1: Grasses / Forage
    - Grasses / Forage with Mean TWetness > 1 at Level 1: unclassified
    - Grasses / Forage with Mean TGreeness > 19 at Level 1: unclassified
    - Grasses / Forage with Mean TM 4 > 39 at Level 1: unclassified
    - Grasses / Forage with Mean NDMI > 0.28 at Level 1: unclassified
    - Grasses / Forage with Mean TM 5 < 18.8 at Level 1: unclassified
    - Grasses / Forage with Mean TM 1 > 8 at Level 1: Bare Soil / Fallow
  - Small Grains
    - unclassified at Level 1: Small Grains
    - Small Grains with Mean TM 4 > 40 at Level 1: unclassified
    - Small Grains with Mean TM 7 > 14 at Level 1: unclassified
    - all classified with Mean TM 4 <= 0.009 at Level 1: Null
    - unclassified at Level 1: Grasses / Forage

Figure C1: North study area process tree

- Classification
  - Clear Classification
  - Canola (*)
    - unclassified at Level 1: Canola
    - Canola with Mean TM 4 < 37 at Level 1: unclassified
    - Canola with Mean TBrightness < 35 at Level 1: unclassified
    - Canola with Mean TM 2 < 7.2 at Level 1: unclassified
    - Canola with Standard deviation TM 2 > 1.5 at Level 1: unclassified
    - Canola with Mean TGreeness < 18 at Level 1: unclassified
    - Canola with GLCM Homogeneity (quick 8/11) TGreeness (all dir.) < 0.25 at Level 1: ur
    - Canola with Mean TWetness < 3.5 at Level 1: unclassified
  - Bare Soil
    - unclassified at Level 1: Bare Soil / Fallow
    - Bare Soil / Fallow with Mean TWetness > 0.01 at Level 1: unclassified
    - Bare Soil / Fallow with Mean TM 3 < 10 at Level 1: unclassified
    - Bare Soil / Fallow with Mean TBrightness < 37 at Level 1: unclassified
    - unclassified with Mean TWetness <= 0.01 at Level 1: Grasses / Forage
  - Legumes
    - unclassified at Level 1: Legumes
    - Legumes with Mean TWetness < 2 at Level 1: unclassified
    - Legumes with Mean TBrightness < 35 at Level 1: unclassified
    - Legumes with Mean TM 2 < 5 at Level 1: unclassified
  - Grasses / Forage
    - unclassified at Level 1: Grasses / Forage
    - Grasses / Forage with Mean TWetness > 6 at Level 1: unclassified
    - Grasses / Forage with Mean TGreeness > 25 at Level 1: unclassified
    - Grasses / Forage with Mean TM 4 > 39 at Level 1: unclassified
    - Grasses / Forage with Mean NDMI > 0.4 at Level 1: unclassified
    - Grasses / Forage with Mean TM 2 >= 9 at Level 1: unclassified
    - Grasses / Forage with X distance to image left border < 1500 Pxl at Level 1: Null
    - Null with Y distance to image bottom border > 4200 Pxl at Level 1: Grasses / Forage
    - Grasses / Forage with Mean TM 5 < 20 at Level 1: unclassified
    - Null at Level 1: Grasses / Forage
  - Small Grains
    - unclassified at Level 1: Small Grains
    - Small Grains with Mean TM 4 > 40 at Level 1: unclassified
    - Small Grains with Mean TM 1 > 3.9 at Level 1: Bare Soil / Fallow
    - all classified with Mean TM 4 <= 0.009 at Level 1: Null
    - Small Grains with Mean TM 2 < 1 at Level 1: Null
    - Small Grains with Mean TM 1 < 0.1 at Level 1: Null
    - Small Grains with Mean TM 7 < 1 at Level 1: Null
    - unclassified at Level 1: Small Grains

Figure C2: South study area process tree

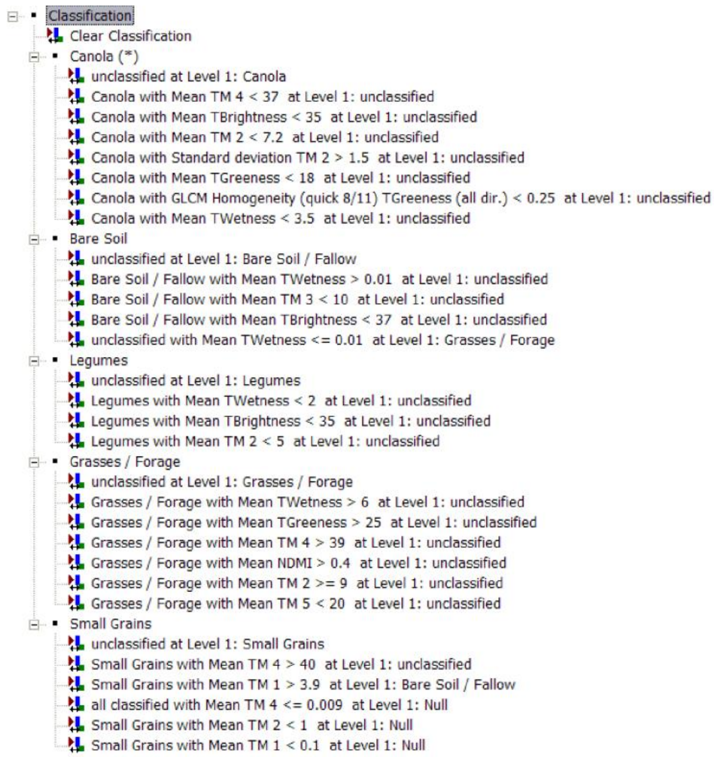

Figure C3: Landsat image 41/26 process tree

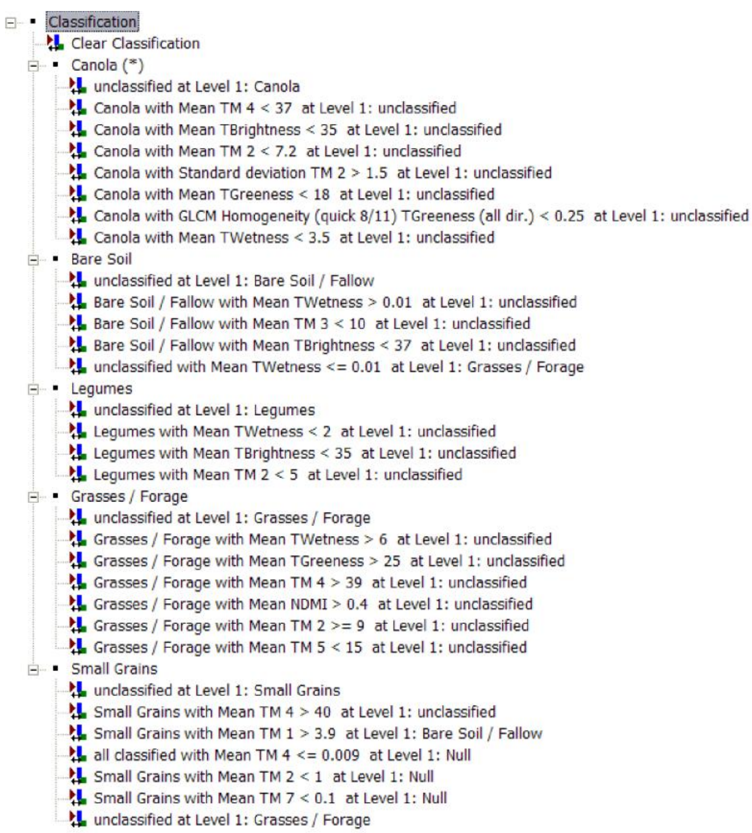

Figure C4: Landsat image 43/24 process tree

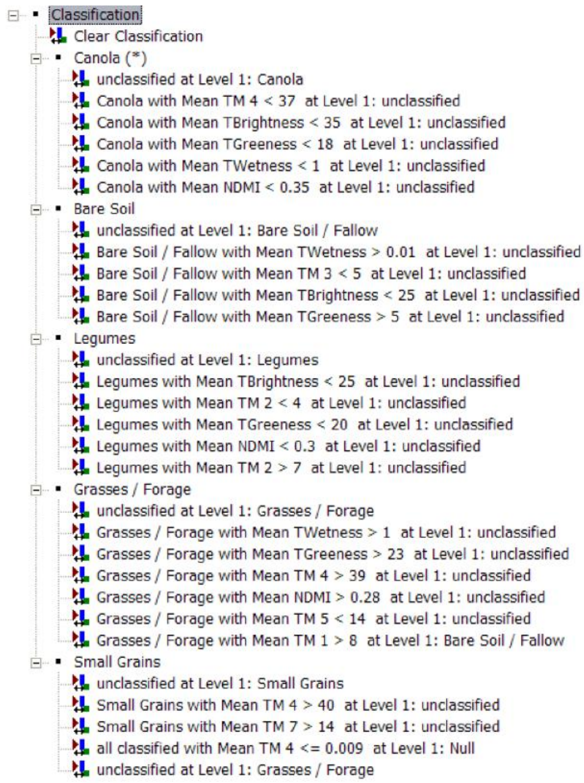

Figure C5: Landsat scene 44/22 process tree

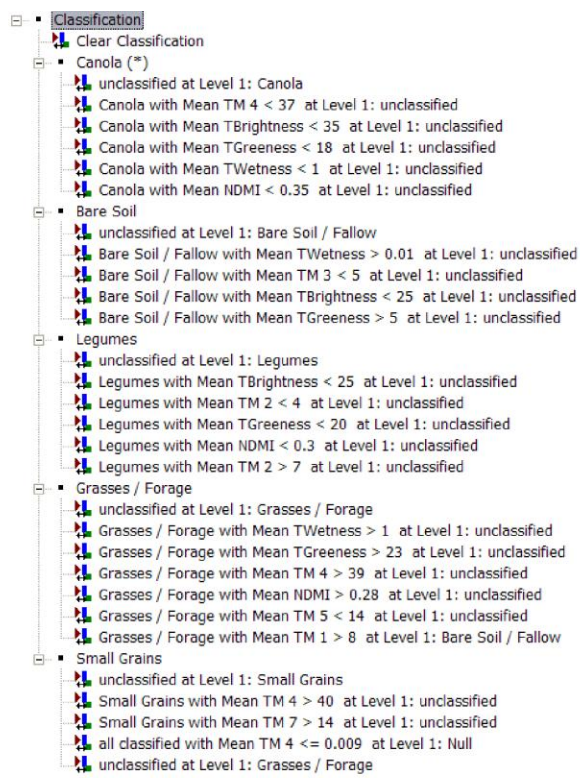

Figure C6: Landsat image 44/23 process tree

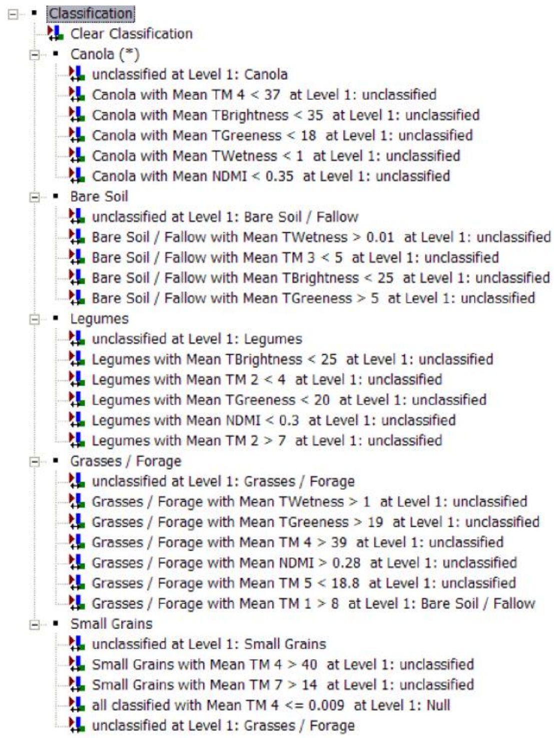

Figure C7: Landsat image 45/21 process tree

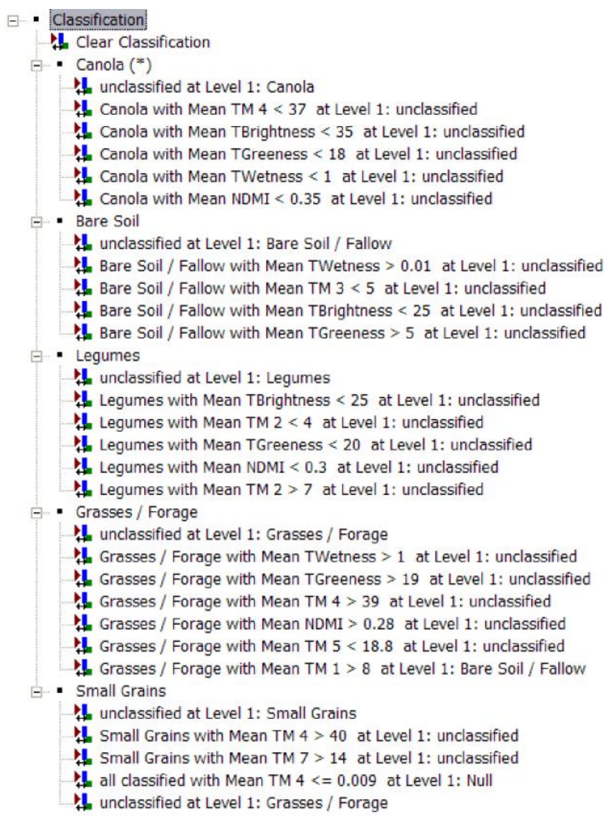

Figure C8: Landsat image 46/21 process tree

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.

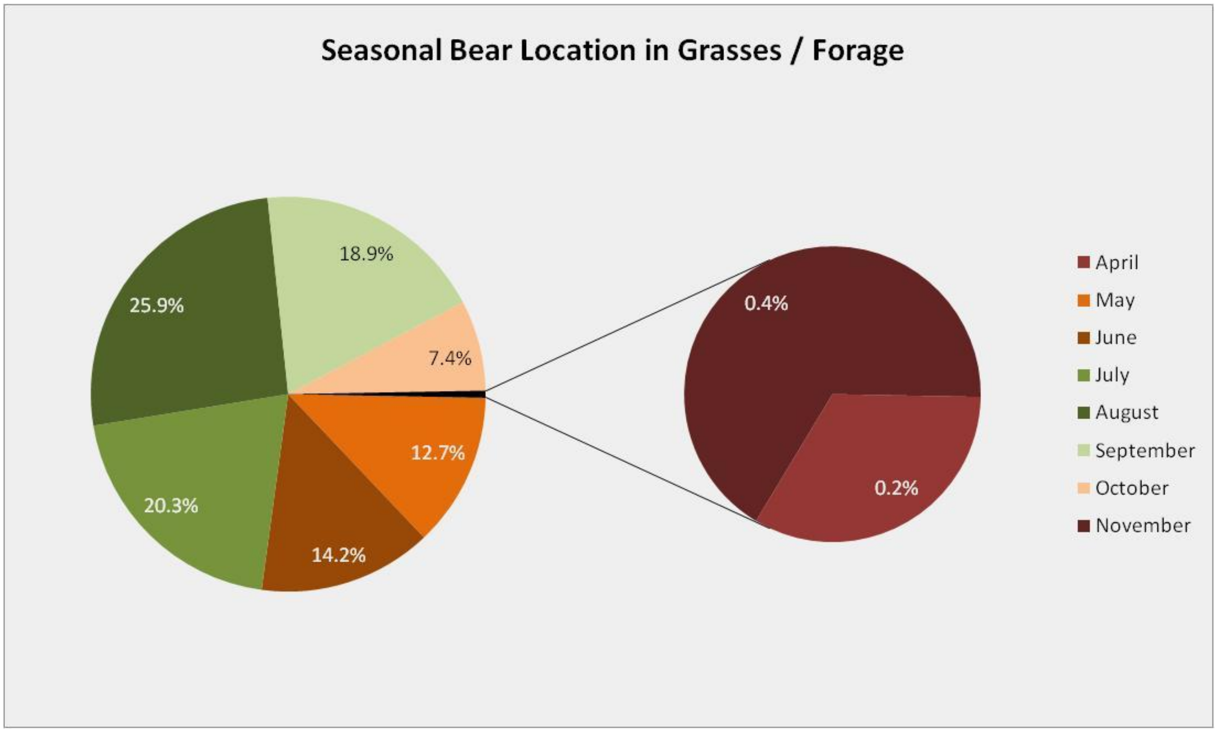

Figure D1: Data represents 18 bears (10 male, 8 female) with 1035 location points.

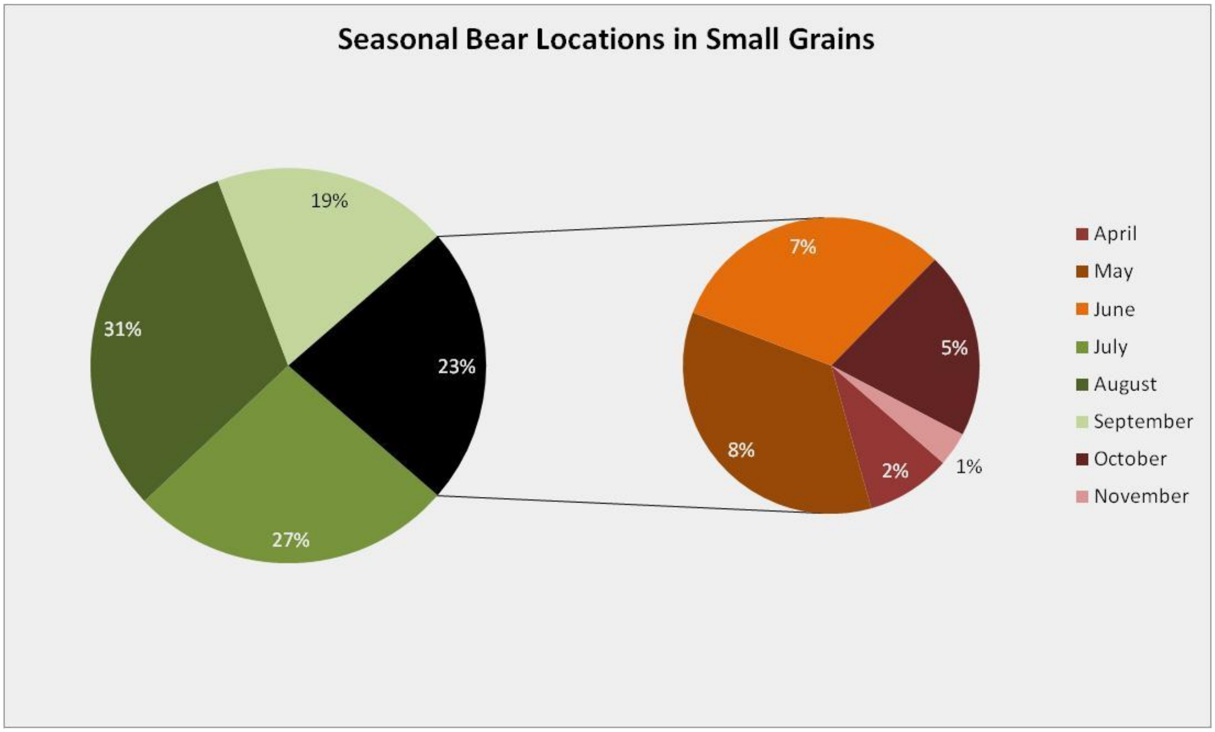

Figure D2: Data represents 12 bears (7 male, 5 female) with 237 location points.

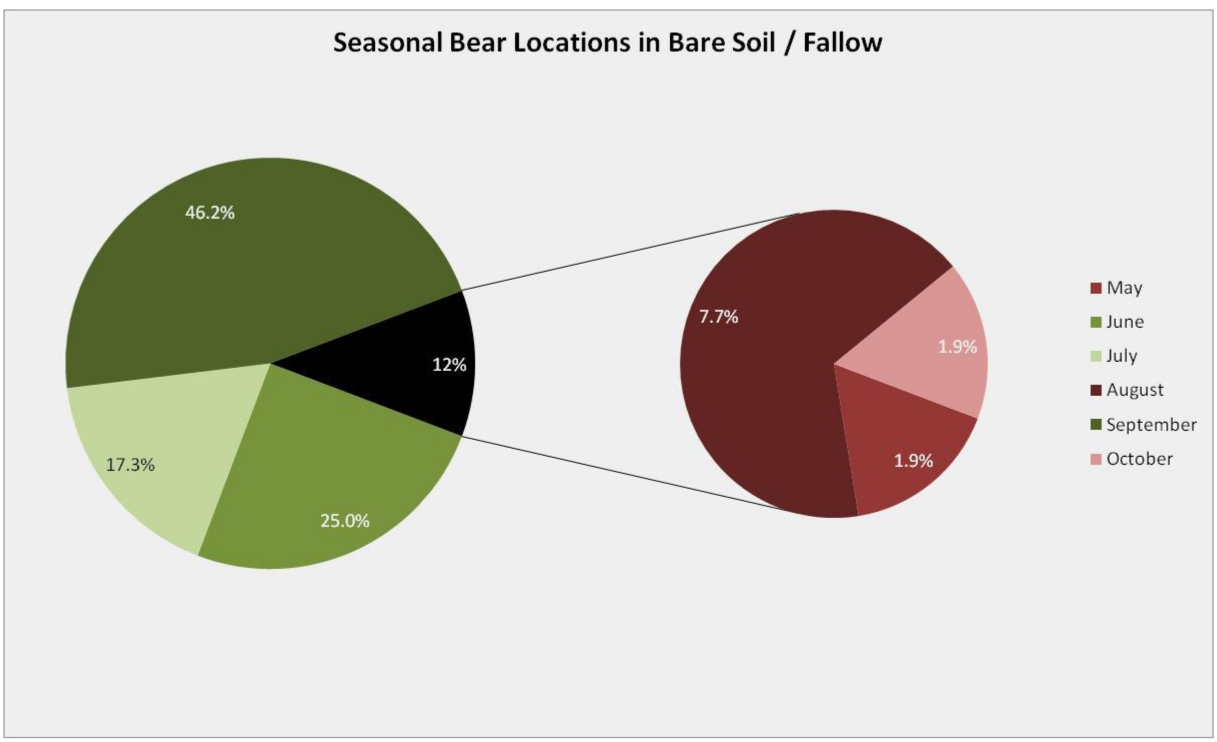

Figure D3: Data represents 7 bears (2 male, 5 female) with 52 location points.

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

	Bare Soil / Fallow	Canola	Grass / Forage	Legumes	Small Grains
Average Producer	97.30%	59.86%	46.82%	40.78%	65.62%
Average User	26.52%	72.14%	57.59%	53.18%	89.31%
Average KIA* Per Class	96.97%	54.21%	30.24%	33.78%	53.63%
South Producer	94.65%	30.51%	63.59%	12.78%	60.31%
South User	9.65%	52.08%	54.07%	6.37%	91.57%
South KIA Per Class	94.03%	22.24%	44.38%	-0.55%	43.69%
North Producer	99.95%	89.22%	30.05%	68.78%	70.94%
North User	43.39%	92.20%	61.10%	100.00%	87.06%
North KIA Per Class	99.92%	86.19%	16.10%	68.10%	63.56%

Average Overall Accuracy	59.39%
Average KIA	46.40%
South Overall Accuracy	53.09%
South KIA	36.36%
North Overall Accuracy	65.70%
North KIA	56.44%

*KIA = Kappa Index of Agreement

Table E2: Supervised Nearest Neighbor classification details

	Bare Soil / Fallow	Canola	Grass / Forage	Legumes	Small Grains
Average Producer	94.62%	95.40%	80.46%	80.01%	79.96%
Average User	55.45%	95.65%	86.07%	68.46%	84.58%
Average KIA Per Class	94.44%	94.39%	72.29%	79.03%	70.60%
South Producer	89.48%	90.88%	78.72%	91.24%	85.23%
South User	33.40%	91.35%	80.48%	80.98%	89.00%
South KIA Per Class	89.17%	88.87%	70.14%	90.54%	74.13%
North Producer	99.76%	99.93%	82.20%	68.78%	74.69%
North User	77.50%	99.95%	91.66%	55.93%	80.16%
North KIA Per Class	99.71%	99.90%	74.45%	67.53%	67.06%
Average Overall Accuracy	85.72%				
Average KIA	80.08%				
South Overall Accuracy	84.79%				
South KIA	77.80%				
North Overall Accuracy	86.66%				
North KIA	82.36%				

Table E3: Supervised Sequential Masking (SSM) classification details

	Bare Soil / Fallow	Canola	Grass / Forage	Legumes	Small Grains
Average Producer	96.06%	100.00%	83.81%	97.66%	80.93%
Average User	71.83%	92.71%	87.31%	85.64%	83.98%
Average KIA Per Class	95.40%	100.00%	76.54%	97.43%	72.05%
South Producer	100.00%	100.00%	87.44%	95.32%	86.71%
South User	43.66%	92.58%	91.86%	71.28%	94.37%
South KIA Per Class	100.00%	100.00%	82.56%	94.87%	77.40%
North Producer	92.12%	100.00%	80.17%	100.00%	75.15%
North User	100.00%	92.83%	82.76%	100.00%	73.59%
North KIA Per Class	90.80%	100.00%	70.51%	100.00%	66.70%
Average Overall Accuracy	87.97%				
Average KIA	83.37%				
South Overall Accuracy	90.04%				
South KIA	85.61%				
North Overall Accuracy	85.90%				
North KIA	81.13%				