

# **Sensitivity of high-resolution satellite sensor imagery to regenerating forest age and site preparation for wildlife habitat analysis**

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  
**Amé Leontina Wunderle**

## **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.

Requests for permission to copy or to make other use of material in this thesis in whole or part should be addressed to:

Head of the Department of Geography

University of Saskatchewan

Saskatoon, Saskatchewan (S7N 5A5)

## ABSTRACT

In west-central Alberta increased landscape fragmentation has lead to increased human use, having negative effects on wildlife such as the grizzly bear (*Ursus arctos L.*). Recently, grizzly bears in the Foothills Model Forest were found to select clear cuts of different age ranges as habitat and selected or avoided certain clear cuts depending on the site preparation process employed. Satellite remote sensing offers a practical and cost-effective method by which cut areas, their age, and site preparation activities can be quantified. This thesis examines the utility of spectral reflectance of SPOT-5 pansharpened imagery (2.5m spatial resolution) to identify and map 44 regenerating stands sampled in August 2005. Using object based classification with the Normalized Difference Moisture Index (NDMI), green, and short wave infrared (SWIR) bands, 90% accuracy can be achieved in the detection of forest disturbance. Forest structural parameters were used to calculate the structural complexity index (SCI), the first loading of a principal components analysis. The NDMI, first-order standard deviation and second-order correlation texture measures were better able to explain differences in SCI among the 44 forest stands ( $R^2=0.74$ ). The best window size for the texture measures was 5x5, indicating that this is a measure only detectable at a very high spatial resolution. Age classes of these cut blocks were analysed using linear discriminant analysis and best separated (82.5%) with the SWIR and green spectral bands, second order correlation under a 25x25 window, and the predicted SCI. Site preparation was best classified (90.9%) using the NDMI and homogeneity texture under a 5x5 window. Future applications from this research include the selection of high probability grizzly habitat for high spatial resolution imagery acquisition for detailed mapping initiatives.

## **ACKNOWLEDGEMENTS**

This research was funded by the Natural Sciences and Engineering Research Council of Canada and the Foothills Model Forest. I thank PCI Geomatics for the use of the PANSHARP module for this study. I would also like to take this opportunity to thank my supervisor, Dr. Steven Franklin for his support and excellent advice over the past 2 years. I am grateful to my committee, Dr. Xulin Guo and Dr. Marc Cattet for their encouragement and enthusiasm throughout my time at the University of Saskatchewan. I would like to thank Dr. Greg McDermid, Alysha Pape, Karen Graham, Jerome Cranston, and Gordon Stenhouse for the invaluable advice provided. In addition, I thank the Alberta Government, Fish and Wildlife conservation division for the use of their cabin during our field season in August, 2005.

## **DEDICATION**

This thesis would not have been possible if not for the unfailing support and encouragement of my parents, Debbie and Marcel Nussbaum, and my sister, Anneke Nussbaum, who helped me through many times of frustration. I also dedicate this work to my grandparents, Edith Larson and Clifford Kolstad who were both unfortunately unable to see me through the last steps. Their belief in me will never be forgotten. Lastly, without the example set by my wonderful husband, Kai Wunderle, I never would have believed that I could do it in the first place.

# TABLE OF CONTENTS

<b>PERMISSION TO USE</b> .....	<b>i</b>
<b>ABSTRACT</b> .....	<b>ii</b>
<b>ACKNOWLEDGEMENTS</b> .....	<b>iii</b>
<b>DEDICATION</b> .....	<b>iv</b>
<b>LIST OF TABLES</b> .....	<b>vii</b>
<b>LIST OF FIGURES</b> .....	<b>viii</b>
<b>LIST OF ABBREVIATIONS</b> .....	<b>ix</b>
<b>1.0 INTRODUCTION AND OVERVIEW</b> .....	<b>1</b>
1.1 GROUND LEVEL FEATURES OF HARVESTED AREAS IN THE BOREAL FOREST .....	2
<i>1.1.1 Harvested Areas</i> .....	3
<i>1.1.2 Site Preparation Methods</i> .....	5
1.2 REMOTE SENSING OF HARVESTED AREAS .....	6
1.3 REMOTE DETECTION OF SITE PREPARATION METHODS.....	10
1.4 REMOTE SENSING FOR USER-ORIENTED HABITAT MAPPING .....	11
1.5 RESULTING RESEARCH OBJECTIVES .....	16
1.6 ORGANIZATION OF THESIS .....	17
1.7 REFERENCES.....	19
<b>2.0 REGENERATING BOREAL FOREST STRUCTURE ESTIMATION USING SPOT-5 PANSHARPENED IMAGERY</b> .....	<b>24</b>
2.1 ABSTRACT .....	24
2.1 INTRODUCTION.....	25
2.4 METHODS .....	29
<i>2.4.1 Study area and field data collection</i> .....	29
<i>2.4.2 Imagery Acquisition and Pre-processing</i> .....	31
<i>2.4.3 Texture calculation</i> .....	32
<i>2.4.4 Statistical Analysis</i> .....	34
<i>2.4.4. Classification of SCI and Product Validation</i> .....	35
2.5 RESULTS AND DISCUSSION .....	35
2.6 CONCLUSIONS .....	39
2.7 ACKNOWLEDGEMENTS.....	40
2.8 REFERENCES.....	41

<b>3.0 BOREAL FOREST AGE AND SITE PREPARATION CLASSIFICATION IN WEST-CENTRAL ALBERTA USING SPOT-5 PANSHARPENED IMAGERY, TEXTURE, AND THE STRUCTURAL COMPLEXITY INDEX</b>	<b>45</b>
3.1 ABSTRACT .....	45
3.2 INTRODUCTION .....	46
3.4 METHODS .....	50
3.4.1 <i>Study Area and Field Data Collection</i> .....	50
3.4.2 <i>Imagery Acquisition and Pre-processing</i> .....	53
3.4.3 <i>Texture calculation</i> .....	54
3.4.4 <i>Classification Techniques and Product Validation</i> .....	55
3.4.5 <i>Statistical Analysis</i> .....	56
3.5 RESULTS AND DISCUSSION .....	57
3.6 CONCLUSIONS .....	64
3.7. ACKNOWLEDGEMENTS .....	65
3.8 REFERENCES .....	66
<b>4.0 SYNTHESIS AND RESEARCH APPLICATIONS</b> .....	<b>70</b>
4.1 SIGNIFICANT CONTRIBUTIONS TO RESEARCH IN REMOTE SENSING SCIENCE AND FORESTRY .....	70
4.2 APPLICATIONS FOR WILDLIFE HABITAT MANAGEMENT .....	74
4.3 LIMITATIONS .....	78
4.4 FUTURE RESEARCH .....	79
4.5 REFERENCES .....	80
<b>APPENDIX A: COMMUNICATION</b> .....	<b>84</b>
<b>APPENDIX B: FIELD SHEET</b> .....	<b>85</b>
<b>APPENDIX C: MAPS</b> .....	<b>86</b>

## LIST OF TABLES

TABLE 1.1 ALBERTA VEGETATION INVENTORY: LISTING OF BIOPHYSICAL PARAMETERS OF INTEREST TO FORESTRY RESEARCH .....	5
TABLE 1.2 SITE PREPARATION PRACTICES IN ALBERTA AND RESULTING LAND FEATURES ..	6
TABLE 1.3 EXAMPLES OF BIOPHYSICAL VARIABLES MEASURABLE WITH SELECTED INSTRUMENTS.....	7
TABLE 2.1 FIELD DATA COLLECTION.....	29
TABLE 2.2 DATA POINTS COLLECTED IN THE FIELD .....	31
TABLE 2.3 EIGENVALUES FOR STRUCTURAL COMPLEXITY INDEX .....	34
TABLE 3.1 FIELD DATA COLLECTION.....	51
TABLE 3.2 DATA POINTS COLLECTED IN THE FIELD .....	53
TABLE 4.1 SEVERAL WILDLIFE STUDIES (INEXHAUSTIVE) AND HABITAT MODELING NEEDS SPECIFIED .....	75
TABLE 4.2 CORRELATIONS FOR FEMALE GRIZZLY, FALL SEASON WITH AGE CLASS AND SCI FOR THE 44 SAMPLED STANDS (N=372) .....	76



## LIST OF FIGURES

FIGURE 1.1 LEVEL OF MEASURABLE INFORMATION CONTENT OF CUT BLOCKS .....	3
FIGURE 1.2 CONCEPTUAL FRAMEWORK OF THE CLASSIFICATION PROCESS.....	18
FIGURE 2.1 A. STUDY AREA LOCATED IN THE FOOTHILLS MODEL FOREST DEPICTED WITH THE SPOT-5 IMAGERY COLLECTED ON JULY 21, 2005; B. PLOT LOCATIONS ALONG A 100M TRANSECT WITHIN EACH STAND.....	30
FIGURE 2.2 THE REFLECTANCE VALUES OVER A 30X30M WINDOW WITH SPOT-5 ORIGINAL 10M IMAGERY (LEFT); THE INCREASED INFORMATION CONTENT OF A 30X30M WINDOW WITH SPOT-5 PANSHARPENED IMAGERY (RIGHT). .....	32
FIGURE 2.3 CORRELATION BETWEEN SCI AND FIELD MEASURED BIOPHYSICAL PARAMETERS, $p \leq 0.01$ .....	36
FIGURE 2.4 CORRELATIONS BETWEEN SCI AND SPOT-5 SPECTRAL DATA; $p < 0.05$ .....	37
FIGURE 2.5 CORRELATIONS BETWEEN SCI AND SPOT-5 TEXTURAL DATA; $p < 0.05$ .....	37
FIGURE 2.6 COMPARISON OF ADJUSTED PREDICTED SCI VERSUS ADJUSTED ACTUAL SCI; ADJ. $R^2 = 0.70$ ; $p=0.01$ , $N=44$ .....	38
FIGURE 3.1 A. STUDY AREA LOCATED IN THE FOOTHILLS MODEL FOREST DEPICTED WITH SPOT-5 IMAGERY [JULY 21, 2005] B. [INSET] STAND LEVEL SAMPLING METHOD.....	52
FIGURE 3.2 COMPARISON OF SPOT-5 ORIGINAL 10M (A) AND PAN-SHARPENED 2.5M (B) IMAGERY; R=SWIR, G=RED, B=NIR .....	54
FIGURE 3.3 SUBSET OF SPOT-5 IMAGE SHOWING ORIGINAL IMAGE (LEFT) AND CLASSIFIED FOREST DISTURBANCE (RIGHT).....	58
FIGURE 3.4 RESULTS OF DISCRIMINANT ANALYSES FOR AGE CLASSIFICATION OF REGENERATING BOREAL FOREST WITH 5 YEAR AGE CLASSES; ORIGINAL CLASSIFICATION ACCURACY IN ITALICS, CROSS VALIDATED ACCURACY IN BOLD.....	60
FIGURE 3.5 RESULTS OF DISCRIMINANT ANALYSES FOR AGE CLASSIFICATION OF REGENERATING BOREAL FOREST WITH 5 YEAR AGE CLASSES TO AGE 19 AND 10 YEAR AGE CLASSES TO AGE 50.....	62
FIGURE 4.1 STRUCTURAL COMPLEXITY INDEX VALUES (PREDICTED) FOR ALL FIELD SAMPLED STANDS VERSUS AGE CLASS. SAMPLED POLYGONS ARE SEGMENTS WITHIN EACH STAND; STANDARD ERROR OF THE MEAN WAS 0.06.....	72
FIGURE 4.2 AGE CLASS VERSUS THE MEAN RESOURCE SELECTION FUNCTION FOR FALL FEMALE GRIZZLY BEARS. SAMPLED POLYGONS ARE SEGMENTS WITHIN EACH STAND; STANDARD ERROR OF THE MEAN WAS 0.08.....	77

## LIST OF ABBREVIATIONS

ASL	Above sea level
BA	Basal Area
BA <sub>sd</sub>	Basal Area standard deviation over each stand
BA <sub>avg</sub>	Basal Area mean over each stand
CASI	Compact Airborne Spectrograph Imager
CD	Crown Diameter
CD <sub>sd</sub>	Crown Diameter standard deviation over each stand
CD <sub>avg</sub>	Crown Diameter mean over each stand
DBH	Diameter at Breast Height
DBH <sub>sd</sub>	Diameter at Breast Height standard deviation over each stand
DBH <sub>avg</sub>	Diameter at Breast Height mean over each stand
FMF	Foothills Model Forest
Landsat ETM+	Landsat Satellite 7 Enhanced Thematic Mapper Plus
Landsat TM	Landsat Satellite 5 Thematic Mapper
LiDAR	Light Detecting and Ranging
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
NIR	Near infrared reflectance
RMSE	Root mean square error
SASI	Shortwave Airborne Spectrograph Imager
SAVI	Soil-adjusted Vegetation Index
SCI	Structural Complexity Index
SD	Stem Density
SD <sub>avg</sub>	Stem Density mean over each stand
SPOT-5 HRG	Système pour l'Observation de la Terre, High Resolution Geometric
SPOT-4 HRV-IR	Système pour l'Observation de la Terre, High Resolution Visible-Infrared
SWIR	Shortwave infrared reflectance

## **1.0 INTRODUCTION AND OVERVIEW**

Resource extraction activities in previously remote areas potentially increase landscape fragmentation (Mattson *et al.*, 1996). Although fragmentation is not always considered negative in terms of wildlife habitat (Nielsen *et al.*, 2004b), it increases human activity within remote areas (Mattson *et al.*, 1996; Craighead *et al.*, 1995), thus endangering vulnerable wildlife species to their largest predator (Craighead *et al.*, 1995). This is currently a problem in the Central Rockies Ecosystem in west-central Alberta as resource management practices expand further into grizzly bear (*Ursus arctos* L.) homeland ranges (Nielsen *et al.*, 2004a, 2004b; Wielgus and Vernier, 2003; Gibeau *et al.*, 2002; Mattson *et al.*, 1996). Not only is it difficult for these bears to find areas where they can be secure (Nielsen *et al.*, 2004a; Mattson *et al.*, 1996; Craighead *et al.*, 1995), but they must also rediscover old habitats within the newly fragmented area (Nielsen *et al.*, 2004b, 2004c).

Recently, grizzly bears in the Foothills Model Forest near Hinton, Alberta, were found to select clear cut areas of different age ranges as habitat (Nielsen *et al.*, 2004b). They also selected or avoided certain cut areas depending on the site preparation process employed, leading Nielsen *et al.* (2004c) to conclude that availability of attractive food sources in a cut block varied with both age and site preparation. The data used in these studies were obtained using a comprehensive Geographic Information System (GIS) of forestry inventory parameters--obtained from the Foothills Model Forest--over an area of approximately 10,000 square kilometres. A GIS can be a useful tool, when regularly

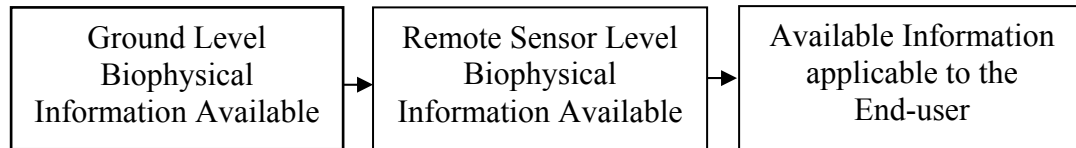
updated; however, such substantial area coverage is rarely the case, due to cost and time constraints of ground level field data collection. Additionally, large areas do not necessarily coincide with forest management units of large forest products companies, resulting in remote areas without available information.

The grizzly bear range and the area of interest in population viability analysis can be greater than 10,000 square kilometres (McDermid, 2005; Gibeau *et al.*, 2002, Nielsen *et al.*, 2003) rendering any effort to improve a GIS using typical field methods unfeasible. Satellite remote sensing, however, is an alternative for classifying large areas at multiple spatial and temporal resolutions (McDermid, 2005). Using remote sensing to incorporate age and site preparation with cut area detection would not only be helpful for wildlife habitat research, but also to large scale mapping projects, such as the Earth Observation for Sustainable Development of Forests (Wulder *et al.*, 2003), which need current and accurate land cover from every area of Canada.

### ***1.1 Ground Level Features of Harvested Areas in the Boreal Forest***

In order to determine the information content of a remotely sensed image, it must not only be clear what is being observed at the ground level, but also what can be detected from the platform level. Once these parameters have been identified, the available information is filtered to encompass only those variables of importance to the end-user. From these data, mapping products can be created for the end-users—e.g. for use in habitat analysis. This thesis will discuss the importance and relationship between these biophysical parameters, hierarchically—ground data, remote sensor potential, user needs, and possible products for harvest type, structure, site preparation, and scarification (**Figure 1.1**). Grizzly bears may select clear cuts based on successional

stage or age and site preparation methods used (Nielsen *et al.*, 2004b); therefore, this research is appropriately oriented towards detecting those two important factors.



**Figure 1.1 Level of Measurable information content of cut blocks**

At the ground level, harvested and regenerating areas are very conspicuous. As can be expected, they are characterized by an unnatural polygonal shape, lack of canopy (in the case of clear cuts), and even-aged re-growth species of similar height and structure (in regenerating areas). Additionally, clear cut areas may have site preparation treatments applied that have either little or large impact on the soil, creating a different micro-environment for incoming seeds or silviculture practices. Hence, there is a need to identify the variables which are observable from the ground level in harvested and regenerating areas, and how these change once the area is subjected to different site preparation treatments.

### **1.1.1 Harvested Areas**

Cut areas within a forested matrix are not necessarily similar as they result from a variety of methods foresters use to harvest the targeted tree species. Clear cuts are the most prominent type of forest harvest method within the FMF boreal forest region. Clear-cut areas are large (generally  $\geq 2$  ha) conspicuous areas of completely cleared forest (Vankat, 2002). There is a layer of woody debris, logs, and soil (duff layer) through which many herbaceous and shrubby species find it difficult to establish and grow slowly (Binkley, 1999). These areas are disturbed further via compaction resulting from mechanical site preparation for improved planting conditions, or they are

eventually overcome by natural vegetation. In cuts that have occurred in the last fifteen years, small (approximately 100 square metres) treed clusters called “leave areas” are left behind as a result of new provincial government policies (Alberta Sustainable Resource Development, 2006). This thesis will deal with detecting and delineating different levels of clear cut harvesting and the nature of regeneration (i.e. structural attributes) within these areas to offer a more detailed description of grizzly bear habitat features.

Clear cut areas in Alberta were not extensively monitored before the 1980’s (McKendrick *et al.*, 2001), leaving behind a legacy of “ageless” regenerating growth. With the introduction of regulatory regeneration for environmental assessment, forest management planning, and computer based mapping systems such as the GIS, harvesting, preparing, and planting activities needed to be submitted to the government for future cutting permits. In addition to mapping these important activities, foresters mapped other attributes of the area using both current and historical aerial photography, giving rise to forest inventory databases. These databases are a set of multi-year data with the purpose of recording several components of the managed forest. The data are collected by a variety of industrial and academic professionals in order to monitor all processes occurring in this eco-region and use resources responsibly. The involvement of many facilities (university, government, forest products company) in the acquisition of these parameters unfortunately results in information, which may not correspond, be inaccurate, or may not exist. This lack of correspondence is a result of methods used, time of procurement, and issues of miscommunication. However, although these databases are not comprehensive or annually updated for larger areas due to cost and

practicality, they do offer an important listing of data that can be used as a basis for future study (e.g. Alberta Vegetation Inventory, **Table 1.1**). In order to quantify or compare cut and regenerating areas with old growth forested area and other disturbed or non-forested areas, other methods of comprehensive data collection must be used, indicating the importance of remote sensing as an alternative.

<b>Table 1.1 Alberta Vegetation Inventory: Listing of Biophysical Parameters of interest to forestry research</b>	
<b>Biophysical Parameter</b>	<b>Description</b>
Vegetation cover (more detailed for > 6% coverage)	detailed from vegetation surveys (herbaceous or shrub non forest)
Timber productivity rating	Based on height and age of dominant and co-dominant trees to determine site index that is then classified as good, medium, fair, or unproductive
Crown closure	Rated as A (6-30%), B (31-50%), C (51-70%), D (71-100%)
Height	Determined through field measurements and recorded to the nearest metre: average of dominant and co-dominant trees
Species composition	Five (max) species in decreasing order of crown closure within the plot
Age of the stand	Based on its origin or birth year; adjustment factors are used to account for different growth rates among species
Stand structure / understory	Single, two storey, horizontal, and complex stands: aid in volume measurement.
Non-vegetated land	Includes anthropogenic (industry) and natural (rock, lakes, sand)
Moisture regime	Interpreter's assessment is based on plant indicators or environmental properties, including soil properties
Stand condition and extent	Indicates burn, clear-cut, disease, windfall, kill, snags, scattered timber; also looks at snag density and effect on crown closure
Treatment	Site preparation and silviculture, thinning, irrigation, grazing area
Non-vegetated – linear clearing	major highways; Seismic lines, pipelines, and trails are too small to be delineated and have “no reduction of crown closure rating”
Topography	Aspect, slope, and elevation
Residual trees and leave areas	Can help determine the resulting “natural” succeeding species of the disturbed area

*Source: Alberta Environmental Protection, 1991*

### **1.1.2 Site Preparation Methods**

The purpose behind mechanical preparation of a cut site is to help create an environment more conducive for the regeneration of timber species that will be seeded, planted, or left to regenerate naturally. It follows then, that different site preparation

processes will be used to promote the health and growth of different tree species. **Table 1.2** is a synthesis of different site preparation practices that occur in the Foothills Model Forest (Nielsen *et al.*, 2004b) including the purposes they serve and resulting features that indicate their use (Coates and Haeussler, 1987; National Forestry Database Program, 2004).

<b>Table 1.2 Site preparation practices in Alberta and resulting land features</b>		
<b>Process</b>	<b>Procedure</b>	<b>Feature</b>
Modified Blade	Also called the Beales blade, a toothed blade is mounted on the front end of the prime mover. It does not remove much topsoil, rather piles and bunches slash and brush to create planting lines.	Exposes mineral soil and creates lines of brush piles along the perimeter of the cut area
Bracke	Using a toothed set of four tines pulled behind a prime mover, these objects create patches of varying size, length and frequency depending on wheels used. Sometimes used with inverted mounding, turning the dirt over at set intervals.	Produces scarified patches 2.5 m wide and 60-80 cm long; these can be wider/longer and less frequent with different equipment changes or with mounding options
Donaren Mound	Large or small amounts of debris and soil are overturned using large toothed disc wheels.	Small mounds of debris regularly distributed throughout the site
Excavator Mound		Larger mounds of debris and upturned soil at fewer points throughout the site
Light Drag	Large or small anchor chains with bars welded to them are dragged through the duff layer.	Thin lines of exposed soil in a regular pattern, generally parallel
Heavy Drag	Use depends on the depth of the duff and debris in the harvest block.	Thick deeper lines of exposed soil, also parallel
Drag shark fin barrels	Barrel with blades on it, makes big gauges into the dirt	Short diagonal gauges in the parallel line that its being pulled
Disc trencher	Similar to agricultural tillage. Done in winter time when soil is frozen	Creates 2 big parallel furrows with side cars material forming two berms
Crossley Plough	Similar to agricultural tillage. Done in winter time when soil is frozen	Creates different levels of smaller furrows
C&H Plough		
C&S Ripper		
Natural Regeneration	Allow special “leave” areas and residuals to act as a seed bank and naturally regenerate the cut area	Full layer of debris, log piles, some mounding (depending upon area)

### ***1.2 Remote Sensing of Harvested Areas***

As is expected, with increasing distance from an object, less detail is noticeable and the accuracy of feature detection declines. In the case of remote sensing, many



different methods have been created to detect different variables and/or different features with higher degrees of accuracy for use in quantitative analysis. **Table 1.3** outlines a similar list of biophysical parameters that were summarized in **Table 1.1**, highlighting the best methods established to detect these variables using remote sensing imagery.

<b>Table 1.3 Examples of biophysical variables measurable with selected instruments</b>			
Parameters to be measured	Dataset Used	Methods	References
Vegetation cover (herb & shrub) - general	Landsat TM and ETM+	Vegetation indices such as SAVI, or NDVI; texture analysis; pansharpener	Hall <i>et al.</i> (2003); Fox <i>et al.</i> (2002)
Leaf Area Index	Landsat TM; CASI; AVHRR	Texture and NDVI; SAVI; VI3 (similar to NDMI)	Wulder <i>et al.</i> (1998); Hall <i>et al.</i> (2003); Eklundh <i>et al.</i> (2003); Boyd <i>et al.</i> (2000)
Structure	Landsat TM; SPOT-4; LiDAR	Structural Complexity Index; canonical correlation analysis	Cohen and Spies (1992); Hansen <i>et al.</i> (2001a); Lefsky <i>et al.</i> (2005)
Harvest Type (Full or partial)	Landsat TM	Image differencing using NDMI or Tasseled Cap	Wilson and Sader (2002); Franklin <i>et al.</i> (2001a); Sader <i>et al.</i> (2003); Healey <i>et al.</i> (2005)
Area and Shape Cut	Landsat TM and ETM+	recognition, NDMI; Tasseled cap; regression estimator methods	Flanders <i>et al.</i> (2003); Wilson and Sader (2002); Franklin <i>et al.</i> (2001a); Deppe (1998)
Tree health within a regenerating block	Landsat TM; CASI	Tasseled Cap; semivariograms of image texture	Franklin <i>et al.</i> (2001b); Lévesque and King, (1999, 2003)
Debris from logging	Landsat TM	Fractal dimension and Moran's I on multiscale data	Read, 2003; Jusoff and D'Souza (1996)
Site Preparation	--	--	--
Silviculture	--	--	--
Species cover	IKONOS; Landsat TM	spectral and texture analysis; regression	Franklin <i>et al.</i> (2001b); Gerylo <i>et al.</i> (2002)
Stand age	Landsat ETM+; IKONOS; CASI; SPOT HRV	Multivariate regression; texture analysis; artificial neural networks with ancillary data	Wulder <i>et al.</i> (2004); Franklin <i>et al.</i> (2001b); Jensen <i>et al.</i> (1999); Kimes <i>et al.</i> (1996, 1999)
Height	Landsat TM; CASI; LiDAR; aerial photography	Spectral texture analyses with supervised classification; object based classification	Franklin <i>et al.</i> (2003); Coops <i>et al.</i> (2004); Lefsky <i>et al.</i> (1999, 2005); Tuominen and Pekkarinen (2005)
Diameter at breast height (DBH)	Landsat TM	Inferred from stem density using spectral texture analyses	Franklin <i>et al.</i> (2003)
Moisture levels in the canopy and soil	Landsat ETM+; Radar	Tasseled cap index; NDVI; NDWI; SAR	Franklin <i>et al.</i> (2001a); Moran <i>et al.</i> (2004)
Roads and equipment impacts	Landsat TM; IKONOS	Fractal dimension and Moran's I on multiscale data	Read (2003)
Stem density	Landsat TM	Spectral texture analyses	Franklin <i>et al.</i> (2003)
Residual trees and leave areas	Landsat ETM+; Landsat TM	NDMI; Tasseled cap	Wilson and Sader (2002); Franklin <i>et al.</i> (2001a)

Many of the parameters listed in **Table 1.3** are only valuable to measure once the area in question, i.e. harvested areas, can be detected. Unfortunately, harvested areas in the Central Rocky Mountains currently are not readily identified using most satellite sensor image classification techniques as they are neither uniform nor unique to many classification algorithms (McDermid, 2005). These areas are, however, visually discernible to the analyst due to their unnatural shape and brighter reflectance values in comparison to natural forest stands (Cohen *et al.*, 1998). This situation led Flanders *et al.* (2003) to suggest that *eCognition* object based software may be able to classify cut blocks with a higher level of accuracy (70-90%) than previous methods, due to its ability to quantify shape at the classification stage. Even though *eCognition* is available many analysts still find masking cut block areas imported from a GIS database to be more accurate and less time consuming (e.g. McDermid, 2005; Souza *et al.*, 2003; Cohen *et al.*, 1998), which returns us to the question of GIS database reliability and previous methodology.

Earlier cut block detection methods almost exclusively focused on Landsat TM imagery and several image differencing methods (Thomas *et al.*, 1993; Green *et al.*, 1994). For that reason, Cohen *et al.* (1998) compared both merged and simultaneous image differencing with unsupervised classification of Landsat-based tasselled cap index components in the Pacific Northwest to determine the most accurate. The resulting harvest map was created with 90%+ accuracy using the merged differencing technique, although the results are questionable as pixels located at forested/non-forested boundaries were excluded from the error analysis. Franklin *et al.*, (2000, 2001a) also utilized merged image differencing with the Landsat-based tasselled cap components,

specifically wetness, to determine the rate of change in the Fundy Model Forest. They found that the wetness measure was very sensitive in cutovers and to even less distinctive changes, such as herbicide application in recent cutovers and commercial thinning treatments.

To test image differencing methods with different vegetation indices, Wilson and Sader (2002) compared the Normalized Difference Vegetation Index (NDVI) with Normalized Difference Moisture Index (NDMI). They found the NDMI index also to be more sensitive to cut areas (both cleared and partial), reinforcing the idea from Franklin *et al.* (2001a) that the moisture level of the cut area changes with removal of the canopy. This change is also greater than the change in other Tasselled Cap Components (brightness and greenness) and more recently the Tasselled Cap Wetness component has been found to be significantly correlated with the NDMI (Healey *et al.*, 2005) in the detection of forest disturbance. However, having a longer historical record in imagery to which an image differencing procedure can be applied is vital for detecting the cut blocks. Unfortunately, long (more than 5 years) historical data sets can be expensive and are not available for all sensors.

Recent research has also indicated that the spatial resolution of Landsat ETM+ (25m) limits the level of forest canopy damage detection in the Amazon rainforest (Asner *et al.*, 2002) as the imagery is L-resolution, i.e. pixels are larger than the forest structural features the study had wanted to detect. For that reason, higher spatial resolution sensors (either orbital or airborne) must be at the forefront of future research. In addition, they must include a middle or short wave infrared band (such as SPOT-5 or

Compact Airborne Spectrograph Imager [CASI]) to include the wetness or moisture components determined necessary in the previous discussion.

### ***1.3 Remote Detection of Site Preparation Methods***

To date, site preparation methods and their impacts on the ground within a cut block have not received attention in the field of remote sensing. This situation will, however, change as new applications are considered. For example, discerning the site preparation process utilized at a clear cut has been recognized as very useful information for wildlife habitat analysis (Nielsen *et al.*, 2004b, 2004c). Jusoff and D'Souza (1996) were able to visually discern six levels of soil disturbance of logged areas in a SPOT/HRV image, suggesting that statistical classification of high spatial resolution imagery may result in a strong relationship between high impact preparation techniques (such as excavator mound or disc trencher) and optical imagery analysis. The relationship between spectral response patterns observed in pixels that are larger than the individual features that characterize the site preparation treatment and the amount of soil exposure, residual vegetation, and shadow fraction, may provide an indication of the appropriate method of extracting this information from the image using classification or regression techniques.

The main characteristics of clear cut areas that have undergone site preparation are outlined in **Table 1.2**. These include mounding, regular patterns, exposed soil, and plough furrows. It is the latter characteristic that creates a possible link with agricultural tillage practices. Agricultural tillage practices have only recently been researched using high resolution remote sensing. Viña *et al.* (2003) detected two tillage practices (conventional and conservation) with IKONOS imagery using a logistic regression

model on generated PCA components of the NDVI index. Thus, one would expect that the regular pattern of exposed soil created by several scarification procedures (trenching, heavy/light drag) would show a textural difference from a harvested area left for natural regeneration. In Amazonia, Read (2003) conducted a study on logging effects and the impact of machinery and roads on harvested areas using IKONOS and Landsat 7 ETM+. Results showed that measurements of spatial auto-correlation (Moran's I index) and fractal Dimension (D) were more effective than a first order texture analysis to detect high impact logging activities on IKONOS than on TM. Also using IKONOS imagery, Franklin *et al.* (2001b) discovered that large moving windows and second order texture values that describe the spatial co-occurrence homogeneity of the window were very effective in distinguishing between species composition and structure of a forested stand. This measurement simply quantifies the spatial relationship that grey tones of pixels exhibit over a specified area or pixel window. It could then be expected, that a second-order texture value, applied to harvested areas may also show differences attributing to tillage. These studies suggest that the size of the resulting features from processes such as tilling or ploughing may be detected in relatively coarse resolution satellite imagery (e.g. Landsat and SPOT), but that higher accuracy can likely be obtained using high spatial resolution imagery (< 4m).

#### ***1.4 Remote Sensing for User-oriented Habitat Mapping***

Several studies have focused on connecting remotely sensible biophysical variables of forested and non-forested area to descriptive values required by end-users conducting wildlife habitat research (e.g. Popplewell *et al.*, 2003; Betts *et al.*, 2003; Fox *et al.*, 2002; Franklin *et al.*, 2002; Hansen *et al.*, 2001b; Craighead *et al.*, 1995). The

targeted biophysical variables are based on established habitat use by the species. Two more prominent measures of boreal forest grizzly habitat are stand structure and age (Nielsen *et al.*, 2004b; Wielgus and Vernier, 2002; Craighead *et al.*, 1995). Stand structure is generally defined as the horizontal and vertical arrangement of both overstory and understory trees within a forested stand (Vankat, 2002; Binkley, 1999). Both age and stand structure have been derived using different inferential statistical techniques such as multivariate regression (Wulder *et al.*, 2004; Gerylo *et al.*, 2002), first- and second-order spatial analyses, e.g. for texture (Franklin *et al.*, 2001b), or a hybrid decision tree that includes maximum likelihood classification, brightness differencing, and spatial/contextual rule-bases (Hansen *et al.*, 2001b) (see also **Table 1.3**). A review of the most accurate and current methods used to detect both stand age and structure follow.

One of the more elusive yet highly desired descriptors is stand age. The equivocal nature of this parameter is a result of confounding effects caused by many eco-region specific variables that do not allow methodology to move smoothly across boundaries. Such effects include slope (degree, altitudinal and directional), moisture regime, soil class, prevailing climate, local herbaceous and shrub vegetation cover, and species composition of the overstory (Sabot *et al.*, 2002; Nielsen *et al.*, 2004b,c). It may be thus more informative to use a model that describes the successional stage of a stand and includes many if not all of the previously listed variables.

To view the relationships between stand level variables and age, Sabot *et al.* (2002) used Spectral Mixture Analysis with Landsat TM imagery to look at end members (akin to residuals) of shadowed pixels. Their results were able to show that as

the clear-cuts re-grow, green vegetation increases and non-photosynthetic material decreases in the shadow. Although, age was classed (young, regenerating, old growth), it was not uniquely determined as there was an increased uncertainty of age with increased re-growth. This methodology, although intuitive, involves too much field work, and a very tedious and meticulous analysis thus, there would be no cost saving benefits in an application based project. Gerylo *et al.* (2002) used lower cost field sampling (air) and Landsat TM and was able to infer forest age and crown closure over homogeneous jack pine and spruce stands. Using multivariate regression over the spectral data ( $R^2 = 0.73$ ) where the best bands for distinguishing young versus mature forest were the near infrared and shortwave infrared bands because of greater shadowing effects. Again, Gerylo *et al.* (2002) were unable to detect age class ranges that would be applicable to wildlife studies or forest inventory information, which require a maximum age range of 20 years per class (e.g. BC Ministry of Forests, 2001). In addition, pure species stands, although they do occur more readily throughout the managed boreal forest, are not as numerous as mixed stands. Thus more information is needed in order to better understand the relationship between age and the structure of the forest.

That said, stand age classification has been achieved using simple stepwise multivariate regression with Tasselled cap components ( $R^2 = 0.68$ ) and Landsat 7 Enhanced Thematic Mapper Plus [ETM+] (Wulder *et al.*, 2004), but data from this satellite are currently unavailable over large areas as only one fifth of each scene (approximately 3000 km<sup>2</sup>) is usable. In addition, the standard error (2.4 years) was calculated to be higher than the one year interval proposed. Both Kimes *et al.* (1996) and Jensen *et al.* (1999) attempted to extract forest age using the neural network

classification techniques and Landsat TM imagery with some measure of success. However, neural networks are highly overdeveloped classification systems that often do not work well across eco-regions. This situation suggests not only that the information content of other satellite sensors with different spatial resolution and spectral characteristics should be tested, but also that age may not be the indicator that is most important.

Focusing only on structural parameters, Tuominen and Pekkarinen, (2005) tested a very high spatial resolution (VHR) colour infrared photography dataset to determine if height, diameter at breast height (DBH), basal area (BA), and volume (four major indicators of structure) could be predicted. Instead of focusing on pixel-level classification, they used an alternative to complex object based classification, i.e. a square window of NDVI pixels were extracted over the objects of interest. Second order textural measures of contrast, correlation and homogeneity showed the highest correlations with the biophysical parameters using the 0.5m dataset over scaled up to 1-2m datasets, similar to results experienced by Levesque and King (2003). This is in contrast, however, to results obtained by Bruniquel-Pinel and Gastellu-Etchegorry (1998) who had difficulty extracting reliable texture information in relation to forest canopy structure over actual high spatial resolution datasets (RAMI, 1.67m) as compared with simulated images (same resolution). These anomalies with optical datasets have led scientists to exploit newer technology, i.e. Light Detecting and Ranging (LiDAR) imagery, and have been able to view forest stand structure in a 3-D manner. Lefsky *et al.* (2005) created structural indices through canonical correlation analysis of the image and ancillary field data. Three of these indices related directly to



contrasts between mature and old-growth stands and suggests that the utility of this dataset to detect and classify structure and age is very promising. LiDAR datasets are, however, unfeasible for very large areas due to their expense, thus a more cost-effective and less time-consuming technique would be favourable to application based projects. Consequently, methods used by Cohen and Spies (1992) to analyse the overall structure within a stand are more favourable. The utility of their measure, the Structural Complexity Index (SCI), was further expanded by Hansen *et al.* (2001a) in the Revelstoke area of British Columbia. The SCI is created by calculating the first loading of a principal components analysis over stand level forest inventory parameters (basal area, crown diameter, diameter at breast height, and stem density). These values (ranging from -6 to +6 in both studies) were found highly correlated with age of the multicanopy forest and with the Landsat TM Tasseled Cap Wetness component. Although the SCI is based on optical imagery, higher spatial resolution (i.e. between 1-4m) may be useful in detecting this structural feature, which was not attempted using the Landsat TM datasets in either of the previous two studies. The SCI has never been used in simple boreal forests, only for forests of multi-layered canopy. For that reason, the SCI may still be helpful when dealing with differences in regenerating forest and should be tested. Thus, the successional level of a regenerating stand needs not only to be defined by the specific characteristics inherent in the eco-region, but also should be targeted for study. The value of the SCI could be used in a model to predict the corresponding age typical for the northern boreal forest.

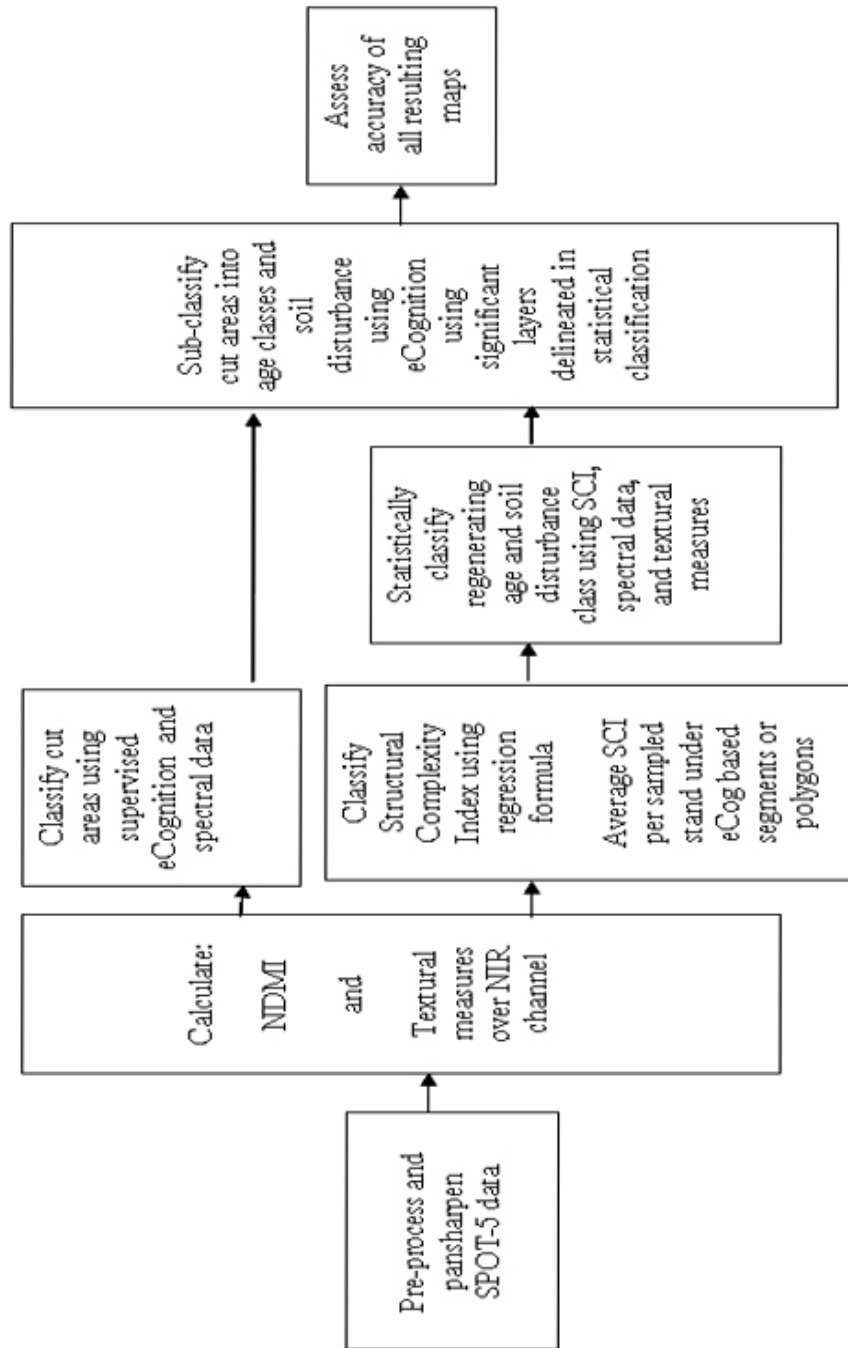
### ***1.5 Resulting Research Objectives***

The research questions addressed in this thesis are based on an attempt to complete our understanding of the level of information in boreal forest cut block areas that can be obtained by satellite remote sensing. The above discussion suggests that a combination of a vegetation index containing a strong moisture element, such as the NDMI or SWIR band in association with object-based classification, will yield information rich results discerning cut areas within a single SPOT-5 image with a spatial resolution of 10m for multispectral data and 2.5m for panchromatic data. Once detected, applying first and second order texture analysis measures may help to infer site preparation practices performed in each area, although these procedures may only be reliable for the highest spatial resolution data, i.e. pansharpened SPOT-5 data. By using the structural attributes or an index such as the SCI, spectral, and textural data with the classified images, these relationships may prove even stronger or help indicate other parameters of use to wildlife biologists in discerning grizzly bear habitat. The possible products to be created are those resulting from need expressed by the previous discussion. Specifically, this thesis:

- i) establishes the relationship between the Structural Complexity Index, forest cutover age class, and site preparation practices and creates models which predict both cutover characteristics from the available spectral response and textural patterns;
- ii) tests the ability of eCognition (object-based image processing software) to detect cut blocks with a high level of accuracy using high spatial resolution pansharpened SPOT-5 imagery.

## ***1.6 Organization of Thesis***

This thesis has been divided into four parts based on the previous literature review and overview of the research problem. Two significant research manuscripts have resulted from the analysis. The first manuscript (Chapter 2.0) is based on estimating stand structure using the Structural Complexity Index within the boreal forest. As indicated previously, the SCI has been used only with complex forested systems. Testing this index within a simpler forest and modeling it over an image are two important methodological contributions that deserve their own elaboration. The second manuscript (Chapter 3.0), however, is based on cut block classification, and subsequent age and site preparation classification using texture and spectral data. It is linked with the first paper in that it also adds the predicted SCI to the model to test if this addition is significant. Chapter 3.0 addresses a different audience than the first, in that it applies remote sensing methods to habitat modeling. Furthermore, the overall contribution can be considered in two dimensions: the first to remote sensing science, and the second to wildlife habitat analysis. Lastly, a fourth chapter focused on the application of this work to wildlife habitat analysis follows where applications to current research and limitations of the study are discussed. A flow chart of tasks has been included to give the reader a clear vision of the focus and direction of this research (**Figure 1.2**).



**Figure 1.2 Conceptual framework of the classification process**

## 1.7 References

- Alberta Environmental Protection (1991). Alberta Vegetation Inventory Standards Manual, Version 2.1. Resource Data Division, Data Acquisition Branch.
- Alberta Sustainable Resource Development (2006). Alberta timber harvest planning and operating ground rules framework for renewal. *Public Lands and Forests Division Forest Management Branch*, Published February 2006.
- Asner, G. P., Keller, M., Pereira, R., and Zweede, J. C., 2002. Remote sensing of selective logging in Amazonia: Assessing limitations based on detailed field observations, Landsat ETM+, and textural analysis. *Remote Sensing of Environment*, **80**, 483-496.
- Betts, M. G., Franklin, S. E., and Taylor, R. G., 2003. Interpretation of landscape pattern and habitat change for local indicator species using satellite imagery and geographic information system data in New Brunswick, Canada. *Canadian Journal of Remote Sensing*, **33**, 1821-1831.
- Binkley, D. 1999. Disturbance in Temperate Forests of the Northern Hemisphere. In Ecosystems of the World 16: Ecosystems of Disturbed Ground, L.R. Walker ed., Elsevier: New York.
- Boyd, D. S., Wicks, T. E., and Curran, P. J., 2000. Use of middle infrared radiation to estimate the leaf area index of a boreal forest. *Tree Physiology*, **20**, 755-760.
- Bruniquel-Pinel, V. and Gastellu-Etchegorry, J.P., 1998. Sensitivity of texture of high resolution images of forest to biophysical and acquisition parameters. *Remote Sensing of Environment*, **65**, 61-85.
- Coates, D. and Haeussler, S. 1987. A guide to the use of mechanical site preparation equipment in north central British Columbia, 2<sup>nd</sup> Edition. Rev. MacKinnon, A., Bedford, L., and Maxwell, J. Government of Canada: Northern Silviculture Committee and Canadian Forestry Service.
- Cohen, W. G., Fiorella, M., Gray, J., Helmer, E., and Anderson, K. 1998. An efficient and accurate method for mapping forest clearcuts in the Pacific Northwest using Landsat imagery. *Photogrammetric Engineering and Remote Sensing*, **64**, 293-300.
- Cohen, W. B. and Spies, T. A., 1992. Estimating structural attributes of Douglas-Fir / Western Hemlock forest stands from Landsat and SPOT Imagery. *Remote Sensing of Environment*, **41**, 1-17.
- Coops, N. C., Wulder, M. A., Culvenor, D. S., and St-Onge, B., 2004. Comparison of forest attributes extracted from fine spatial resolution multispectral and lidar data. *Canadian Journal of Remote Sensing*, **30** (6), 855-866.
- Craighead, J.J., Sumner, J.S., and Mitchell, J.A. 1995. The Grizzly Bears of Yellowstone: Their ecology in the yellowstone ecosystem, 1959-1992. Island Press: Washington, D.C.

- Deppe, F., 1998. Forest area estimation using sample surveys and Landsat MSS and TM data. *Photogrammetric Engineering & Remote Sensing*, **64**, 285-292.
- Eklundh, L., Hall, K., Eriksson, J. A., and Pilesjö, P., 2003. Investigation of the use of Landsat thematic mapper data for estimation of forest leaf area index in southern Sweden. *Canadian Journal of Remote Sensing*, **29** (3), 349-362.
- Flanders, D., Hall-Beyer, M., and Pereverzoff, J., 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. Technical note in: *Canadian Journal of Remote Sensing*, **29** (4), 441-452.
- Fox, L., Garrett, M. L., Heasty, R., and Torres, E., 2002. Classifying wildlife habitat with pan-sharpened Landsat 7 Imagery, Proceedings, *ISPRS Commission I Symposium*, Volume 4, Pecora 15/Land Satellite Information, Denver, Colorado, USA, November 10-15.
- Franklin, S. E., Hall, R. J., Smith, L., and Gerylo, G. R. 2003. Discrimination of conifer height, age and crown closure classes using Landsat-5 TM imagery in the Canadian Northwest Territories. *International Journal of Remote Sensing*, **24** (9), 1823-1834.
- Franklin, S. E., D. R. Peddle, J. A. Dechka, and G. B. Stenhouse, 2002, Evidential reasoning using Landsat TM, DEM, and GIS data in support of grizzly bear habitat analysis, *International Journal of Remote Sensing*, **23**(21), 4633-4652
- Franklin, S. E., Lavigne, M. B., Moskal, L. M., Wulder, M. A., and McCaffrey, T. M., 2001a. Interpretation of forest harvest conditions in New Brunswick using Landsat TM enhanced wetness difference imagery (EWDI). *Canadian Journal of Remote Sensing*, **27**, 118-128.
- Franklin, S. E., Wulder, M. A., and Gerylo, G. R., 2001b. Texture analysis of IKONOS panchromatic data for Douglas-fir forest age class separability in British Columbia. *International Journal of Remote Sensing*, **22** (13), 2627-2632.
- Franklin, S. E., Moskal, L. M., Lavigne, M., and Pugh, K. 2000. Interpretation and classification of partially harvested forest stands in the Fundy Model Forest using multitemporal Landsat TM digital data. *Canadian Journal of Remote Sensing*, **26**, 318-333.
- Gerylo, G. R., Hall, R. J., Franklin, S. E. and Smith, L., 2002. Empirical relations between Landsat TM spectral response and forest stands near Fort Simpson, Northwest Territories, Canada. *Canadian Journal of Remote Sensing*, **28** (1), 68-79.
- 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
- Green, K., Kempka, D., and Lackey, L., 1994. Using remote sensing to detect and monitor land-cover and land-use change. *Photogrammetric Engineering & Remote Sensing*, **60**, 331-337.

- Hall, R. J., Davidson, D. P., and Peddle, D. R., 2003. Ground and remote estimation of leaf area index in Rocky Mountain forest stands, Kananaskis, Alberta. *Canadian Journal of Remote Sensing*, **29** (3), 411-427.
- Hansen, M. J., Franklin, S. E., Woudsma, C., and Peterson, M., 2001a. Forest structure classification in the North Columbia Mountains using the Landsat TM Tasselled Cap Wetness Component. *Canadian Journal of Remote Sensing*, **27** (1), 20-32.
- Hansen, M. J., Franklin, S. E., Woudsma, C. G. and Peterson, M., 2001b. Caribou habitat mapping and fragmentation analysis using Landsat MSS, TM, and GIS data in the North Columbia Mountains, British Columbia, Canada. *Remote Sensing of Environment*, **77**, 50-65.
- Healey, S. P., Cohen, W. B., Zhigiang, Y. and Krankina, O. N., 2005. Comparison of Tasselled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment*, **97**, 301-310.
- Jensen, J. R., Qiu, F., and Ji, M., 1999, Predictive modeling of coniferous forest age using statistical and artificial neural network approaches applied to remote sensor data. *International Journal of Remote Sensing*, **20**(14), 2805-2822.
- Jusoff, K. and D'Souza, G., 1996. Quantifying disturbed hill dipterocarp forest lands in Ulu Tembeling, Malaysia with HRV/SPOT images. *ISPRS Journal of Photogrammetry & Remote Sensing*, **51**, 39-48.
- Kimes, D. S., Holben, B. N., Nickeson, J. E., and McKee, W. A., 1996, Extracting forest age in a Pacific Northwest Forest from Thematic Mapper and topographic data. *Remote Sensing of Environment*, **56**, 133-140.
- Lefsky, M. A., Hudak, A T., Cohen, W. B., and Acker, S. A., 2005. Patterns of covariance between forest stand and canopy structure in the Pacific Northwest. *Remote Sensing of Environment*, **95**, 517-531.
- Lefsky, M. A., Harding, D., Cohen, W. B., Parker, G., and Shugart, H. H., 1999. Surface Lidar remote sensing of basal area and biomass in deciduous forests of Eastern Maryland, USA. *Remote Sensing of Environment*, **67**, 83-98.
- Lévesque, J. and King, D. J., 2003. Spatial analysis of radiometric fractions from high-resolution multispectral imagery for modelling individual tree crown and forest canopy structure and health. *Remote Sensing of Environment*, **84**, 589-602.
- Lévesque, J. and King, D. J., 1999. Airborne digital camera image semivariance for evaluation of forest structural damage at an acid mine site. *Remote Sensing of Environment*, **68**, 112-124.
- Mattson, D.J., Herrero, S., Wright, R.G., and Pease, C.M. 1996. Science and management of Rocky Mountain Grizzly Bears. *Conservation Biology*, **10** (4), 1013-1025.
- McDermid, G. 2005. PhD thesis Remote estimation of land cover and LAI over large areas for wildlife habitat applications, Faculty of Environmental Studies, University of Waterloo.

- McKendrick, N., Fluet, C., Davidson, D. J., Krogman, N., and Ross, M., 2001. *Integrated resource management in Alberta's boreal forest: opportunities and constraints*. Interim project report 2001-22 for Sustainable Forest Management Network, University of Alberta: Edmonton.
- Moran, M.S., Peters-Lidard, C.D., Watts, J.M., and McElroy, S. 2004. Estimating soil moisture at the watershed scale with satellite-based Radar and land surface models. *A Review in the Canadian Journal of Remote Sensing*, **30** (5), 805-826.
- National Forestry Database Program. 2004. REGEN: A program for reporting regeneration results. [http://nfdp.ccfm.org/regen/index\\_e.php](http://nfdp.ccfm.org/regen/index_e.php). [Last Visited: 29 Oct 2004].
- Nielsen, S. E., Herrero, S., Boyce, M. S., Mace, R. D., Benn, B., Gibeau, M. L., and Jevons, S., 2004a, Modelling the spatial distribution of human-caused grizzly bear mortalities in the Central Rockies ecosystem of Canada. *Biological Conservation*, **120**, 101-113.
- Nielsen, S. E., Boyce, M. S., and Stenhouse, G. B., 2004b, 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., Munro, R. H. M., Bainbridge, E. L., Stenhouse, G. B., and Boyce, M. S., 2004c. Grizzly bears and forestry II. Distribution of grizzly bear foods in clearcuts of west-central Alberta, Canada. *Forest Ecology and Management*, **199** 67-82;
- Nielsen, S. E., Boyce, M. S., Stenhouse, G. B., and Munro, R. H. M., 2003. Development and testing of phenologically driven grizzly bear habitat models. *Ecoscience*, **10** (1), 1-10.
- Popplewell, C., Franklin, S. E., Stenhouse, G. B., and Hall-Beyer, M., 2003, Using landscape structure to classify grizzly bear density in Alberta Yellowhead Ecosystem bear management units, *Ursus*, **14**, 27-34.
- Read, J. M. 2003. Spatial analyses of logging impacts in Amazonia using remotely sensed data. *Photogrammetric Engineering & Remote Sensing*, **69** (3), 275-282.
- Sabol, D. E., Gillespie, A. R., Adams, J. B., Smith, M. O., and Tucker, C. J., 2002. Structural Stage in Pacific Northwest forests estimated using simple mixing models of multispectral images. *Remote Sensing of Environment*, **80**, 1-16.
- Sader, S. A., Bertrand, M., and Wilson, E. H., 2003. Satellite change detection of forest harvest patterns on an industrial forest landscape. *Forest Science*, **49** (3), 341-353.
- Souza, C., Firestone, L., Silva, L.M. and Roberts, D. (2003). Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models. *Remote Sensing of Environment*, **87**, 494-506.
- Thomas, M., Roller, N., Colwell, J., and Kottack, C., 1993. Integrating regional studies of deforestation into a global change context, *Proceedings, 25<sup>th</sup> International*



*Symposium, Remote Sensing and Global Change*, Volume 1, Environmental Research Institute of Michigan, Graz, Austria, 4-8 April, pp. 559-570.

- Tuominen, S. and Pekkarinen, A., 2005. Performance of different spectral and textural aerial photograph features in multi-source forest inventory. *Remote Sensing of Environment*, **94**, 256-268.
- Vankat, J. L., 2002. Boreal and temperate forests. In Encyclopaedia of life sciences. Macmillan Publishers Ltd: [www.els.net](http://www.els.net)
- Viña, A., Peters, A. J., and Ji, L., 2003. Use of multispectral IKONOS imagery for discriminating between conventional and conservation agricultural tillage practices. *Photogrammetric Engineering & Remote Sensing*, **69** (5), 537-544.
- Wielgus, R. B. and Vernier, P. R., 2003. Grizzly bear selection of managed and unmanaged forests in the Selkirk Mountains. *Canadian Journal of Forest Research*, **33** (5), 822-829.
- Wilson, E. H., and Sader, S., 2002, Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment*, **80**, 385-396.
- Wulder, M.A., Skakun, R. S., Kurz, W. A., and White, J. C., 2004. Estimating time since forest harvest using segmented Landsat ETM+ imagery. *Remote Sensing of Environment*, **93** 179-187
- Wulder, M. A., Dechka, J. A., Gillis, M. A., Luther, J. E., Hall, R. J., Beaudoin, A., and Franklin, S. E., 2003, Operational mapping of the land cover of the forested area of Canada with Landsat data: EOSD land cover program. *The Forestry Chronicle*, **79**(6), 1075-1083.
- Wulder, M. A., Ellsworth F. L., Franklin, S. E., and Lavigne, M. B., 1998, Aerial image texture information in the estimation of northern deciduous and mixed wood forest leaf area index (LAI). *Remote Sensing of Environment*, **64**, 64-76.

## **2.0 REGENERATING BOREAL FOREST STRUCTURE ESTIMATION USING SPOT-5 PANSHARPENED IMAGERY**

### ***2.1 Abstract***

Forest structure is an important target variable within the fields of wildlife ecology and remote sensing. Remote sensing has been often suggested as a viable alternative to time consuming field and aerial investigations to determine forest structural attributes. In this study, 44 stands of recently harvested, regenerating, and old growth forest within the Foothills Model Forest in west-central Alberta were selected to test the ability of pan-sharpened SPOT-5 spectral response to classify stand structure. For each stand, a Structural Complexity Index (SCI) was calculated from field data using principal components analysis. To complement the spectral response data set and further increase accuracy, the normalized difference moisture index (NDMI) and three window sizes (5x5, 11x11, and 25x25) of first- (mean and standard deviation) and second-order (homogeneity, entropy, and correlation) textural measures were calculated over the pan-sharpened image. Stepwise multivariate regression analysis was used to determine the best explanatory model of the SCI using the spectral and textural data. The NDMI, first-order standard deviation and second-order correlation texture measures were better able to explain differences in SCI among the 44 forest stands ( $R^2=0.74$ ). The best window size for the texture measures was 5x5, indicating that this is a measure only detectable at a very high spatial resolution. The resulting classified SCI values were comparable to the actual field level SCI ( $R^2=0.70$ ,  $p=0.01$ ) and were limited by the

strong variability within stands. Future research may find this measure useful as either as a separate parameter or as an indicator of forest age for use in wildlife habitat modeling.

## **2.1 Introduction**

Remote sensing of forest structure is of considerable importance to wildlife studies where structural parameters (for example, canopy closure, tree stem density, basal area, crown diameter, and vegetation class) have been shown additive in varied ecological habitat models (Nielsen *et al.*, 2004a,b,c; Betts *et al.*, 2003; Popplewell *et al.*, 2003; Wielgus and Vernier, 2003; Fox *et al.*, 2002; Hansen *et al.*, 2001b; Mattson *et al.*, 1996; Craighead *et al.*, 1995). Grizzly bear (*Ursus arctos L.*) habitat use has long been linked with food availability and security (Nielsen *et al.*, 2004c; Wielgus and Vernier, 2003; Craighead *et al.*, 1995). Nielsen *et al.* (2004b,c) have linked grizzly bear foods to a set of forest stands based on their canopy structure, age, and terrain-related variables. These parameters were obtained from a geographic information system (GIS) database over an area equalling 10,000 square kilometres. Generally, extensive and detailed coverage is not reliable as it is the result of the amalgamation of several datasets generated by differing methods. McDermid (2005) has proven that remote sensing can produce a consistent dataset over a sizeable area (>100,000 square kilometres) thus providing a viable alternative to previous methods.

Exact forest structure estimation is, however, difficult to determine with remotely sensed data due to many environmental factors such as relative location, topography, aspect, soil composition, and water availability (Sabot *et al.*, 2002; Bruniquel-Pinel and Gastellu-Etchegorry, 1998). Consequently, recent remote sensing research has focused on testing a variety of reproducible techniques and imagery in

different forest ecosystems using medium spatial resolution imagery such as SPOT-4 and Landsat TM (e.g. Lefsky *et al.*, 2005; Tuominen and Pekkarinen, 2005; Coburn and Roberts, 2004; Franklin *et al.*, 2003; 2001a; Cohen and Spies, 1990; 1992; 1995). For a more in-depth review, the reader is referred to Lefsky *et al.* (2005). The strongest relationships between forest biophysical parameters and spectral data have occurred with the near infrared (NIR), shortwave infrared (SWIR) bands, or their spectral derivatives. For example, both Franklin *et al.*, (2001a) and Hansen *et al.* (2001a) found a positive relationship between structural maturity of boreal and multiple layer canopy forest and Landsat-5 TM wetness. The normalized difference moisture index (NDMI), a ratio between the NIR and SWIR bands, has been shown capable of delineating partial cutting in the north-eastern USA (Jin and Sader, 2005; Sader *et al.*, 2003; Wilson and Sader, 2002). Moreover, the NDMI and Landsat Tasseled Cap Wetness index were found to be correlated and worked equally well at predicting forest disturbances (Healey *et al.*, 2005). The NDMI has not been tested in the western-central boreal forest of Alberta for structure determination and may prove to be a valuable predictor.

Complex forested areas are defined by increasing structural stand measures, such as height, crown closure, stem density, crown diameter, and basal area. Forest stands may then be best defined by their ‘increased score’ on a structural complexity index (SCI) which is derived by principal components analysis over the typical stand field measurements (diameter at breast height, crown diameter, stem density, and basal area). A single component is extracted to capture most of the variance within the structure of the stand. Cohen and Spies (1992), and Hansen *et al.* (2001a) tested slightly different versions of the SCI in conifer forests in Oregon and British Columbia, respectively, and

found that the SCI was strongly correlated with forest age, height, and crown closure, as well as with medium spatial resolution optical remotely sensed data (individual bands and spectral indices) obtained from SPOT-4 HRV (20m) and Landsat TM (30m) sensor data. These images retain the spectral resolution (i.e. the SWIR band to measure wetness) to estimate the SCI and other, specific biophysical parameters of interest (e.g. Espirito-Santo *et al.*, 2005; Wulder *et al.*, 2004; Gerylo, *et al.*, 2002; Franklin *et al.*, 2001a; 2000; Boyd and Curran, 2000; Kimes, *et al.*, 1996; 1999). However, the structural complexity index and individual forest measures may be mapped with a higher degree of accuracy with higher spatial resolution imagery. Early studies (e.g. Cohen and Spies 1990) suggested that 20m SPOT sensor data could outperform 30m TM data in mapping forest characteristics under certain conditions (but not always – see Franklin 2001c for a more detailed discussion); more recently, IKONOS and several high resolution airborne high resolution datasets have been tested with promising results, particularly when texture measures are introduced (Tuominen and Pekkarinen, 2005; Lévesque and King, 1999; 2003; Franklin *et al.*, 2001b).

Better mapping or classification results with higher spatial resolution imagery may be counterintuitive as a larger degree of variability exists within these images that routinely confuse a classifier (Franklin, *et al.*, 2001b). This variability, however, can be captured and used to benefit the analysis through the use of textural measures in the classification process (Clausi, 2002; Haralick *et al.* 1973). Recently, studies have suggested testing a variety of window sizes in order to determine which would best quantify and classify the spatial variation within forested stands. Coburn and Roberts (2004) found that while a measure of texture always improved the forest classification,

the degree of spatial variation influenced the effectiveness of the window sizes used. They determined that areas of lower spatial variation were better classified using smaller windows, whereas areas displaying a larger degree of spatial variation were best classified using larger windows (see also Franklin *et al.*, 2000). A related approach has been to attempt, using fusion techniques, to improve the lower spatial resolution imagery from SPOT, or Landsat, with higher spatial resolution panchromatic bands, not necessarily from the same sensor (Zhang, 1999, 2002; Jensen, 2005). These data sets then cover the same large area, but have increased spatial resolution in the multispectral imagery. For example, Fox *et al.* (2002) fused Landsat ETM+ data with the 15m panchromatic band and were able to accurately classify California vegetation into four classes of canopy closure as well as discriminated finer thematic classes of vegetation patches.

The present study was designed to test the ability of SPOT-5 High Resolution Geometric (HRG) imagery to accurately predict and classify SCI. This research is based on a simple hypothesis, i.e. that texture analyses of higher spatial resolution spectral bands created through fusion techniques, particularly the near infrared and the short-wave infrared, may classify structural complexity in mixed northern boreal forest, a prime habitat for the grizzly bear. Specific objectives include: i) assess the ability of pan-sharpened high spatial resolution spectral data to predict structural complexity index values; ii) determine the additive power of first- and second-order textural measures; and iii) confirm suggestions in recent research that textural measures calculated within larger sized windows are more useful in modeling forest biophysical parameters than those of smaller size.

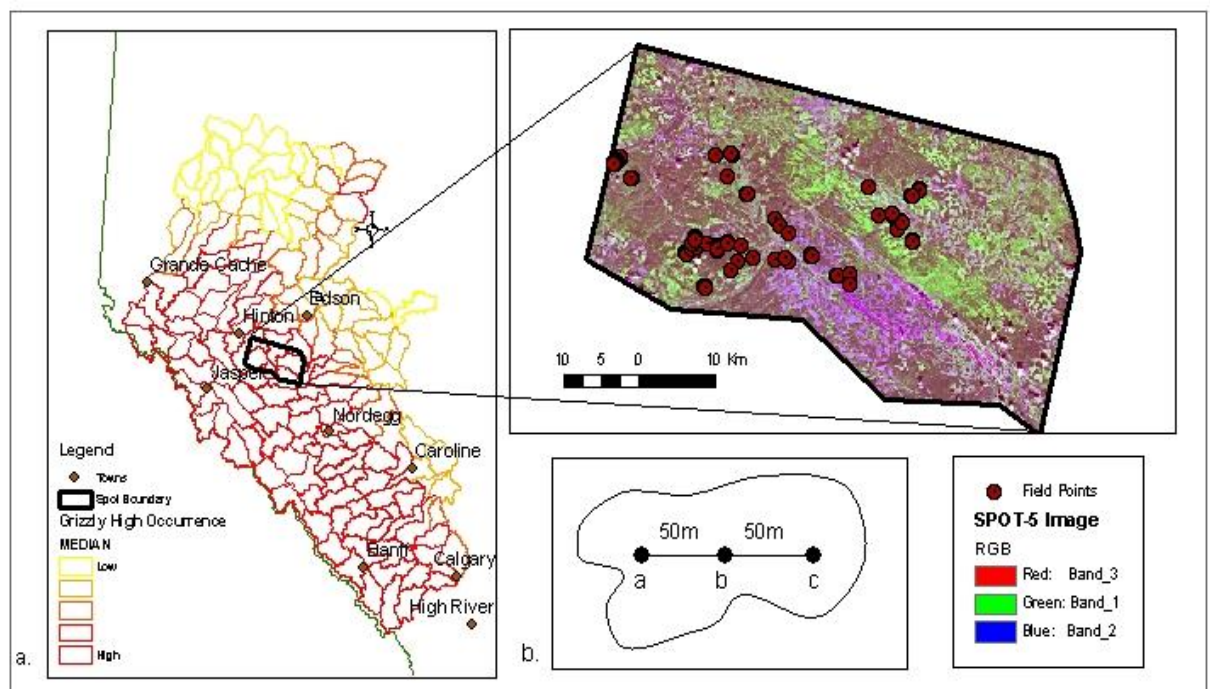
## 2.4 Methods

### 2.4.1 Study area and field data collection

The research was conducted in the Foothills Model Forest near Hinton, west-central Alberta (52°59'N, 116°59'W), over an area of 2,000 square kilometres (**Figure 2.1a**). The foothills of west-central Alberta have a 100-year burn cycle and an active forest management regime resulting in stands at differing levels of succession throughout the region (Nielsen *et al.*, 2004b). Species cover consists mainly of lodgepole pine (*Pinus contorta*), white spruce (*Picea glauca*), balsam fir (*Abies balsamea*), and trembling aspen (*Populus tremuloides*) in a variety of mixed and pure stands over a variable topography (1100m to 1600m ASL). Field data necessary to calibrate individual image spectral response patterns are listed in **Table 2.1**.

<b>Table 2.1 Field Data Collection</b>	
Site preparation type (soil disturbance patterns)	observational / measurement of patterns; GIS where available
Crown closure of regenerating stands (CC)	hemispherical photography (Nikon Coolpix 8700, FC-E9 hemi-lens; results analysed using Winscanopy Software 2.0)
Crown Diameter (CD)	Cross-sectional measurement of 2 representative trees in plot
Species composition and understory vegetation	Alberta Vegetation Index
Diameter at Breast Height (DBH)	Measurement using specialized DBH tape for trees selected using the bitterlich prism
Height	Clinometer measurement of same 2 representative trees as crown diameter
Age	Time since disturbance or plant (if available) in GIS database
Stem Density (SD)	Based on a stem count over a 2.5x2.5m plot for plots when DBH<7.5cm; Bitterlich prism (2 or 4) was used for all other plots.
Basal Area (BA)	Calculated based on SD and DBH; mean over the stand.

GPS points for the high resolution data were determined *a priori* based on a stratified random sampling method. This was necessary in order to ensure that enough data were collected for each of the three target areas: recent cut blocks (aged 0-5), regenerating areas (6-40), and older stands (31-50) (**Table 2.2**). Field plots were consistent with measurement techniques outlined by McDermid (2005) that indicate that plot size should be based on the pixel size, i.e. 2.5m x 2.5m for data to be used with SPOT-5 high spatial resolution data. Three plots within each stand were measured along a 100m transect (see **Figure 2.1b**) to enable an average of the data to be generated over the entire stand (see **Appendix B** for field sheet).



**Figure 2.1 a.** Study area located in the Foothills Model Forest depicted with the SPOT-5 imagery collected on July 21, 2005; **b.** Plot locations along a 100m transect within each stand



<b>Table 2.2 Data points collected in the field</b>	
Age Class	Number Collected
0-5	11
6-10	5
11-15	5
16-20	4
21-30	7
31-40	7
41-50	5

#### **2.4.2 Imagery Acquisition and Pre-processing**

SPOT-5 10 m multispectral and 2.5 m panchromatic imagery were acquired on July 21, 2005 over the study area and were geo- and ortho-rectified to 0.49 pixel root mean square error with 31 ground control points using nearest neighbour resampling. Atmospheric correction was completed following the methods outlined in Lanzl and Richter (1991) which use a digital elevation model to account for illumination effects. The image was projected to UTM Zone 11, NAD83. The normalized difference moisture index (a ratio of NIR and SWIR) was calculated over the pansharpened image following Wilson and Sader (2002). To fuse the SPOT-5 panchromatic band with the multispectral channels, the Advanced Pansharpening approach developed by Zhang (1999, 2002) was used. This technique is based on a least-squares method to determine the best-fit between the multispectral, panchromatic and the fused images with the dual purpose of incorporating the higher resolution spatial detail and preserving the spectral information for classification purposes. To complete this task, the variance within the spectral channels is kept smooth, which is necessary for classification analyses (Zhang, 2002). The advantages of the Pansharpening method over other techniques of pan-fusion (IHS, PCA, and wavelet transformations) are that spectral distortion is minimized and

operator dependency is reduced. **Figure 2.2** shows the increase in information content from the SPOT-5 10m resolution NIR band to the 2.5m pansharpened band.

157	143	151	90	118	121	150	138	144	144	125	140	151	152	135
			112	122	142	146	151	142	143	138	146	152	154	158
			132	114	113	138	126	136	140	141	149	143	138	163
			137	133	131	118	123	145	173	153	135	136	127	143
			161	172	119	131	136	150	158	152	137	139	149	133
			164	158	150	160	164	161	151	139	136	145	141	147
184	151	152	153	157	157	173	159	169	143	141	143	143	144	136
			174	164	160	180	162	151	143	153	146	138	142	130
			194	175	165	178	167	169	157	155	137	142	141	149
			176	173	168	172	165	165	171	161	147	150	143	143
			180	182	170	170	172	181	179	170	158	158	147	158
183	182	171	174	184	175	178	186	166	170	156	163	172	143	151

**Figure 2.2** The reflectance values over a 30x30m window with SPOT-5 original 10m imagery (left); the increased information content of a 30x30m window with SPOT-5 pansharpened imagery (right).

### 2.4.3 Texture calculation

The texture analyses were based upon the pan-sharpened near infrared channel following results reported by Gong *et al.* (2003) and Coburn and Roberts (2004) indicating that the relationship between the NIR and vegetation increases the information available using texture analyses. First-order measures were used to evaluate the mean and standard deviation of the near-infrared spectral reflectance under each moving window. Second-order grey level co-occurrence matrix (GLCM) textural analyses of homogeneity (2.1), entropy (2.2), correlation (2.3), and contrast (2.4) were examined. GLCM statistical analysis measures the pair-wise occurrence of grey values within the moving window (Clausi, 2002; Haralick *et al.*, 1973). Homogeneity, entropy, and standard deviation were used based on results with inventory parameters in conifer stands by Franklin *et al.* (2000), Gerylo *et al.* (2002), and Tuominen and Pekkarinen (2005). Contrast and correlation texture measures have been recently shown to provide

similar results as the variogram (contrast) and spatial auto-correlation (correlation) by van der Sandman and Hoekmann (2005). As the variogram and spatial auto-correlation have been used successfully to delineate single forest structural parameters (e.g. Wulder *et al.* 1998; Bruniquel-Pinel and Gastellu-Etchegorry, 1998) their use may be beneficial to the classification of the structural complexity index. The textural measures are defined as follows:

$$Homogeneity = \sum_{j=1}^n \sum_{i=1}^m \frac{P_{ij}}{(1 + [i - j]^2)} \quad (2.1)$$

$$Entropy = \sum_{j=1}^n \sum_{i=1}^m -P_{ij} \ln P_{ij} \quad (2.2)$$

$$Correlation = \sum_{i=1}^n \sum_{j=1}^m \frac{(i - \bar{i})(j - \bar{j})P_{ij}}{\sigma_i \sigma_j} \quad (2.3)$$

$$Contrast = \sum_{i=1}^n \sum_{j=1}^m P_{ij}(i - j)^2 \quad (2.4)$$

where  $P_{ij}$  is the spatial co-occurrence matrix,  $i$  and  $j$  are the positional values within the matrix and  $\sigma_i$  and  $\sigma_j$  are the according standard deviations. Moving window sizes of 5x5, 11x11, and 25x25 were tested with both first- and second-order texture measures. These moving window sizes were chosen based on results with high spatial resolution datasets (IKONOS or SPOT) and conifer species (Franklin *et al.*, 2000; 2001b; Coburn and Roberts, 2004). The present research was intended to understand the particular windows best suited for boreal forest structural complexity index determination.

#### 2.4.4 Statistical Analysis

To simulate the Structural Complexity Index (SCI), a principal components analysis based on the correlation matrix was undertaken in SPSS (Version 13.0) using the following variables: DBH, DBH standard deviation, BA, SD, CD mean and CD standard deviation. **Table 2.3** shows the resulting eigenvalues for the six components extracted. This choice was based on the methodology followed in Cohen and Spies (1992) and Hansen *et al.* (2001a). The factor loading score for the first component was used as the SCI value and ranged between -4 and +4.

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	4.735	78.925	78.925
2	.710	11.840	90.765
3	.244	4.064	94.829
4	.174	2.908	97.736
5	.101	1.676	99.412
6	.035	.588	100.000

*Extraction Method: Principal Component Analysis.*

Simple Pearson's Product-moment correlations were used to identify the spectral and textural image data most associated with the separate biophysical variables and to the SCI. Stepwise multivariate regression analysis was used in this study as it only includes variables that significantly increase the significance of the model to a value of 95% or higher and show little to no collinearity. Several models were tested to determine the how the addition of texture helps to improve SCI prediction. This was done in steps, by first-order measures, second-order texture, and then by window size to determine additive explanatory power that each made to the overall model.

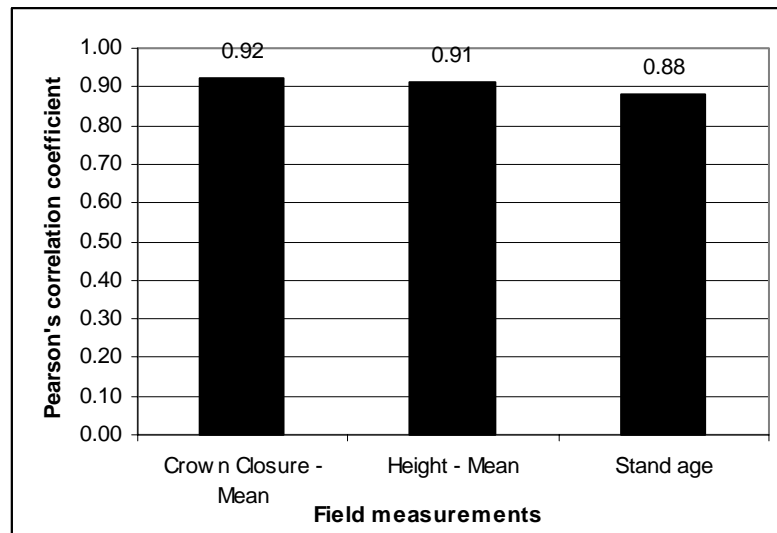
#### **2.4.4. Classification of SCI and Product Validation**

To create an SCI layer, the resulting linear regression equation was applied to the pansharpened image following continuous modeling methods similar to McDermid (2005). The SCI classification (pixel level) was validated by first averaging the pixels within each measured polygon to determine the remote sensing based *polygon level* SCI map. Once complete, linear regression was used to determine the strength of the classification to the averaged field level values (stand or polygon level). To alleviate concern over the use of the entire training data for use in model creation and validation, all results were cross-validated using the leave-one out method available in SPSS (Version 13.0).

#### **2.5 Results and Discussion**

**Figure 2.3** shows the correlation between the stand level field variables and the SCI at the *polygon level*. The SCI is highly correlated with all biophysical parameters, but the most important associations are with crown closure, age, and height, variables that were not used in the calculation of the SCI. This shows the strength of the SCI as an overall measure of structure. In **Figure 2.4**, the highest spectral correlations with the SCI are with the shortwave infrared (SWIR) band and the NDMI. This supports previous research by Cohen and Spies (1992) and Hansen *et al.* (2001) that have shown that the Tasseled Cap Wetness Index from Landsat TM (a similar measure to NDMI as previously discussed) was a strong predictor of the SCI. Additionally, Wulder *et al.* (2004) have shown that the SWIR band alone is able to separate regenerating boreal forest age classes (akin to structure) in northern British Columbia. Correlations with specific textural measures (**Figure 2.5**) show that all texture measures are related to the SCI and only vary with window size (with the exception of homogeneity). The strongest

associations occur with the correlation texture measure under the 11x11 window size and with the contrast texture measures under the 5x5 and 11x11 window sizes. The correlation texture measure is similar to the spatial auto-correlation measure (van der Sandman and Hoekman, 2005) in that it is high when there is a strong local linear dependency between pixels versus distance and low when there is not. Thus the larger the area over which the texture is calculated in these regenerating stands, the more local correlation in comparison with distance we see. The contrast measure peaks at the 5x5, remains the same at the 11x11, and declines again at the 25x25 window sizes. This can be explained as the contrast texture measures the local variance under the window and sees the highest variation at the 11x11 window size (or over an area of 756 m<sup>2</sup>). The variance of NIR decreases at the 25x25 window size as it takes the entire cut block into consideration. The weakest associations appear with the standard deviation texture measure under the 5x5 window size, all homogeneity measures, and the entropy texture measure under the 11x11 window size.



**Figure 2.3 Correlation between SCI and field measured biophysical parameters,  $p \leq 0.01$**

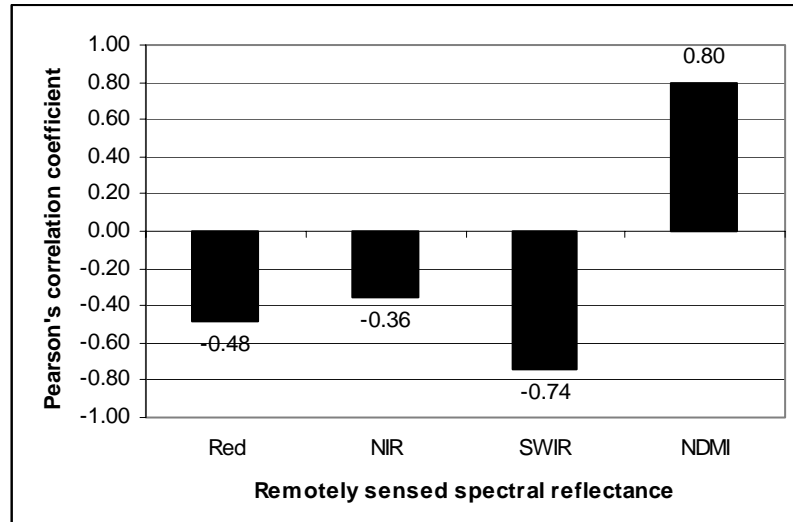


Figure 2.4 Correlations between SCI and SPOT-5 spectral data;  $p < 0.05$

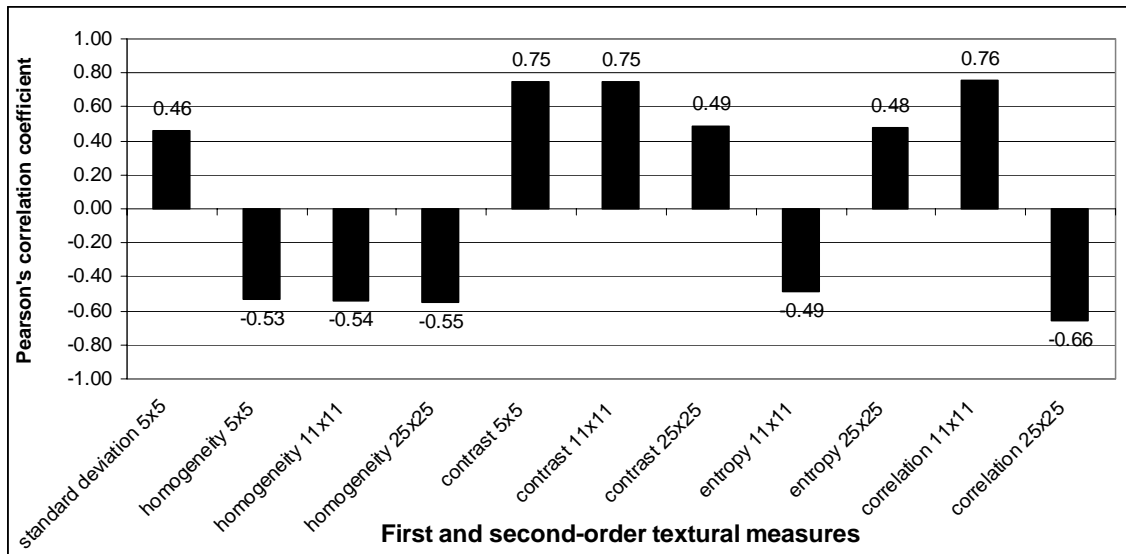


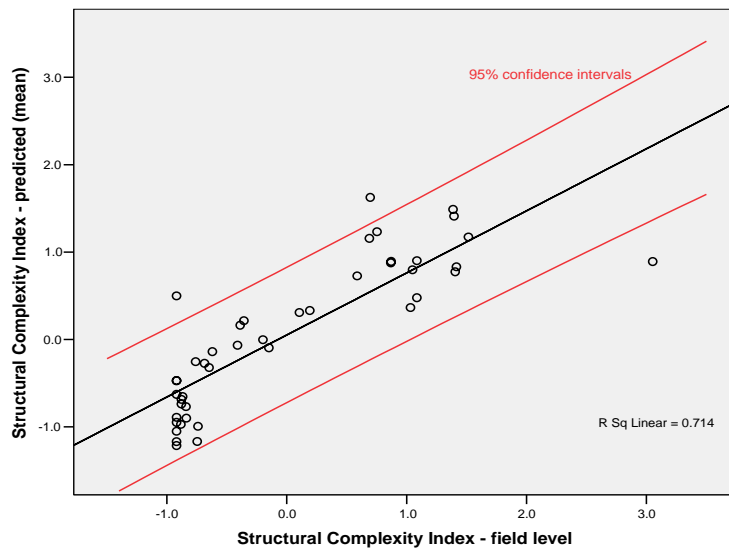
Figure 2.5 Correlations between SCI and SPOT-5 textural data;  $p < 0.05$

Standard deviation, homogeneity, and entropy focus on similarity between pixel values or textural smoothness. For example, a highly variable forested area will appear rougher than a recent cut which shows similar values of reflectance. From the previous information, it is impossible to choose which of the most strongly related parameters may be the best predictors of the SCI. For that reason, a stepwise multivariate linear regression analysis was completed whereby SCI was a function of the NDMI, and both

the standard deviation (sd) and correlation texture (corr) measures at the 5x5 window size ( $R^2 = 0.74$ ,  $n=44$ ,  $p=0.01$ ).

$$\text{SCI} = -4.841 - 9.76 (\text{corr}_{5 \times 5}) + 0.52 (\text{sd}_{5 \times 5}) + 0.029 (\text{NDMI}) \quad (2.5)$$

This result may be surprising due to the previously discussed relationships regarding window size and textural measure. However, the addition of the spectral index, NDMI, to a model including the larger sized windows of any of the texture measures would increase collinearity and decrease model robustness. This model illustrates that using the spectral variation in the NDMI with measures of smoothness (standard deviation) and linear dependency (correlation) is a strong predictor of SCI at the stand or polygonal level.



**Figure 2.6 Comparison of adjusted predicted SCI versus adjusted actual SCI; Adj.  $R^2 = 0.70$ ;  $p=0.01$ ,  $n=44$**

Results from the pixel based classification regression comparison (**Figure 2.6**) show that the relationship between both the predicted SCI and actual SCI is strong (Adj.  $R^2 = 0.70$ ). Although, this relationship is based on one field dataset ( $n=44$ ) whereby both model and validation have been obtained, it demonstrates that this measure may be of



significance in the boreal forest of west-central Alberta. Future research must focus on obtaining a larger field dataset with which this measure can be exploited more fully as well as determine its use in habitat modeling.

## ***2.6 Conclusions***

Many studies have attempted to determine the strongest relationship between remotely sensed spectral information and forest biophysical parameters in the boreal forest of Canada. These studies have been based on coarser spatial resolution data and were thus unable to fully exploit the ability of textural analysis to assist the prediction of these parameters. Research that focused on using similar textural measures to this study, however, did not analyse the power of the short wave infrared band. This study, however, used a higher spatial resolution multispectral data set created using a pan-sharpening tool to ascertain the sensitivity of forest structure to the normalized difference moisture index, measures of NIR texture and the Structural Complexity Index. This research also applies the equation for SCI to the original image in an attempt to classify structure for use in grizzly bear habitat research, which was previously undocumented. There are three important conclusions resulting from this research:

- The strongest relationships between spectral data and the SCI were found with the NDMI and the SWIR band. For example, the highest correlations obtained were 0.80 and -0.74 respectively. These results indicate that future research should be accordingly focused on using optical imagery with a shortwave infrared band (1.55-1.75  $\mu\text{m}$ ).
- The most useful window size was the 5x5 pixels which covers an area equal to 12.5m x 12.5m. This interpretation is based on the strongest stepwise multiple

regression results, where the 5x5 window size added the most information to the model. This indicates that high resolution optical imagery is also very important when attempting to classify an array of structural parameters. Texture from a 4m resolution data set would be the minimum requirement if the smallest (3x3) window size were used. Of the few commercial satellites available, only SPOT-5 original 10m/20m has the most beneficial spectral resolution and can be fused to create a 2.5m spatial resolution dataset. Although both Quickbird and IKONOS have higher spatial resolutions, neither includes the short wave infrared band necessary for this application. Further research is recommended using SPOT or the newer hyperspectral satellites, such as HERO available in 2010.

- Results from the relationship between SCI and spectral and textural data were applied to the SPOT pansharpened image and were confirmed using linear regression ( $\text{Adj. } R^2 = 0.70$ ). These results could be tested with current habitat models to determine if they can be used as a surrogate for stand age. In addition, these results may be additive in combination with other parameters such as age class, height, or crown closure.

## ***2.7 Acknowledgements***

This research was funded by the Natural Sciences and Engineering Research Council of Canada and the Foothills Model Forest. I thank PCI Geomatics for the use of the PANSHARP module for this study. I would also like to take this opportunity to thank Dr. Greg McDermid, Alysha Pape, Karen Graham, Jerome Cranston, Dr. Marc Cattet, and Dr. Xulin Guo for the invaluable advice provided. In addition, I thank the

Alberta Government, Fish and Wildlife conservation division for the use of their cabin during our field season in August, 2005.

## **2.8 References**

- British Columbia Ministry of Forests, 2001. Data Dictionary for the geographic information systems forest inventory. <http://www.gov.bc.ca/srm>. [Last visited 20 May 2005].
- Betts, M. G., Franklin, S. E., and Taylor, R. G., 2003. Interpretation of landscape pattern and habitat change for local indicator species using satellite imagery and geographic information system data in New Brunswick, Canada. *Canadian Journal of Remote Sensing*, **33**, 1821-1831.
- Boyd, D. S., Wicks, T. E., and Curran, P. J., 2000. Use of middle infrared radiation to estimate the leaf area index of a boreal forest. *Tree Physiology*, **20**, 755-760.
- Bruniquel-Pinel, V. and Gastellu-Etchegorry, J.P., 1998. Sensitivity of texture of high resolution images of forest to biophysical and acquisition parameters. *Remote Sensing of Environment*, **65**, 61-85.
- Clausi, D.A. 2002. An analysis of co-occurrence texture statistics as a function of grey level quantization. *Canadian Journal of Remote Sensing*, **28** (1), 45-62.
- Coburn, C.A. and Roberts, A.C.B. 2004. A multiscale texture analysis procedure for improved forest stand classification. *International Journal of Remote Sensing*, **25** (20), 4287-4308.
- Cohen, W.B. and Spies, T.A. 1990. Remote sensing of canopy structure in the Pacific Northwest. *Northwest Environment Journal*, **6**, 415-418.
- Cohen, W. B. and Spies, T. A., 1992. Estimating structural attributes of Douglas-Fir / Western Hemlock forest stands from Landsat and SPOT Imagery. *Remote Sensing of Environment*, **41**, 1-17.
- Cohen, W.B., Spies, T.A., and Fiorella, M. 1995. Estimating the age and structure of forests in a multi-ownership landscape of Western Oregon, U.S.A. *International Journal of Remote Sensing*, **16** (4), 721-746.
- Craighead, J.J., Sumner, J.S., and Mitchell, J.A. 1995. The Grizzly Bears of Yellowstone: Their ecology in the yellowstone ecosystem, 1959-1992. Island Press: Washington, D.C.
- Espirito-Santo, F.D.B., Shimabukuro, Y.E., and Kuplich, T.M. 2005. Mapping forest successional stages following deforestation in Brazilian Amazonia using multi-temporal Landsat images. *International Journal of Remote Sensing*, **26** (3), 635-642.
- Fox, L., Garrett, M. L., Heasty, R., and Torres, E., 2002. Classifying wildlife habitat with pan-sharpened Landsat 7 Imagery, Proceedings, *ISPRS Commission I Symposium*, Volume 4, Pecora 15/Land Satellite Information, Denver, Colorado, USA, November 10-15.

- Franklin, S. E., Hall, R. J., Smith, L., and Gerylo, G. R. 2003. Discrimination of conifer height, age and crown closure classes using Landsat-5 TM imagery in the Canadian Northwest Territories. *International Journal of Remote Sensing*, **24** (9), 1823-1834.
- Franklin, S. E., D. R. Peddle, J. A. Dechka, and G. B. Stenhouse, 2002, Evidential reasoning using Landsat TM, DEM, and GIS data in support of grizzly bear habitat analysis, *International Journal of Remote Sensing*, **23**(21), 4633-4652
- Franklin, S. E., Lavigne, M. B., Moskal, L. M., Wulder, M. A., and McCaffrey, T. M., 2001a. Interpretation of forest harvest conditions in New Brunswick using Landsat TM enhanced wetness difference imagery (EWDI). *Canadian Journal of Remote Sensing*, **27**, 118-128.
- Franklin, S. E., Wulder, M. A., and Gerylo, G. R., 2001b. Texture analysis of IKONOS panchromatic data for Douglas-fir forest age class separability in British Columbia. *International Journal of Remote Sensing*, **22** (13), 2627-2632.
- Franklin, S.E. 2001c. Remote sensing for sustainable forest management. New York: Lewis Publishers.
- Franklin, S. E., Moskal, L. M., Lavigne, M., and Pugh, K. 2000. Interpretation and classification of partially harvested forest stands in the Fundy Model Forest using multitemporal Landsat TM digital data.. *Canadian Journal of Remote Sensing*, **26**, 318-333.
- Gerylo, G. R., Hall, R. J., Franklin, S. E. and Smith, L., 2002. Empirical relations between Landsat TM spectral response and forest stands near Fort Simpson, Northwest Territories, Canada. *Canadian Journal of Remote Sensing*, **28** (1), 68-79.
- Gong, P., Mahler, S.A., Biging, G.S., and Newburn, D.A. 2003. Vineyard identification in an oak woodland landscape with airborne digital camera imagery. *International Journal of Remote Sensing*, **24** (6), 1303-1315.
- Hansen, M. J., Franklin, S. E., Woudsma, C., and Peterson, M., 2001a. Forest structure classification in the North Columbia Mountains using the Landsat TM Tasselled Cap Wetness Component. *Canadian Journal of Remote Sensing*, **27** (1), 20-32.
- Hansen, M. J., Franklin, S. E., Woudsma, C. G. and Peterson, M., 2001b. Caribou habitat mapping and fragmentation analysis using Landsat MSS, TM, and GIS data in the North Columbia Mountains, British Columbia, Canada. *Remote Sensing of Environment*, **77**, 50-65.
- Haralick, R.M., Shanmugan, K., and Dinstein, I., 1973, Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. SMC-3, pp. 610-621.
- Healey, S. P., Cohen, W. B., Zhigiang, Y. and Krankina, O. N., 2005. Comparison of Tasselled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment*, **97**, 301-310.

- Jensen, J. R. 2005. Introductory Digital Image Processing: A Remote Sensing Perspective, 3<sup>rd</sup> Edition. Keith C. Clarke, ed. Upper Saddle River, NJ: Pearson Prentice Hall.
- Jin, S. and Sader, S. A., 2005. Comparison of time series tasseled cap wetness and the normalized difference moisture index in detection forest disturbances. *Remote Sensing of Environment*, **94**, 364-372.
- Kimes, D. S., Holben, B. N., Nickeson, J. E., and McKee, W. A., 1996, Extracting forest age in a Pacific Northwest Forest from Thematic Mapper and topographic data. *Remote Sensing of Environment*, **56**, 133-140.
- Kimes, D.S., Nelson, R.F., Salas, W.A., Skole, D.L. 1999. Mapping secondary tropical forest and forest age from SPOT HRV data. *International Journal of Remote Sensing*, **20** (18), 3625-3640.
- Lanzl, F. and Richter, R., 1991. A fast atmospheric correction algorithm for small swath angle satellite sensors. *ICO Topical Meeting on Atmospheric, Volume and Surface Scattering and Propagation Conference Proceedings*, Florence, Italy. August 27-30, 455-458.
- Lefkysy, M. A., Hudak, A T., Cohen, W. B., and Acker, S. A., 2005. Patterns of covariance between forest stand and canopy structure in the Pacific Northwest. *Remote Sensing of Environment*, **95**, 517-531.
- Lévesque, J. and King, D. J., 2003. Spatial analysis of radiometric fractions from high-resolution multispectral imagery for modelling individual tree crown and forest canopy structure and health. *Remote Sensing of Environment*, **84**, 589-602.
- Lévesque, J. and King, D. J., 1999. Airborne digital camera image semivariance for evaluation of forest structural damage at an acid mine site. *Remote Sensing of Environment*, **68**, 112-124.
- Mattson, D.J., Herrero, S., Wright, R.G., and Pease, C.M. 1996. Science and management of Rocky Mountain Grizzly Bears. *Conservation Biology*, **10** (4), 1013-1025.
- McDermid, G. 2005. PhD thesis Remote estimation of land cover and LAI over large areas for wildlife habitat applications, Faculty of Environmental Studies, University of Waterloo.
- Nielsen, S. E., Herrero, S., Boyce, M. S., Mace, R. D., Benn, B., Gibeau, M. L., and Jevons, S., 2004a, Modelling the spatial distribution of human-caused grizzly bear mortalities in the Central Rockies ecosystem of Canada. *Biological Conservation*, **120**, 101-113.
- Nielsen, S. E, Boyce, M. S., and Stenhouse, G. B., 2004b, 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, Munro, R. H. M., Bainbridge, E. L., Stenhouse, G. B., and Boyce, M. S., 2004c. Grizzly bears and forestry II. Distribution of grizzly bear foods in clear-

- cuts of west-central Alberta, Canada. *Forest Ecology and Management*, **199** 67-82;
- Popplewell, C., S. E. Franklin, G. B. Stenhouse, and M. Hall-Beyer, 2003. Using landscape structure to classify grizzly bear density in Alberta Yellowhead Ecosystem bear management units, *Ursus*, **14**, 27-34.
- Sabol, D. E., Gillespie, A. R., Adams, J. B., Smith, M. O., and Tucker, C. J., 2002. Structural Stage in Pacific Northwest forests estimated using simple mixing models of multispectral images. *Remote Sensing of Environment*, **80**, 1-16.
- Sader, S. A., Bertrand, M., and Wilson, E. H., 2003. Satellite change detection of forest harvest patterns on an industrial forest landscape. *Forest Science*, **49** (3), 341-353.
- Tuominen, S. and Pekkarinen, A., 2005. Performance of different spectral and textural aerial photograph features in multi-source forest inventory. *Remote Sensing of Environment*, **94**, 256-268.
- Van der Sandman, J. J. and Hoekman, D. H., 2005. Review of relationships between grey-tone co-occurrence, semivariance, and autocorrelation based image texture analysis approaches. *Canadian Journal of Remote Sensing*, **31** (3), 207-213.
- Wielgus, R. B. and Vernier, P. R., 2003. Grizzly bear selection of managed and unmanaged forests in the Selkirk Mountains. *Canadian Journal of Forest Research*, **33** (5), 822-829.
- Wilson, E. H., and Sader, S., 2002. Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment*, **80**, 385-396.
- Wulder, M.A., Skakun, R. S., Kurz, W. A., and White, J. C., 2004. Estimating time since forest harvest using segmented Landsat ETM+ imagery. *Remote Sensing of Environment*, **93** 179-187
- Wulder, M. A., Ellsworth F. L., Franklin, S. E., and Lavigne, M. B., 1998, Aerial image texture information in the estimation of northern deciduous and mixed wood forest leaf area index (LAI). *Remote Sensing of Environment*, **64**, 64-76.
- Zhang, Y. 1999. A new merging method and its spectral and spatial effects. *International Journal of Remote Sensing*, **20**, 2003-2014.
- Zhang, Y. 2002. A new automatic approach for effectively fusing Landsat 7 as well as IKONOS images. *IEEE/IGARSS Conference*, Toronto, Canada, June 24-28.

### **3.0 BOREAL FOREST AGE AND SITE PREPARATION CLASSIFICATION IN WEST-CENTRAL ALBERTA USING SPOT-5 PANSHARPENED IMAGERY, TEXTURE, AND THE STRUCTURAL COMPLEXITY INDEX**

#### ***3.1 Abstract***

Grizzly bears in west-central Alberta have been shown to select similarly aged regenerating cut blocks at different stages of the feeding season due to easier access of varied foods. Their selection has also been influenced by site preparation activities completed in the areas. Satellite remote sensing offers a practical and cost-effective method by which many biophysical parameters necessary to the detection of cut areas, their age class, and site preparation activities can be quantified. However, most studies attempting this have focused on medium spatial resolution (20-30m) imagery, which is unable to add a textural layer shown useful in the classification of stand structure and single forest inventory variables. This study examines the relationship between spectral reflectance in the short wave infrared (SWIR) and the normalized difference moisture index (NDMI) of SPOT-5 pansharpended imagery (2.5m spatial resolution) to identify and map 44 regenerating stands sampled in August 2005. Second order texture measures are used to determine the age class (five and ten year ranges) of these cut blocks using linear discriminant analysis. The accuracy of this classification is enhanced by including the image based predicted structural complexity index (SCI) map for the area. This layer was based on the first loading of a principal components analysis of field level inventory data. Lastly, for the blocks aged 0-5, site preparation is classified based on two classes (furrow and mound). Results show that using object based classification with the NDMI, green, and SWIR bands, 90% accuracy can be achieved in the detection of forest

disturbance. Age classes were best separated (82.5%) when using the SWIR and green spectral bands, second order correlation texture under a 25x25 window, and the predicted SCI. Site preparation was best separated into two classes (furrow or mound) with 89% accuracy using the NDMI and homogeneity texture under a 5x5 window. Future applications from this research include the selection of high probability grizzly habitat for high spatial resolution imagery acquisition and the creation of detailed age and site preparation disturbance maps using object-based classification techniques.

### **3.2 Introduction**

In west-central Alberta there is concern that existing resource management practices will seriously increase landscape fragmentation leading to increased human use (Nielsen *et al.*, 2004a; Mattson *et al.*, 1996). This may have negative effects on wildlife such as grizzly bear (*Ursus arctos* L.) (Craighead *et al.*, 1995). Recently, grizzly bears in the Foothills Model Forest of west-central Alberta were found to select clear cuts of different age ranges as habitat depending on the feeding season. Older clear cuts (approximately 30 years since disturbance) were used during hypophagia and recently cleared sites were selected during late hyperphagia (Nielsen *et al.*, 2004a). They also elected or avoided certain clear cuts depending on the site preparation process employed preferring furrowed methods to more destructive mounding landscapes (Nielsen *et al.*, 2004b,c; Wielgus and Vernier, 2003). The data used in these studies were obtained using a GIS forestry inventory database, created by the amalgamation of several datasets (Cranston, Pers. Comm., 2006). The existence of a current and comprehensive information source for large areas ( $\geq 10,000$  square kilometres), consistent with those that represent the area of interest in grizzly bear population viability analysis, is the exception rather than the norm. Satellite remote sensing is a viable option for classifying



large areas ( $\geq 100,000$  square kilometres) and creating a consistent dataset for ecological habitat modeling (McDermid, 2005).

Harvested areas in the boreal forest of northern Canada are not easily detected using most typical classification techniques as they are neither uniform nor unique to many classification algorithms (McDermid, 2005). For that reason, most previous research has focused on the use of image differencing techniques to classify these objects (e.g. Jin and Sader, 2005; Sader *et al.*, 2003; Wilson and Sader, 2002; Franklin *et al.*, 2000, 2001a; Cohen *et al.*, 1998). A significant result of these studies was that the short wave infrared was very sensitive in cutovers and to even less distinctive changes, such as herbicide application and commercial thinning treatments. Two indices involving this spectral band, the Normalized Difference Moisture Index (NDMI) and the Tasseled Cap Wetness Index, were sensitive to both cleared and partially cut areas reinforcing the idea from Franklin *et al.* (2001a) and Healey *et al.* (2005) that the moisture level of the cut area changes with removal of the canopy. However, image differencing procedures can only be applied to areas having a longer historical image record and such data sets can be expensive and are not available for all sensors. More recently, as a result of the unnatural shape and differing reflectance of recent cut blocks to older forest stands (Cohen *et al.*, 1998), Flanders *et al.* (2003) tested eCognition object based software and was able to classify very recent cut blocks from Landsat TM with an accuracy reaching 90%. The use of a moisture index with eCognition will be thus more able to detect recently cut stands than either method alone. Once these features are detected, the biophysical parameters of regenerating age and site preparation are needed to be of use to grizzly bear habitat models.

Stand age classification has been achieved using simple stepwise multivariate regression with Tasseled cap components ( $R^2 = 0.68$ ) and Landsat 7 Enhanced Thematic Mapper Plus [ETM+] (Wulder *et al.*, 2004) in northern British Columbia. Regenerating stand age was highly correlated with the green and SWIR bands suggesting again, that a measure of wetness is important. Although the targeted species were regenerating Douglas fir (*Pseudotsuga menziesii*) and western hemlock (*Tsuga heterophylla*), the use of the SWIR and green bands should work equally well in a boreal conifer forest landscape. To determine the role that texture measures play, Franklin *et al.* (2001b) used first- and second-order textural analyses to determine 20-year conifer age for pure stands using IKONOS (4m spatial resolution) imagery. Results showed that stands were separable using a 15x15 window size. This suggests that higher spatial resolution imagery in combination with texture and a measure of wetness may not only allow a smaller age range (i.e. 5 or 10 years) but also increase classification accuracy.

Site preparation methods and their impacts on the ground within a cut block have not received attention in the field of remote sensing. This situation will, however, change as new applications are considered. For example, discerning the site preparation process utilized at a clear-cut has been recognized very useful information for wildlife habitat analysis (Nielsen *et al.*, 2004b, 2004c). Jusoff and D'Souza (1996) were able to visually discern six levels of soil disturbance of logged areas in a SPOT/HRV image, suggesting that statistical classification of high spatial resolution imagery may result in a strong relationship between high impact preparation techniques (such as excavator mound or disc trencher) and optical imagery analysis. These mounding, regular patterns, exposed soil, and plough furrow characteristics create a possible link with agricultural

tillage practices, only recently researched using high resolution remote sensing. Viña *et al.* (2003) detected two tillage practices (conventional and conservation) with IKONOS imagery using a logistic regression model on generated PCA components of the Normalized Difference Vegetation Index. Thus, one would expect that the regular pattern of exposed soil created by several scarification procedures (trenching, heavy/light drag) would show a textural difference from a harvested area left for natural regeneration. These situations suggest that using high spatial resolution imagery (< 4m) is necessary for the detection of both stand age and site preparation. Using IKONOS imagery, Franklin *et al.* (2001b) discovered that large moving windows and second order texture values that describe the spatial co-occurrence homogeneity of the window were very effective in distinguishing between species composition and structure of a forested stand. This measurement simply quantifies the spatial relationship that grey tones of pixels exhibit over a specified area or pixel window. It could be expected then, that a second-order texture value, applied to harvested areas may also show differences attributing to age, structure, and also soil disturbance.

Recent research has indicated that a structure index, known as the Structural Complexity Index (SCI), may be a beneficial component of determining stand age (Chapter 2.0; Cohen and Spies, 1992; Hansen *et al.*, 2001) in a forested matrix. To calculate this index, field level parameters are analysed using principal components analysis, whereby the first loading score is used as the SCI value. The SCI is highly correlated with height, crown closure, and stand age, parameters not included in its creation (Cohen and Spies, 1992; Hansen *et al.*, 2001), indicating its power of structure prediction. Adding this parameter to a model predicting stand age is logical, as age alone

is not independent of its surrounding environment. Moreover, results from Chapter 2.0 have shown that the SCI can be classified at high spatial resolution (<4m) using pansharpened SPOT-5 imagery. This is important as it indicates the ability of a pansharpened dataset to accurately classify this structural measure in the boreal forest.

Earlier cut block detection and age classification methods almost exclusively focused on Landsat TM imagery (Thomas *et al.*, 1993; Green *et al.*, 1994). Recent research has, however, indicated that the spatial resolution of these medium resolution sensors limits the level of forest canopy damage detection in the Amazon Rainforest (Asner *et al.*, 2002) and in the northern temperate forests (Levesque and King, 1999) as the imagery is L-resolution, i.e. pixels are larger than the forest structural features the study had wanted to detect. For that reason, higher spatial resolution sensors including a middle or short wave infrared band (such as pansharpened SPOT-5 or Landsat TM) are needed to include the wetness or moisture components. The objectives of the research are to: **i)** detect and classify biophysical characteristics of clear cut areas and site preparation method using the NDMI, the SCI, texture, and pansharpened SPOT-5 imagery; and **ii)** create a model to correlate the resulting data to clear cut age and site preparation for use in grizzly bear habitat modeling in the Foothills Model Forest near Hinton, Alberta. Using remote sensing to integrate age and site preparation with cut area detection constitutes a significant contribution to wildlife habitat research.

### ***3.4 Methods***

#### **3.4.1 Study Area and Field Data Collection**

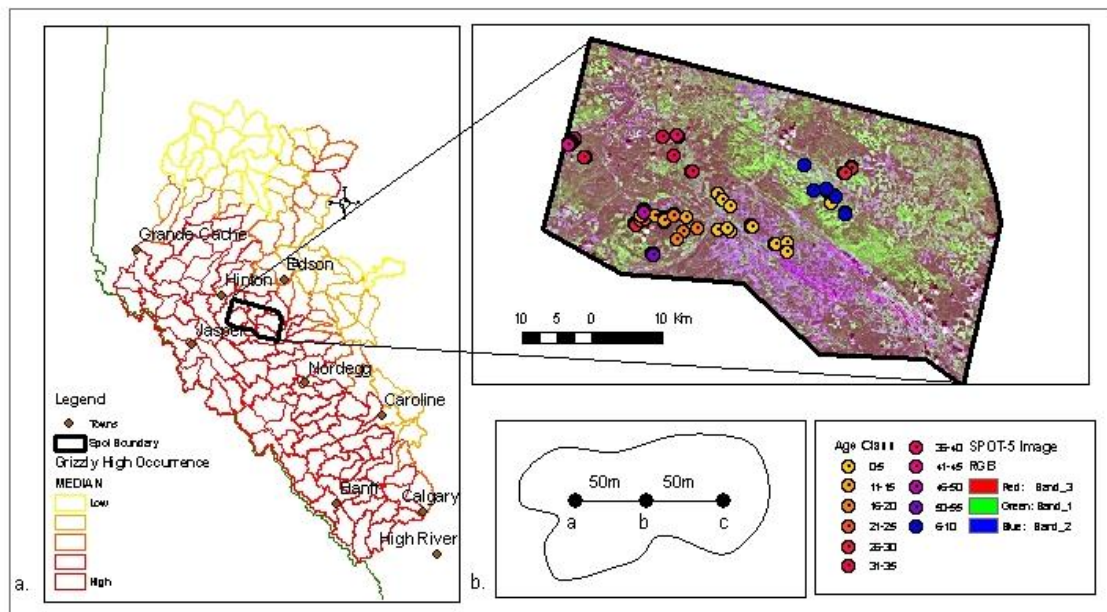
The research was conducted in the Foothills Model Forest (52°59'N, 116°59'W) near Hinton, Alberta over an area of more than 3,600 square kilometres (**Figure 3.1**)

with variable topography (1100m to 1600m ASL). Species cover consists of lodgepole pine (*Pinus contorta*), white spruce (*Picea glauca*), balsam fir (*Abies balsamea*), and trembling aspen (*Populus tremuloides*) in a variety of mixed and pure stands.

<b>Table 3.1 Field Data Collection</b>	
Site preparation type (soil disturbance patterns)	observational / measurement of patterns
Crown closure of regenerating stands (CC)	hemispherical photography (Nikon Coolpix 8700, FC-E9 hemi-lens; results analysed using Winscanopy Software 2.0)
Crown Diameter (CDavg)	Cross-sectional measurement of 2 representative trees in plot; mean over the stand
Crown Diameter (CDsd)	Standard deviation of CD over the stand
Species composition (over and understory)	Alberta Vegetation Index
Diameter at Breast Height (DBH)	Measurement using specialized DBH tape; mean over the stand
Diameter at Breast Height (DBHsd)	Standard deviation of DBH over the stand
Height	Clinometer measurement of same 2 representative trees as crown diameter
Age	Time since disturbance or plant (if available) in GIS database
Stem Density (SD)	Based on a stem count over a 5x5m plot for plots when DBH<7.5cm; Bitterlich prism (2 or 4) was used for all other plots. ; mean over the stand
Basal Area (BA)	Calculated based on SD and DBH; mean over the stand
Basal Area (BAsd)	Standard deviation of BA over the stand
Structural Complexity Index (SCI)	Generated per stand a priori using CD, CDsd, BA, BA sd, DBH, DBHsd, and SD in a principal components analysis; value is the first loading score

Understory species were varied, however, most of the cut blocks visited exhibited a consistent vegetation layer of young trembling aspen shoots and some berry species (for the older yet still open areas) and the most recently logged sites (< 5 years) were littered with logging debris and with limited conifer growth. Site preparation practices consisted

of mounding, furrowing, and complete duff layer removal (Nielsen *et al.*, 2004b). This area is an appropriate choice not only for its location within prime grizzly bear territory, but also because a number of complementary studies in the remote sensing and wildlife ecology fields recently have been completed there (e.g. Nielsen *et al.*, 2004a, 2004b; McDermid, 2005; Franklin *et al.*, 2002). In addition, since the foothills of west-central Alberta have an active forest management regime, many newly cut, regenerating, and older stands occur throughout the region. Taken together, this area is one of the best available regions in which to conduct this study.



**Figure 3.1 a. Study area located in the Foothills Model Forest depicted with SPOT-5 imagery [July 21, 2005] b. [inset] Stand level sampling method**

Field data points for the high resolution data were determined prior to the field season based on a stratified random sampling method. This is necessary in order to ensure that each of the three target areas, recent cut blocks (aged 0-5), regenerating areas (aged 6-30), and older stands (aged 31-50), were equally sampled (**Table 3.2**). Field plots were based on the pixel size, i.e. 2.5m x 2.5m plots for data to be used with high

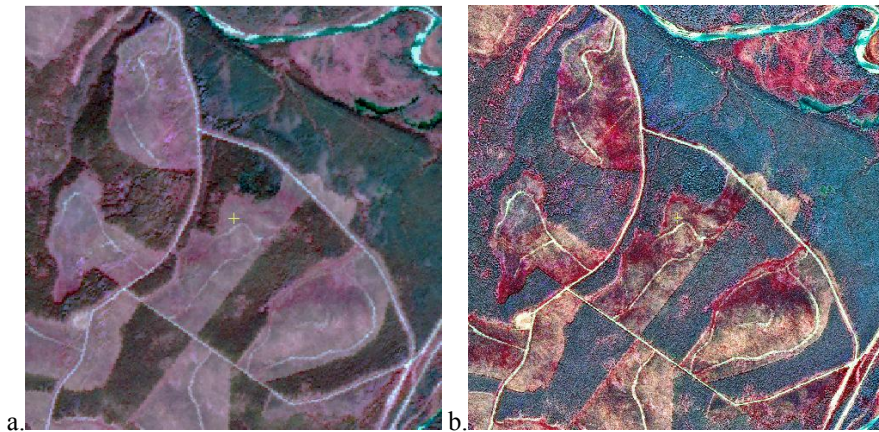
resolution SPOT-5 pansharpened imagery. Each stand was sampled at three points along a 100m transect (50m between plots, **Figure 3.1b**). At each plot the variables listed in **Table 3.1** were measured in the centre to enable an average of the data to be generated over the entire “pixel” sized area (see **Appendix B** for field sheet). The results of all field data will be compared to the available GIS to check its accuracy for later product validation.

<b>Table 3.2 Data points collected in the field</b>	
<b>Age Class</b>	<b>Number Collected</b>
0-5	11
6-10	5
11-15	5
16-20	4
21-30	7
31-40	7
41-50	5

### **3.4.2 Imagery Acquisition and Pre-processing**

SPOT-5 10 m multispectral and 2.5 m panchromatic imagery were acquired on July 21, 2005 over the study area and were ortho-rectified within 0.49 pixel root mean square error (RMSE) using 31 ground control points using nearest neighbour resampling. Atmospheric correction was completed following the methods outlined in Lanzl and Richter (1991) which use a digital elevation model to account for illumination geometry. The image was projected to UTM zone 11, NAD83. To obtain a higher spatial resolution dataset, SPOT-5 panchromatic band was fused with the multispectral channels. This was completed using the Advanced Pansharpening approach developed by Zhang (1999, 2002). This method is derived from a least-squares method to determine the best-fit between the multispectral, panchromatic and the fused images with the dual purpose of incorporating the higher resolution spatial detail and preserving

the spectral information. The latter is necessary for classification of biophysical parameters. To accomplish this, the variance within the spectral channels is kept smooth (Zhang, 2002). The advantages of the Pansharpening technique over other types of pan-fusion (IHS, PCA, and wavelet transformations) are that spectral distortion is minimized and operator dependency is reduced. **Figure 3.2** illustrates the colour



**Figure 3.2** Comparison of SPOT-5 original 10m (a) and pan-sharpened 2.5m (b) imagery; R=SWIR, G=red, B=NIR

comparison of the multispectral near infrared band 3 and its pan-sharpened counterpart. The normalized difference moisture index (NDMI) was calculated over the entire image using the following equation (Wilson and Sader, 2002).

$$\frac{(NIR-SWIR)}{(NIR+SWIR)} \quad (3.1)$$

### 3.4.3 Texture calculation

The texture analyses were based upon the pan-sharpened near infrared channel following Gong *et al.* (2003) and Coburn and Roberts (2004), as it showed the greatest degree of spectral variation for vegetation. First-order measures were used to evaluate the standard deviation of spectral reflectance under each moving window. A second-order grey level co-occurrence matrix (GLCM) textural analysis which measures the



pair-wise occurrence of grey values within the moving window (Clausi, 2002; Haralick *et al.*, 1973) was examined. For this study, the statistical measures of homogeneity (3.2), entropy (3.3), correlation (3.4), and contrast (3.5) were employed based on their sensitivity to forest structural parameters (Franklin, 2001a,b; 2001c; Coburn and

$$Homogeneity = \sum_{j=1}^n \sum_{i=1}^m \frac{P_{ij}}{(1 + [i - j]^2)} \quad (3.2)$$

$$Entropy = \sum_{j=1}^n \sum_{i=1}^m - P_{ij} \ln P_{ij} \quad (3.3)$$

$$Correlation = \sum_{i=1}^n \sum_{j=1}^m \frac{(i - \bar{i})(j - \bar{j})P_{ij}}{\sigma_i \sigma_j} \quad (3.4)$$

$$Contrast = \sum_{i=1}^n \sum_{j=1}^m P_{ij} (i - j)^2 \quad (3.5)$$

Roberts, 2004), where  $P_{ij}$  is the spatial co-occurrence matrix,  $i$  and  $j$  are the positional values within the matrix and  $\sigma_i$  and  $\sigma_j$  are the according standard deviations. Moving window sizes of 5x5, 11x11, and 25x25 were tested with both first- and second-order texture measures. These moving window sizes were chosen based on research with conifer species (Franklin *et al.*, 2000; 2001b; Coburn and Roberts, 2004). The present study was intended to understand the particular windows best suited for boreal forest age and site preparation classification.

#### 3.4.4 Classification Techniques and Product Validation

eCognition version 4.0 was used for object-oriented analysis and classification of forest disturbance over the SPOT-5 pansharpened image. To create image object primitives, a scale parameter of 50 was visually chosen as a result of the 2.5m

pansharpened spatial resolution of the SPOT-5 dataset. The spectral versus shape parameter was set to 0.2:0.8 and smoothness versus compactness was set to 1:9 to emphasize the compact nature and unnatural shape of cut blocks as per Flanders *et al.* (2003). For a more detailed discussion of the software, the reader is referred to Flanders *et al.* (2003), Chubey (2003), and McDermid (2005). Three spectral bands were used for the classification based on the results of the discriminant analyses (see section 3.4.4 below), the NDMI, green, and SWIR bands. This method has the advantage over the more popular pixel-based maximum likelihood classifier as it classifies polygons as a whole, and uses several features (such as mean, distance to neighbour, etc.) to create the most accurate “picture” of the class before classification begins. A standard nearest neighbour feature optimization was run to include the indices that would help separate three classes of stands: disturbed (aged 0-20), older disturbed (aged 21-50), and undisturbed (aged 50+). The resulting features were the minimum distance between each neighbour based on all three spectral values, the mean of all three spectral values, and the maximum difference between them per class. Once completed, a Kappa statistics test (Jensen, 2005) was completed over the entire area based first on initial samples, and secondly on a set of 50 random points throughout the image not used in the analysis.

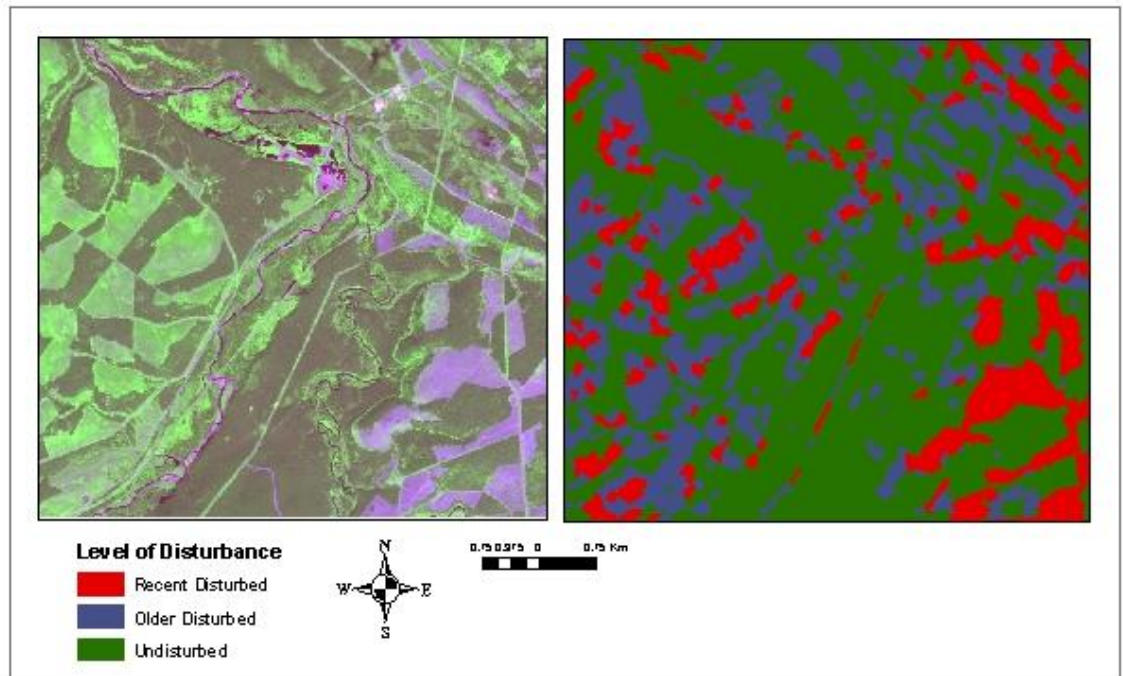
### **3.4.5 Statistical Analysis**

Age classes were determined prior to the statistical analysis based on the stated needs of the end-users. Nielsen *et al.* (2004b) had stated that a maximum ten year range per age class would be needed for the data to be applicable to the resource function modeling for grizzly bear habitat analysis. However, 5-year age ranges (0-5, 6-10, 11-15, 16-20, 21-25, 26-30, 31-35, 36-40, 41-45, 46-50) were chosen in order to determine

how sensitive the classification analysis could be to smaller differences. These age ranges were adjusted in the older stands to 10-year ranges (21-30, 31-40, and 41-50) to determine if these would be more separable. To calculate the SCI for the statistical classification, the first loading of a principal components analysis based on the correlation matrix of the field level inventory variables per stand was completed. Based on the results from Chapter 2.0 the predictive model (a function of the NDMI, standard deviation 5x5, and correlation texture measure 5x5) was used and applied to the image. Mean SCI values were calculated over each sampled cut block and included in the statistical analysis. All age and site preparation classifications were obtained using stepwise linear discriminant analysis (SPSS, Version 13.0), similar to the procedures used by Kimes *et al.* (1996, 1999). This analysis technique is based on canonical correlation analysis and plots each sample point as a function of two parameters highly correlated to the input parameters. All results were cross-validated and both classification accuracies are noted.

### ***3.5 Results and Discussion***

Classification of two levels of forest disturbances (recent: 0-20 years; older: 21-50 years) versus old growth (50+ years) was 94.8% using the 44 sampled stands from the GIS database (**Figure 3.3**). Post-classification analysis using 50 different random samples from a GIS database of all three classes reached 89.8%. The overall accuracy of the eCognition based map is similar to results presented by Flanders *et al.* (2003); however, the results of this study classify forest disturbance past 20 years, unlike the previous study which focused on blocks as recent or old-growth. In addition, three spectral bands were used for this classification, the SWIR, green, and the normalized

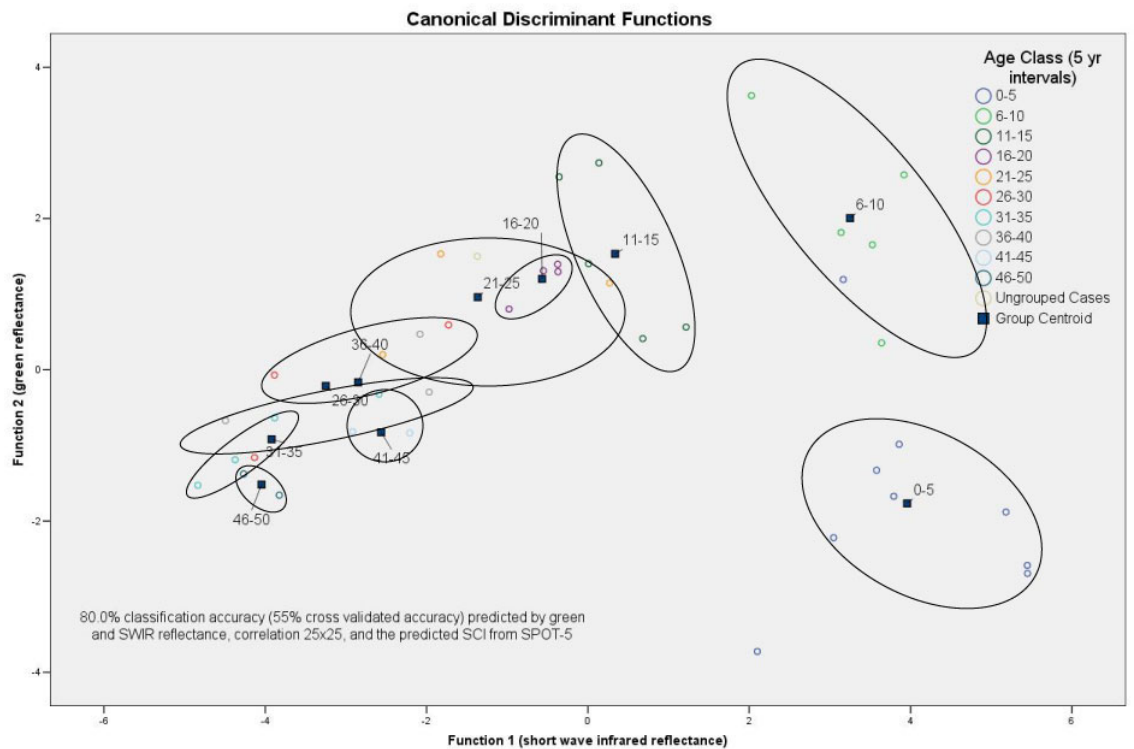
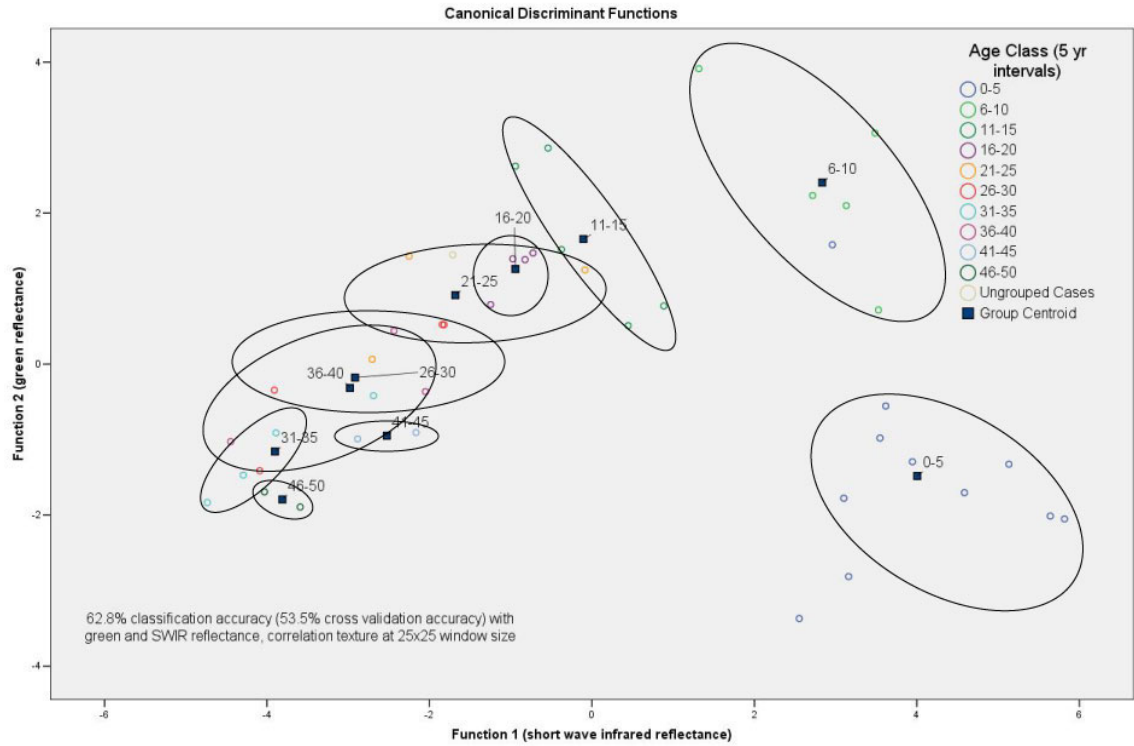


**Figure 3.3** Subset of SPOT-5 image showing original image (left) and classified forest disturbance (right)

difference moisture index which further support previous research by Wulder *et al.* (2004), Franklin *et al.* (2000), and Wilson and Sader (2002) indicating that the removal of canopy moisture in these areas is the most distinguishable characteristic identifiable using remotely sensed imagery. The results achieved in this study are of importance to the analysis of grizzly bear habitat in the Foothills Model Forest of Alberta as it validates our use of pansharpned imagery for forest biophysical classification. In addition, this research has resulted in the creation of a consistent forest disturbance layer for areas of high grizzly occurrence. Although water was not used in the classification, this layer will be of great use in yearly change detection models, a very important aspect of the Foothills Model Forest Grizzly Bear Research Project.

**Figure 3.4** shows the results of the linear discriminant analysis over the 44 field sampled stands in the study area. These two figures represent the separability of five year age classes up to age 50 using the two most robust and accurate models. The

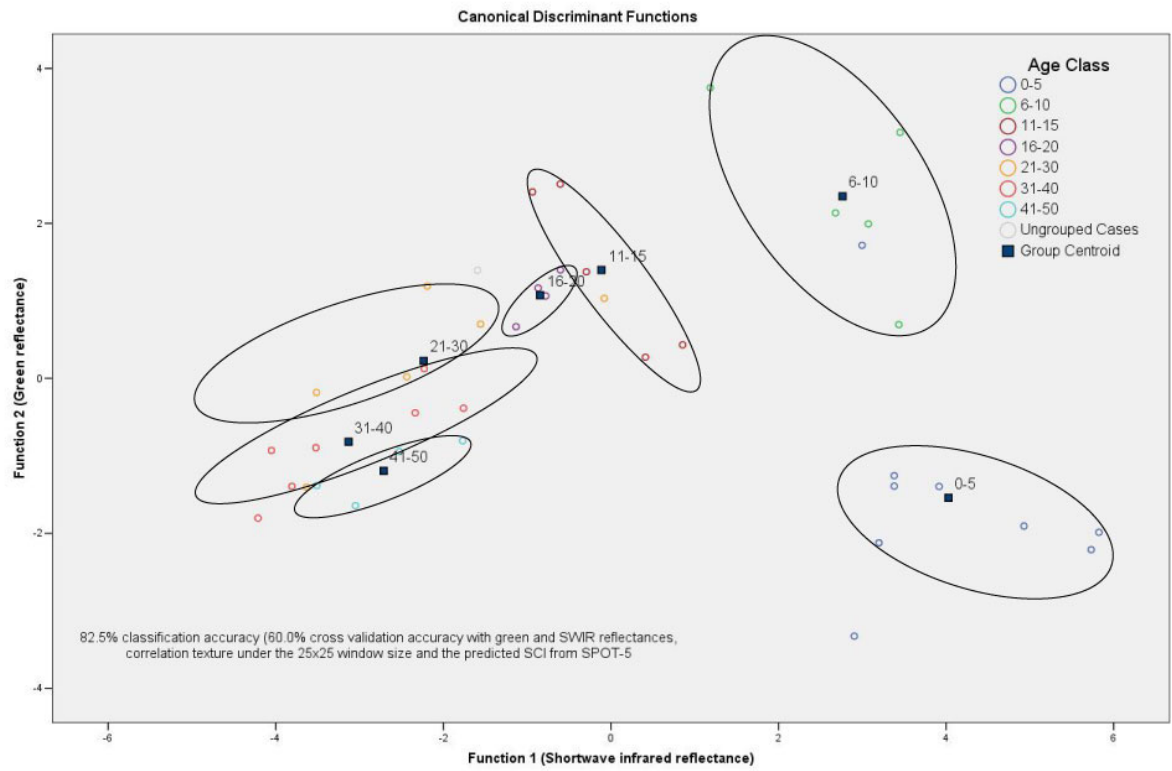
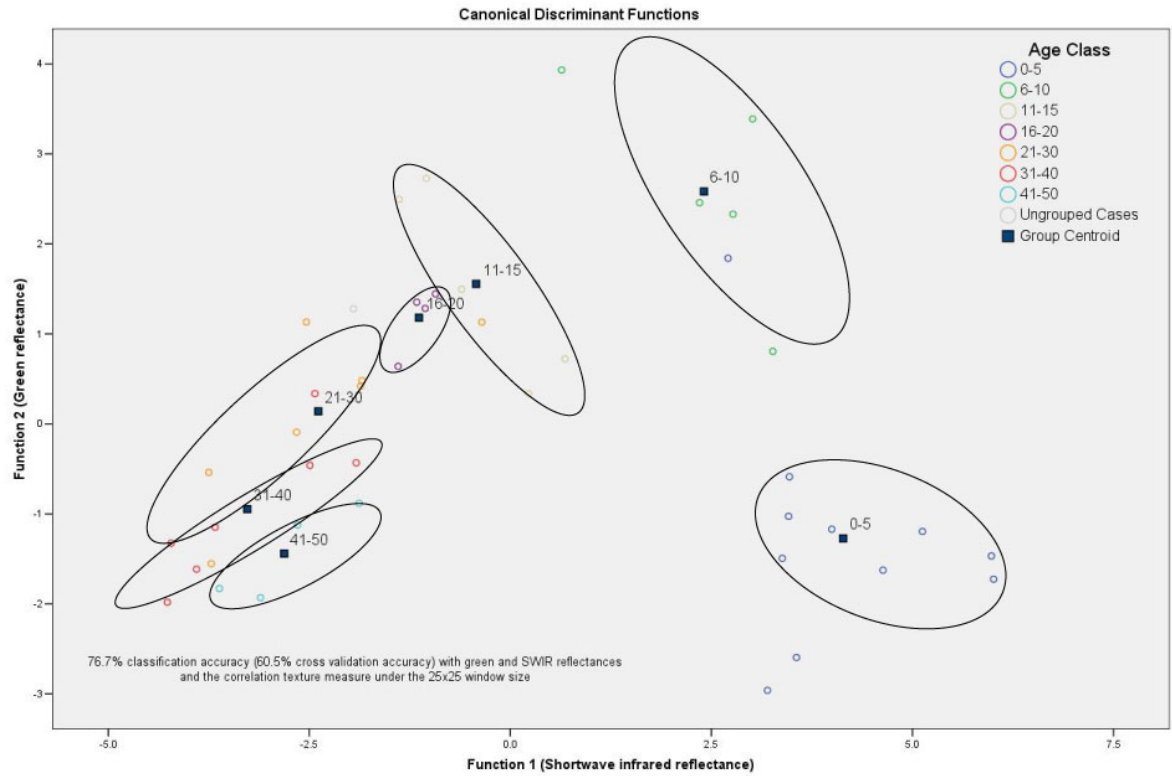
spectral and textural parameters for the first model were chosen using the stepwise method not only to ensure high classification accuracy but also to decrease collinearity. These were the shortwave infrared (SWIR) and green bands, and the correlation texture measure under the 25x25 window. For the second model, only the predicted SCI (from the image) was added. There were three canonical discriminant functions resulting from the first model and four from the second model, each correlating with one of the input parameters. This situation shows that each variable is independent and important to the classification. Ellipses of variable size were drawn manually on the figures to give a more visual representation of the separability of the five year age classes. Firstly, a nice transect can be observed in both graphs. This implies that age class is predictable as the data represent a trajectory of forest growth that can be detected using remotely sensed imagery. In the first model, classification accuracy was 62.8%, with six (of ten) separable classes: 0-5, 6-10, 11-15, 16-25, 26-45, and 46-50. This implies that there is information missing in the image that would possibly separate the middle classes, such as the SCI. When adding the predicted SCI to the model (lower graph of **Figure 3.4**), classification accuracy increases to 80.0% with seven separable classes, separating the 36-40 age class from the 26-45 in the previous model. Pearson's correlation between the SCI and age class in this study was 0.92 ( $p=0.01$ , 2-tailed) showing that the structure and



**Figure 3.4 Results of discriminant analyses for age classification of regenerating boreal forest with 5 year age classes; Original classification accuracy in *italics*, cross validated accuracy in **bold****

age are inextricably linked. This result was stronger in the boreal forest than in more complex forested systems examined by Hansen *et al.* (2001) and Cohen and Spies (1992), which was surprising as the boreal forest in this study area is very simple. This result is partially attributable to the 44 regenerating stands, and the differing structure that they portrayed. These stands were planted in a similar fashion, with similar species (pine or spruce), and followed accordingly similar structural trajectories. Thus it could be expected that similarly aged stands would display a similar structural complexity captured by the SCI. This relationship helps to explain the increase in accuracy once the SCI is added to the second model. Nevertheless, the results still indicate that a different set of age classes should be tested for separability using the available dataset, i.e. 21-30, 31-40, and 41-50. **Figure 3.5** shows the same two models with the modified age classes. The visual trajectory is altered slightly, in that it follows more of a horseshoe than in **Figure 3.4**, however, it is still prominent. Classification accuracy increased from 62.8% to 76.7% in the top graph with seven (of seven) separable age classes. When adding the predicted SCI to the modified age class model, classification accuracy reached 82.5%, not a significant increase from the second model of the previous example; however, the separability of the age classes is clear.

The results support work completed by Wulder *et al.* (2004) in that the green and SWIR bands are important to age classification of forest. The only textural measure of importance to age classification was second-order correlation texture under the 25x25 window size. This measure is a complex measure of spatial smoothness, a reflection of local homogeneity versus global variance, i.e. a measure of linear dependency similar to spatial auto-correlation (van der Sandman and Hoekmann, 2005). Conceptually, the



**Figure 3.5 Results of discriminant analyses for age classification of regenerating boreal forest with 5 year age classes to age 19 and 10 year age classes to age 50**



correlation texture measure will increase in value with a decrease in surface roughness or variance in local reflectance. In forested stands, this value would be high for debris covered cuts, increase with regeneration until the values are similar to the homogeneous recent cut once again. Thus to differentiate between the old growth stands and the recent cuts, the spectral reflectance of SWIR of the polygon is the determinant parameter. Franklin *et al.* (2003) had previously determined homogeneity to be of strongest importance to age class determination in the North West Territories, also a measure of spatial variance or smoothness within the window. However, they did not test the spatial autocorrelation or the second-order correlation texture measure which may have improved their model performance.

Site preparation class was separated into two classes, mounding versus furrow in 25% of the sampled stands in the field (aged 0-5). Fully excavated sites were unavailable for testing in the study area. Results from the stepwise linear discriminant analysis showed that classification accuracy was 90.9% using the NDMI and homogeneity texture measure under the 5x5 window size. Both of these parameters were highly correlated to one single canonical discriminant function, hence the lack of a corresponding graph depicting the classes for two functions. The NDMI in this model represents the level of debris and litter over the cut block. Cut blocks that have been subjected to a furrow style site preparation will have rows of debris interjected with rows of brown or black dirt, perhaps with small seedlings interspersed. Those subjected to mounding will have large piles of debris either throughout the block or along the sides. Either way, these different features will change the value of the NDMI. As discussed earlier, homogeneity measures “smoothness” over the set window size. A 5x5

window covers an area of 12.5m x 12.5m which correlates to the size of average mounds found in this area. In addition, two to four furrows would also be apparent in an area of this size. Consequently, one would expect that a larger window size would be inefficient to capture the variance needed to detect site preparation. Levels of homogeneity will then also be higher (or more smooth) for areas with mounds than for those with furrows. Although the results from this analysis are quite promising, classification was completed over a small sample, i.e. 11 stands (33 plots). This suggests that more research should be undertaken in this area for confirmation of these results.

### ***3.6 Conclusions***

Many studies have attempted to classify regenerating cut blocks and forest age using remotely sensed spectral information in the boreal forest of Canada. Not only have these studies focused on coarser spatial resolution data but they have not utilized all available information in the image, i.e. texture. Research that focused on using textural measures with higher spatial resolution as this study did, were unable to take advantage of the power of the short wave infrared band due to the choice of satellite sensor. This study, however, used a higher spatial resolution multispectral data set created using a pan-sharpening tool to ascertain the sensitivity of forest disturbance, its age, and site preparation to the normalized difference moisture index, measures of NIR texture and the Structural Complexity Index. This research also classified site preparation for use in grizzly bear habitat research, which was previously undocumented. There are four important conclusions resulting from this research:

- Classification accuracy of forest harvest using the NDMI, SWIR, and green reflectance values from high spatial resolution data was 89.8%. These results

were similar to those obtained using a medium spatial resolution dataset; however, the previous study was a more limited application which considered only very recent cuts versus old growth. The addition of information content, such as age class or site preparation, would also be unavailable with a medium spatial resolution sensor.

- Using 2.5m pansharpened SPOT data, age classes of 5 years ranges up to 20 and 10 year ranges up to 50 of regenerating boreal forest can be estimated with high accuracy using a combination of the SWIR, green band, SCI, and correlation texture under a 25x25 window. The resulting map layer will be of use to grizzly bear habitat modeling in all higher bear occurrence watersheds.
- The addition of the predicted Structural Complexity Index increased the age classification accuracy to 82.5%. This measure can also be viewed as a separate measure of texture, derived from actual field level structure and predicted using remotely sensed imagery. Further testing may be required in a variety of forested environments.
- Classification of site preparation methods (furrow versus mounding) shows a promising 90.9% accuracy. However, sample size was too small for a definitive conclusion. Although a visual interpretation of the image indicates the utility of this concept, further examination of this method is required.

### ***3.7. Acknowledgements***

This research was funded by the Natural Sciences and Engineering Research Council of Canada and the Foothills Model Forest. I thank PCI Geomatics for the use of

the PANSHARP module for this study. I would also like to take this opportunity to thank Dr. Greg McDermid, Alysha Pape, Karen Graham, Jerome Cranston, Dr. Marc Cattet, and Dr. Xulin Guo for the invaluable advice provided. In addition, I thank the Alberta Government, Fish and Wildlife conservation division for the use of their cabin during our field season in August, 2005 and West Fraser for sharing their GIS database with regards to harvest and site preparation.

### **3.8 References**

- Asner, G. P., Keller, M., Pereira, R., and Zweede, J. C., 2002. Remote sensing of selective logging in Amazonia: Assessing limitations based on detailed field observations, Landsat ETM+, and textural analysis. *Remote Sensing of Environment*, **80**, 483-496.
- Chubey, M. S., 2003. MSc. Thesis, Object-based analysis of IKONOS-2 imagery for extraction of forest inventory parameters, Faculty of Geography, University of Calgary.
- Clausi, D.A. 2002. An analysis of co-occurrence texture statistics as a function of grey level quantization. *Canadian Journal of Remote Sensing*, **28** (1), 45-62.
- Coburn, C.A. and Roberts, A.C.B. 2004. A multiscale texture analysis procedure for improved forest stand classification. *International Journal of Remote Sensing*, **25** (20), 4287-4308.
- Cohen, W. B. and Spies, T. A., 1992. Estimating structural attributes of Douglas-Fir / Western Hemlock forest stands from Landsat and SPOT Imagery. *Remote Sensing of Environment*, **41**, 1-17.
- Cohen, W. G., Fiorella, M., Gray, J., Helmer, E., and Anderson, K. 1998. An efficient and accurate method for mapping forest clearcuts in the Pacific Northwest using Landsat imagery. *Photogrammetric Engineering and Remote Sensing*, **64**, 293-300.
- Cranston, J. 2006. Personal Communication. GIS Specialist, Foothills Model Forest, Hinton, AB.
- Craighead, J.J., Sumner, J.S., and Mitchell, J.A. 1995. The Grizzly Bears of Yellowstone: Their ecology in the yellowstone ecosystem, 1959-1992. Island Press: Washington, D.C.
- Flanders, D., Hall-Beyer, M., and Pereverzoff, J., 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. Technical note in: *Canadian Journal of Remote Sensing*, **29** (4), 441-452.

- Franklin, S. E., Hall, R. J., Smith, L., and Gerylo, G. R. 2003. Discrimination of conifer height, age and crown closure classes using Landsat-5 TM imagery in the Canadian Northwest Territories. *International Journal of Remote Sensing*, **24** (9), 1823-1834.
- Franklin, S. E., D. R. Peddle, J. A. Dechka, and G. B. Stenhouse, 2002, Evidential reasoning using Landsat TM, DEM, and GIS data in support of grizzly bear habitat analysis, *International Journal of Remote Sensing*, **23**(21), 4633-4652
- Franklin, S. E., Lavigne, M. B., Moskal, L. M., Wulder, M. A., and McCaffrey, T. M., 2001a. Interpretation of forest harvest conditions in New Brunswick using Landsat TM enhanced wetness difference imagery (EWDI). *Canadian Journal of Remote Sensing*, **27**, 118-128.
- Franklin, S. E., Wulder, M. A., and Gerylo, G. R., 2001b. Texture analysis of IKONOS panchromatic data for Douglas-fir forest age class separability in British Columbia. *International Journal of Remote Sensing*, **22** (13), 2627-2632.
- Franklin, S. E., Moskal, L. M., Lavigne, M., and Pugh, K. 2000. Interpretation and classification of partially harvested forest stands in the Fundy Model Forest using multitemporal Landsat TM digital data. *Canadian Journal of Remote Sensing*, **26**, 318-333.
- Green, K., Kempka, D., and Lackey, L., 1994. Using remote sensing to detect and monitor land-cover and land-use change. *Photogrammetric Engineering & Remote Sensing*, **60**, 331-337.
- Gong, P., Mahler, S.A., Biging, G.S., and Newburn, D.A. 2003. Vineyard identification in an oak woodland landscape with airborne digital camera imagery. *International Journal of Remote Sensing*, **24** (6), 1303-1315.
- Hansen, M. J., Franklin, S. E., Woudsma, C., and Peterson, M., 2001. Forest structure classification in the North Columbia Mountains using the Landsat TM Tasselled Cap Wetness Component. *Canadian Journal of Remote Sensing*, **27** (1), 20-32.
- Haralick, R.M., Shanmugan, K., and Dinstein, I., 1973, Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. SMC-3, pp. 610-621.
- Healey, S. P., Cohen, W. B., Zhigiang, Y. and Krankina, O. N., 2005. Comparison of Tasselled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment*, **97**, 301-310.
- Jensen, J. R. 2005. Introductory Digital Image Processing: A Remote Sensing Perspective, 3<sup>rd</sup> Edition. Keith C. Clarke, ed. Upper Saddle River, NJ: Pearson Prentice Hall.
- Jin, S. and Sader, S. A., 2005. Comparison of time series tasselled cap wetness and the normalized difference moisture index in detection forest disturbances. *Remote Sensing of Environment*, **94**, 364-372.

- Jusoff, K. and D'Souza, G., 1996. Quantifying disturbed hill dipterocarp forest lands in Ulu Tembeling, Malaysia with HRV/SPOT images. *ISPRS Journal of Photogrammetry & Remote Sensing*, **51**, 39-48.
- Kimes, D. S., Holben, B. N., Nickeson, J. E., and McKee, W. A., 1996, Extracting forest age in a Pacific Northwest Forest from Thematic Mapper and topographic data. *Remote Sensing of Environment*, **56**, 133-140.
- Kimes, D.S., Nelson, R.F., Salas, W.A., Skole, D.L. 1999. Mapping secondary tropical forest and forest age from SPOT HRV data. *International Journal of Remote Sensing*, **20** (18), 3625-3640.
- Lanzl, F. and Richter, R., 1991. A fast atmospheric correction algorithm for small swath angle satellite sensors. *ICO Topical Meeting on Atmospheric, Volume and Surface Scattering and Propagation Conference Proceedings*, Florence, Italy. August 27-30, 455-458.
- Lévesque, J. and King, D. J., 1999. Airborne digital camera image semivariance for evaluation of forest structural damage at an acid mine site. *Remote Sensing of Environment*, **68**, 112-124.
- Mattson, D.J., Herrero, S., Wright, R.G., and Pease, C.M. 1996. Science and management of Rocky Mountain Grizzly Bears. *Conservation Biology*, **10** (4), 1013-1025.
- McDermid, G. 2005. PhD thesis Remote estimation of land cover and LAI over large areas for wildlife habitat applications, Faculty of Environmental Studies, University of Waterloo.
- Nielsen, S. E., Herrero, S., Boyce, M. S., Mace, R. D., Benn, B., Gibeau, M. L., and Jevons, S., 2004a, Modelling the spatial distribution of human-caused grizzly bear mortalities in the Central Rockies ecosystem of Canada. *Biological Conservation*, **120**, 101-113.
- Nielsen, S. E, Boyce, M. S., and Stenhouse, G. B., 2004b, 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, Munro, R. H. M., Bainbridge, E. L., Stenhouse, G. B., and Boyce, M. S., 2004c. Grizzly bears and forestry II. Distribution of grizzly bear foods in clearcuts of west-central Alberta, Canada. *Forest Ecology and Management*, **199** 67-82;
- Sader, S. A., Bertrand, M., and Wilson, E. H., 2003. Satellite change detection of forest harvest patterns on an industrial forest landscape. *Forest Science*, **49** (3), 341-353.
- Thomas, M., Roller, N., Colwell, J., and Kottack, C., 1993. Integrating regional studies of deforestation into a global change context, Proceedings, 25<sup>th</sup> *International Symposium, Remote Sensing and Global Change*, Volume 1, Environmental Research Institute of Michigan, Graz, Austria, 4-8 April, pp. 559-570.

- Van der Sandman, J. J. and Hoekman, D. H., 2005. Review of relationships between grey-tone co-occurrence, semivariance, and autocorrelation based image texture analysis approaches. *Canadian Journal of Remote Sensing*, 31 (3), 207-213.
- Viña, A., Peters, A. J., and Ji, L., 2003. Use of multispectral IKONOS imagery for discriminating between conventional and conservation agricultural tillage practices. *Photogrammetric Engineering & Remote Sensing*, **69** (5), 537-544.
- Wielgus, R. B. and Vernier, P. R., 2003. Grizzly bear selection of managed and unmanaged forests in the Selkirk Mountains. *Canadian Journal of Forest Research*, **33** (5), 822-829.
- Wilson, E. H., and Sader, S., 2002, Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment*, **80**, 385-396.
- Wulder, M.A., Skakun, R. S., Kurz, W. A., and White, J. C., 2004. Estimating time since forest harvest using segmented Landsat ETM+ imagery. *Remote Sensing of Environment*, **93** 179-187
- Zhang, Y. 1999. A new merging method and its spectral and spatial effects. *International Journal of Remote Sensing*, **20**, 2003-2014.
- Zhang, Y. 2002. A new automatic approach for effectively fusing Landsat 7 as well as IKONOS images. *IEEE/IGARSS Conference*, Toronto, Canada, June 24-28.

## 4.0 SYNTHESIS AND RESEARCH APPLICATIONS

The results of both manuscripts are very clear in terms of both remote sensing science and wildlife habitat management. As previously intimated, this chapter provides not only a synthesis of the most important contributions of this research to both fields but also delineates possible limitations and future research initiatives.

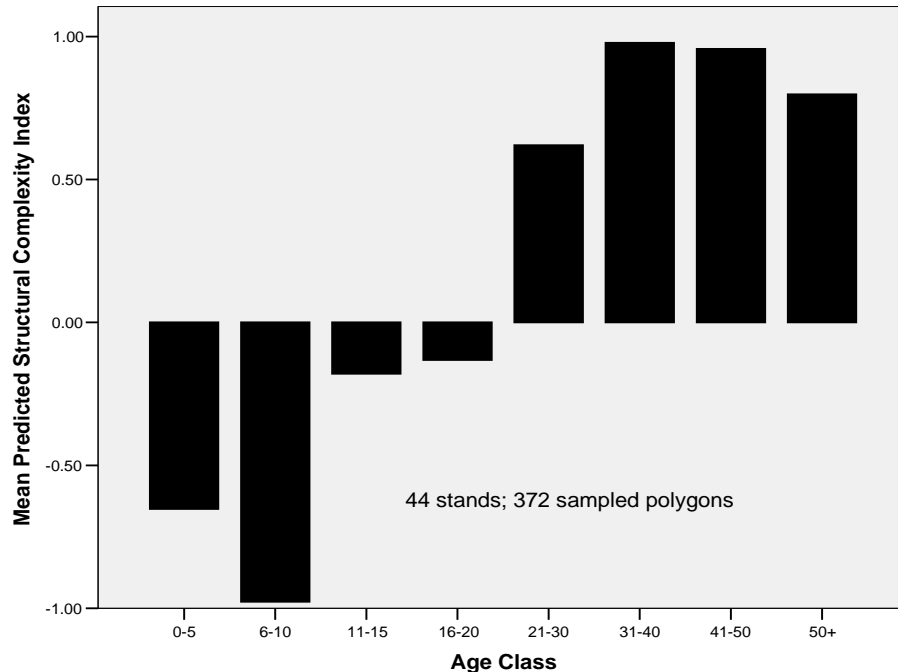
### ***4.1 Significant Contributions to Research in Remote Sensing Science and Forestry***

Cut blocks and regenerating areas were classified with 89% accuracy using spectral parameters (NDMI, green, SWIR bands) of 2.5m pansharpened imagery. This supports Franklin *et al.* (2000, 2001a), Jin and Sader (2005), and Wilson and Sader (2002) who used a measure of wetness (either the enhanced wetness index or the normalized moisture index) to increase their ability to classify partial cuts based on their characteristic moisture deficit. The method of analysis in this study used segmentation based on shape parameters as well as the available spectral data. These results are similar to those experienced by Flanders *et al.* (2003), whose accuracy was 90% using similar methods of analysis; however, that study focused solely on younger cut blocks and used lower spatial resolution Landsat TM imagery (30m). They also did not create a measure of wetness in which to help them identify these areas devoid of moisture. This research was able to classify regenerating areas up to 50 years of age, a result of using higher spatial resolution data with a measure of moisture.

Before attempting to classify regenerating age, a full understanding of field level structure and its relationship with age needed to be understood. In the first manuscript, to estimate regenerating structure, a single measure called the Structural Complexity



Index (SCI) was calculated whereby all variance in a set of field level variables was included in one value. More importantly, this was attempted under a simple boreal canopy, a previously undocumented feat. Results showed a very high correlation to age ( $r=0.92$ ,  $p=0.01$ ), as well as strong partial correlation (controlling for age) relationships with the unused field-level variables of crown closure ( $r_{\text{part}}=0.67$ ,  $p=0.01$ ) and height ( $r_{\text{part}}=0.44$ ,  $p=0.01$ ). Earlier research using this index had focused on more complex forested systems, such as multi-layer canopies in Revelstoke (Hansen *et al.*, 2001a) or in the Pacific Northwest (Cohen and Spies, 1992). Interestingly, the SCI in the more complex forest did not show the strength of relationship to the three field-level variables (age, height, and crown closure) as observed in the boreal forest. This appears to be the result of focusing solely on regenerating areas at the expense of old-growth contrary to both studies conducted by Hansen *et al.* (2001a) and Cohen and Spies (1992). Based on our field observations, after a stand is cut, there is a period of limited growth resulting from high density debris cover. This is followed within a couple of years by site preparation whereby furrowing and mounding of this debris within the cut block is completed to expose the black nutrient rich soil at the surface for successful planting of seedlings. As the seedlings grow and age, the variables such as crown diameter, diameter at breast height, and basal area increase in size, with a decrease in stem density. SCI follows an increasing trend with age as well until the canopy closes fully (80+ %) **(Figure 4.1)**.



**Figure 4.1 Structural Complexity Index values (predicted) for all field sampled stands versus age class. Sampled polygons are segments within each stand; Standard Error of the mean was 0.06**

Spectrally, SCI has been shown to be strongly related to the Tasselled Cap Wetness Index (Hansen *et al.*, 2001a; Cohen and Spies, 1992). This result is supported in the boreal forest where a different method of moisture detection—the normalized difference moisture index (NDMI)—was the most important predictor for SCI. In fact, these results truly support the previously discussed studies by Hansen *et al.* (2001a) and Cohen and Spies (1992), as a recent study by Healey *et al.* (2005) concluded that the NDMI and tasselled cap wetness index are highly correlated and create the same measurement results. This suggests that although complex and simple forested stands show structural differences, spectrally they demonstrate similar reflectance properties. For that reason, the use of texture analysis is necessary to be able to predict the SCI from a satellite based image. Common methods of textural analysis are first- and second-order measures, calculated under moving windows. In order for these measures to be

informative, they must be calculated under H-resolution dataset, i.e. one that has a pixel size smaller than the features in question, here regenerating stands. Thus, the 2.5m spatial resolution is appropriate for this initiative. Both types of textural measures were shown useful in the description of single boreal forest parameters such as tree height, age (Gerylo *et al.* 2002; Franklin *et al.*, 2003; 2001b), tree crown diameter (Levesque and King, 1999, 2003), and volume (Tuominen and Pekkarinnen, 2005). SCI in the boreal forest of our study area was strongly related to second-order correlation texture measure under a 5x5 window (12.5m x 12.5m area) indicating that local homogeneity versus linear correlation is a good indicator of structural differences. The overall relationship between the SPOT-5 spectral and textural values was strong ( $R^2 = 0.74$ ) and once the model was applied to the image, the resulting values were validated using linear regression (Adj.  $R^2 = 0.70$ ). This is the first documented attempt at classifying an image for the Structural Complexity Index. This is a direct result of obtaining a high spatial resolution dataset where both textural measures and the NDMI could be calculated.

Although it is possible that the SCI could act as a surrogate for age in wildlife habitat analyses, age classification of regenerating areas was still attempted for comparison. In addition, the question remained if the SCI could facilitate this initiative. Spectrally, 5-year age classes were best separated using the green and shortwave infrared (SWIR) bands, however still at a low accuracy (35.3%). Wulder *et al.* (2004) describes a similar relationship between these bands in Landsat ETM+ with single-year age classes in a complex regenerating forest on the Pacific coast of Canada. Franklin *et al.* (2003) were able to increase age class separability in northern boreal forest by adding second-order textural measures. The addition of the correlation texture measure under

the 25x25 window size increased classification accuracy to 62.8%. This still suggested that more information was required. After adding the image predicted SCI and changing age classes to ten year from age 20 to 50 (ages 0-20 remained five year classes), classification accuracy reached 82.5%. The SCI then appears to be less of a surrogate for age class, rather a textural predictor. This is the first attempt at using the SCI to increase age classification of forested areas.

Lastly, this study was able to classify site preparation (furrow versus mounding) activities within stands aged 0-5. Classification accuracy was 90.9% using the NDMI and homogeneity texture measure under the 5x5 window size. However, only eleven stands were sampled due to resource and field constrictions. The excellent results based on these points suggests, however, that further research be employed in this area as it is still a needed layer for habitat modeling.

#### ***4.2 Applications for Wildlife Habitat Management***

This research provides valuable habitat information content of high spatial resolution imagery and develops an appropriate model to determine both age class and the structural complexity of a stand. **Table 4.1** presents a selection from the literature whereby habitat variables used for several species of wildlife are indicated. Those in bold signify variables that could be mapped using the models discussed in this thesis. Although this research was undertaken as a result of grizzly bear habitat requirements outlined by Nielsen et al. (2004b,c, 2005), it is clear that the products are applicable to other studies involving wildlife habitat. By providing the products and methods created here (**Appendix C**) to these studies, it is possible that they may be able to make a clearer link with habitat, its change, and thus strongly affect wildlife conservation policies.

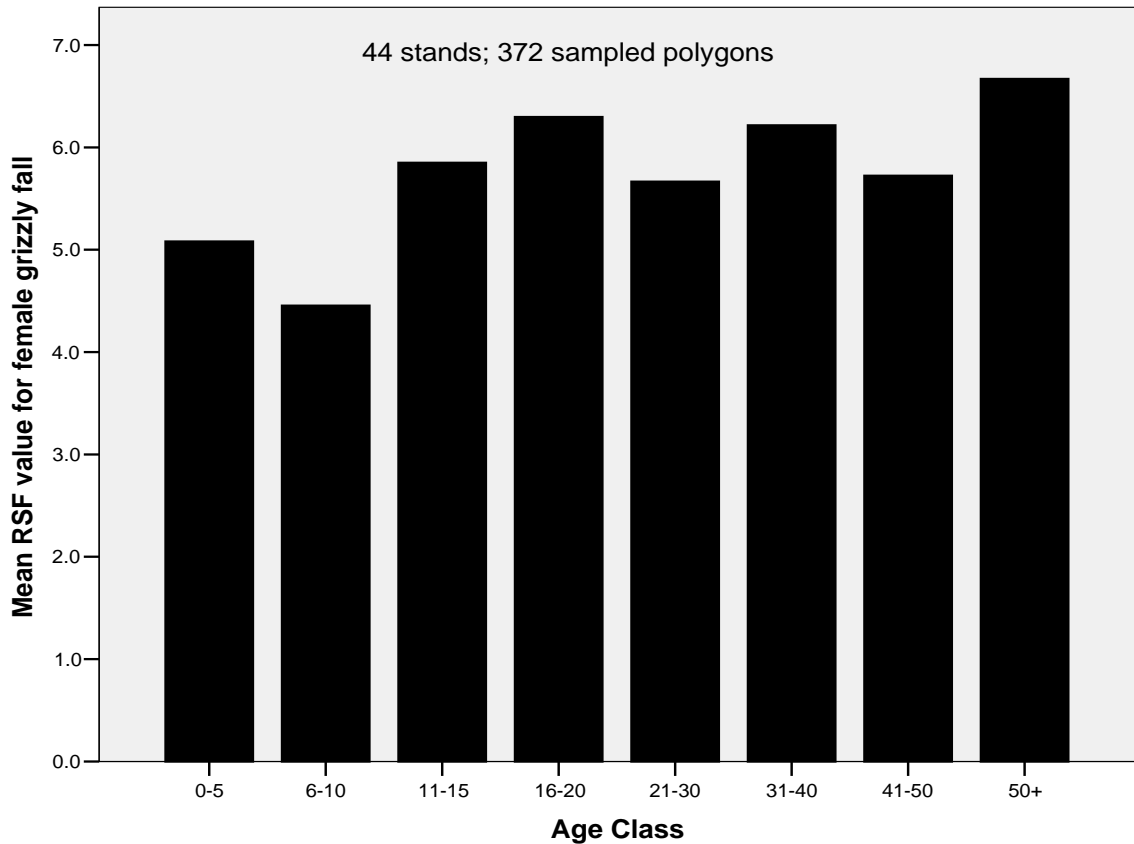
<b>Table 4.1 Several wildlife studies (inexhaustive) and habitat modeling needs specified</b>		
<b>Wildlife Study</b>	<b>Habitat needs</b>	<b>Source</b>
Varied	Land cover; Tree size, <b>crown closure</b> , and species composition, <b>silviculture, age structure</b>	Fox <i>et al.</i> (2002); Cumming <i>et al.</i> (1994)
Grizzly (Can.)	<b>Crown closure, regenerating age, scarification</b> , terrain, tree species, land cover	Nielsen <i>et al.</i> (2004a,b,c); Popplewell <i>et al.</i> (2003); Wielgus and Vernier (2003); Betts <i>et al.</i> (2003); Franklin <i>et al.</i> (2002); Gibeau <i>et al.</i> (2002) Mattson <i>et al.</i> (1996); Craighead <i>et al.</i> (1995)
Caribou	Species composition, <b>age structure</b> , land cover	Hansen <i>et al.</i> (2001b)
Moose	<b>Regenerating forest, age structure, silviculture</b> , burn history	Rempel <i>et al.</i> (1997)
Bird	<b>Vertical forest complexity, age structure</b> , land cover	McGarigal and McComb (1995); Flather <i>et al.</i> (1992)
Elk	Land cover; <b>forest age structure and disturbance history</b>	Boyce, <i>et al.</i> (2003); Irwin and Peek (1983)
Wolf	<b>Forest structure</b> and species cover; land cover	Massolo and Meriggi (1998)

To determine the utility of the three map products produced (**Appendix C**), the age class and SCI layers were compared to the Resource Selection Functions (RSF) created by Nielsen (2005) for the same area. The RSF functions display a low value (on a scale of 1 to 7) where grizzly bear occurrence is unexpected and high where habitat is highly suitable. The RSF values for the fall season (female adult grizzly) were averaged under each polygon within the 44 field sampled stands. The shape-based segmentation had resulted in several polygons per stand, culminating in 372 sampled polygons overall. Spearman's Rank correlation (non-parametric, two-tailed) coefficients were calculated to evaluate the relationship between these stands, RSF, and age class (**Table 4.2**).

Table 4.2 Correlations for female grizzly, fall season with age class and SCI for the 44 sampled stands (n=372)	
	RSF Value
Age Class	0.54
Predicted SCI	0.45
Actual SCI	0.53
All correlations are significant at the 0.01 level (2-tailed).	

Results between age class and RSF were stronger than between the predicted SCI and RSF. This situation indicates that the predicted SCI may not be an appropriate surrogate for age as previously hypothesized; however, the actual SCI values show a similar association with the RSF values as that with age class suggesting that further research is required. **Figure 4.2** illustrates the changing relationship between RSF and age class. Although the graph shows RSF increasing with age, there are some small variations based on food quality, quantity, and access along this trend. Based on our field level observations, regenerating areas under five years of age are more accessible and have a higher ant and horsetail (*Equisetum spp.*) coverage, hence their modeled selection (see Nielsen 2004b,c for more detail). As the cut blocks age, they incur “weedy” aspen growth making them less accessible and attractive to wildlife, although there may be berries growing in the area. These berries plants have established themselves and matured as the block grows further (aged 11-20), as well as increased conifer growth begins to thin the aspen coverage due to increased crown closure. Within the 21-30 age class, the regenerating forest has a very thick understory, making traversing the area difficult. In addition, higher crown closures reduce the amount of light available for larger berry producing species and may cause a decrease in production. As the stands age further the increased crown closure limits understory

growth, thus decreasing tangling underbrush and makes the stand more accessible and secure (Mattson *et al.* 1996; Nielsen *et al.* 2004a). For a more detailed analysis of the results and indications of RSF modeling and its link with forest structure, the reader is referred to Nielsen (2005).



**Figure 4.2** Age class versus the mean resource selection function for fall female grizzly bears. Sampled polygons are segments within each stand; Standard Error of the mean was 0.08

The deliverable products were created by segmentation and classification based on shape parameters as a result of this research. The four maps included in **Appendix C** are the original SPOT-5 imagery, disturbance classification, SCI classification, and regenerating age classification. They will be provided to the Foothills Model Forest Grizzly Bear Research Project for use in further analysis. As shown in **Figure 4.2**, the map layers resulting from this thesis are valuable, enforcing the idea that consistent

remote detection of regenerating forest age of cut areas is critical in grizzly bear habitat analysis and other wildlife studies. In addition, this thesis offers a prospect for future classification of site preparation activities within areas where GIS is unavailable. The product of this research thus provides a practical alternative to expensive field work in the areas of forest inventory and wildlife habitat analysis.

### ***4.3 Limitations***

Within the context of this research there are a few limitations. Satellite-based datasets are limited not only by their spatial and spectral resolutions, but also by radiometric resolution, an indicator of their sensitivity to changes in reflection. SPOT-5 is an 8 bit sensor (255 shades of grey) whereas other sensors with similar spectral and spatial resolutions such as the CASI (compact airborne spectrograph imager with the SASI sensor) provide an 11 bit resolution (2,046 shades of grey). Although there are other, more sensitive, sensors available commercially, they require not only increased processing time to provide similar results, but are also 5 times more expensive for the same area coverage. As this research is focused on providing a cost-effective method whereby both forest management teams and wildlife habitat research are able to create these layers, a satellite based dataset, such as SPOT-5 is preferable.

The analysis of the dataset was limited by the use of a 30m digital elevation model (DEM) to geometrically correct 2.5m spatial resolution imagery. Although this situation is not ideal, the purchase of a higher level DEM was impossible, as it did not exist. Technology such as LiDAR would provide such a DEM but at an exorbitant cost. Atmospheric correction was completed using methods based on the ATCOR-3 PCI module. Although this module does take elevation into consideration it is by no means



the most accurate way to do so. Nevertheless, both of these difficulties do not overwhelm the results and have been used in previous research with success. Limitations arising from data fusion are apparent; however, the added detail far outweighed any small detraction from the original spectral image. The methods whereby texture is calculated are over 30 years old, and have been shown by some to be less than optimal (Hay *et al.* 1996). On the other hand, this research was based on results with previous research and attempted to build upon them. Again, although there were some limitations within the study, it is believed that they are not of a significant nature and that the results would only be stronger without them.

#### ***4.4 Future Research***

High spatial resolution imagery is expensive for large area mapping and is thus difficult to practically rationalize. For that reason, future initiatives for the grizzly bear project will include obtaining a set of SPOT-5 images over the same area and in another high probability grizzly occurrence area to test the methods of analysis. In addition, high spatial resolution change detection will be completed over the area mapped within this thesis. To combat the problems with using a 30m DEM to correct the 2.5m image, we will be obtaining a stereo-pair (SPOT-5) at each area which may increase the DEM spatial resolution to 15m. This initiative will test the use of SCI, texture, and spectral information to again, classify age class and site preparation for habitat analysis.

A second possible direction of research is the acquisition of a high radiometric and spatial resolution dataset such as Quickbird (2.4m multispectral, 0.64 m panchromatic) to determine if similar relationships are available with the 2.4m dataset

and how that changes with the increase to 0.64m. Also, it can be examined if the higher radiometric resolution will offset the lower spectral resolution (i.e. no SWIR band).

Lastly, the direction of current research points securely in the direction of both hyperspectral and LiDAR datasets. Perhaps the use of these datasets together will provide increased information about the nature of regenerating stands within the boreal forest. As future satellite sensors will also be of this calibre (for example, Hyperspectral Environment and Resource Observer [HERO]), such research could provide a way to use these sensors in a more efficient manner.

#### ***4.5 References***

- Betts, M. G., Franklin, S. E., and Taylor, R. G., 2003. Interpretation of landscape pattern and habitat change for local indicator species using satellite imagery and geographic information system data in New Brunswick, Canada. *Canadian Journal of Remote Sensing*, **33**, 1821-1831.
- Boyce, M. S., Mao, J. S., Merrill, E. H., Fortin, D., Turner, M. G., Fryell, J., and Turchin, P., 2003. Scale and heterogeneity in habitat selection by elk in Yellowstone National Park. *Ecoscience*, **10** (4), 421-431.
- Cohen, W. B. and Spies, T. A., 1992. Estimating structural attributes of Douglas-Fir / Western Hemlock forest stands from Landsat and SPOT Imagery. *Remote Sensing of Environment*, **41**, 1-17.
- Craighead, J.J., Sumner, J.S., and Mitchell, J.A. 1995. The Grizzly Bears of Yellowstone: Their ecology in the yellowstone ecosystem, 1959-1992. Island Press: Washington, D.C.
- Cumming, S. G., Burton, P. J., Prahacs, S., and Garland, M. R., 1994. Potential conflicts between timber supply and habitat protection in the boreal mixedwood of Alberta Canada: A simulation study. *Forest Ecology and Management*, **68** (2-3), 281-302.
- Flanders, D., Hall-Beyer, M., and Pereverzoff, J., 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. Technical note in: *Canadian Journal of Remote Sensing*, **29** (4), 441-452.
- Flather, C. H., Brady, S. J., and Inkey, D. B., 1992. Regional habitat appraisals of wildlife communities: a landscape-level evaluation of a resource planning model using avian distribution data. *Landscape Ecology*, **7** (2), 137-147.

- Fox, L., Garrett, M. L., Heasty, R., and Torres, E., 2002. Classifying wildlife habitat with pan-sharpened Landsat 7 Imagery, Proceedings, *ISPRS Commission I Symposium*, Volume 4, Pecora 15/Land Satellite Information, Denver, Colorado, USA, November 10-15.
- Franklin, S. E., Hall, R. J., Smith, L., and Gerylo, G. R. 2003. Discrimination of conifer height, age and crown closure classes using Landsat-5 TM imagery in the Canadian Northwest Territories. *International Journal of Remote Sensing*, **24** (9), 1823-1834.
- Franklin, S. E., D. R. Peddle, J. A. Dechka, and G. B. Stenhouse, 2002, Evidential reasoning using Landsat TM, DEM, and GIS data in support of grizzly bear habitat analysis, *International Journal of Remote Sensing*, **23**(21), 4633-4652
- Franklin, S. E., Lavigne, M. B., Moskal, L. M., Wulder, M. A., and McCaffrey, T. M., 2001a. Interpretation of forest harvest conditions in New Brunswick using Landsat TM enhanced wetness difference imagery (EWDI). *Canadian Journal of Remote Sensing*, **27**, 118-128.
- Franklin, S. E., Wulder, M. A., and Gerylo, G. R., 2001b. Texture analysis of IKONOS panchromatic data for Douglas-fir forest age class separability in British Columbia. *International Journal of Remote Sensing*, **22** (13), 2627-2632.
- Franklin, S. E., Moskal, L. M., Lavigne, M., and Pugh, K. 2000. Interpretation and classification of partially harvested forest stands in the Fundy Model Forest using multitemporal Landsat TM digital data. *Canadian Journal of Remote Sensing*, **26**, 318-333.
- Gerylo, G. R., Hall, R. J., Franklin, S. E. and Smith, L., 2002. Empirical relations between Landsat TM spectral response and forest stands near Fort Simpson, Northwest Territories, Canada. *Canadian Journal of Remote Sensing*, **28** (1), 68-79.
- Gibeau, M. L., Clewenger, 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
- Hansen, M. J., Franklin, S. E., Woudsma, C., and Peterson, M., 2001a. Forest structure classification in the North Columbia Mountains using the Landsat TM Tasseled Cap Wetness Component. *Canadian Journal of Remote Sensing*, **27** (1), 20-32.
- Hansen, M. J., Franklin, S. E., Woudsma, C. G. and Peterson, M., 2001b. Caribou habitat mapping and fragmentation analysis using Landsat MSS, TM, and GIS data in the North Columbia Mountains, British Columbia, Canada. *Remote Sensing of Environment*, **77**, 50-65.
- Hay, G. J., Niemann, K. O., and McLean, G., 1996. An object-specific image texture analysis of H-resolution forest imagery. *Remote Sensing of Environment*, **55**, 108-122.

- Healey, S. P., Cohen, W. B., Zhigiang, Y. and Krankina, O. N., 2005. Comparison of Tasselled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment*, **97**, 301-310.
- Irwin, L. L. and Peek, J. M., 1983. Elk habitat use relative to forest succession in Idaho. *Journal of Wildlife Management*, **47** (3), 664-672.
- Jin, S. and Sader, S. A., 2005. Comparison of time series tasselled cap wetness and the normalized difference moisture index in detection forest disturbances. *Remote Sensing of Environment*, **94**, 364-372.
- Lévesque, J. and King, D. J., 2003. Spatial analysis of radiometric fractions from high-resolution multispectral imagery for modelling individual tree crown and forest canopy structure and health. *Remote Sensing of Environment*, **84**, 589-602.
- Lévesque, J. and King, D. J., 1999. Airborne digital camera image semivariance for evaluation of forest structural damage at an acid mine site. *Remote Sensing of Environment*, **68**, 112-124.
- Massolo, A. and Meriggi, A., 1998. Factors affecting habitat occupancy by wolves in northern Apennines (northern Italy): a model of habitat suitability. *Ecography*, **21** (2), 97-107.
- Mattson, D.J., Herrero, S., Wright, R.G., and Pease, C.M. 1996. Science and management of Rocky Mountain Grizzly Bears. *Conservation Biology*, **10** (4), 1013-1025.
- 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., Herrero, S., Boyce, M. S., Mace, R. D., Benn, B., Gibeau, M. L., and Jevons, S., 2004a, Modelling the spatial distribution of human-caused grizzly bear mortalities in the Central Rockies ecosystem of Canada. *Biological Conservation*, **120**, 101-113.
- Nielsen, S. E, Boyce, M. S., and Stenhouse, G. B., 2004b, 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, Munro, R. H. M., Bainbridge, E. L., Stenhouse, G. B., and Boyce, M. S., 2004c. Grizzly bears and forestry II. Distribution of grizzly bear foods in clearcuts of west-central Alberta, Canada. *Forest Ecology and Management*, **199** 67-82;
- Nielsen, S. E. 2005. Habitat ecology, conservation, and projected population viability of grizzly bears (*Ursus arctos* L.) in west-central Alberta, Canada. PhD Dissertation, University of Alberta, Edmonton, Alberta, Canada.
- Popplewell, C., Franklin, S. E., Stenhouse, G. B. and Hall-Beyer, M., 2003, Using landscape structure to classify grizzly bear density in Alberta Yellowhead Ecosystem bear management units, *Ursus*, **14**, 27-34.

- Rempel, R. S., Elkie, P. C., Rodgers, A. R., and Gluck, M. J., 1997. Timber-management and natural-disturbance effects on moose habitat: Landscape evaluation. *Journal of Wildlife Management*, **61** (2), 517-524.
- Tuominen, S. and Pekkarinen, A., 2005. Performance of different spectral and textural aerial photograph features in multi-source forest inventory. *Remote Sensing of Environment*, **94**, 256-268.
- Wielgus, R. B. and Vernier, P. R., 2003. Grizzly bear selection of managed and unmanaged forests in the Selkirk Mountains. *Canadian Journal of Forest Research*, **33** (5), 822-829.
- Wilson, E. H., and Sader, S., 2002, Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment*, **80**, 385-396.
- Wulder, M.A., Skakun, R. S., Kurz, W. A., and White, J. C., 2004. Estimating time since forest harvest using segmented Landsat ETM+ imagery. *Remote Sensing of Environment*, **93** 179-187

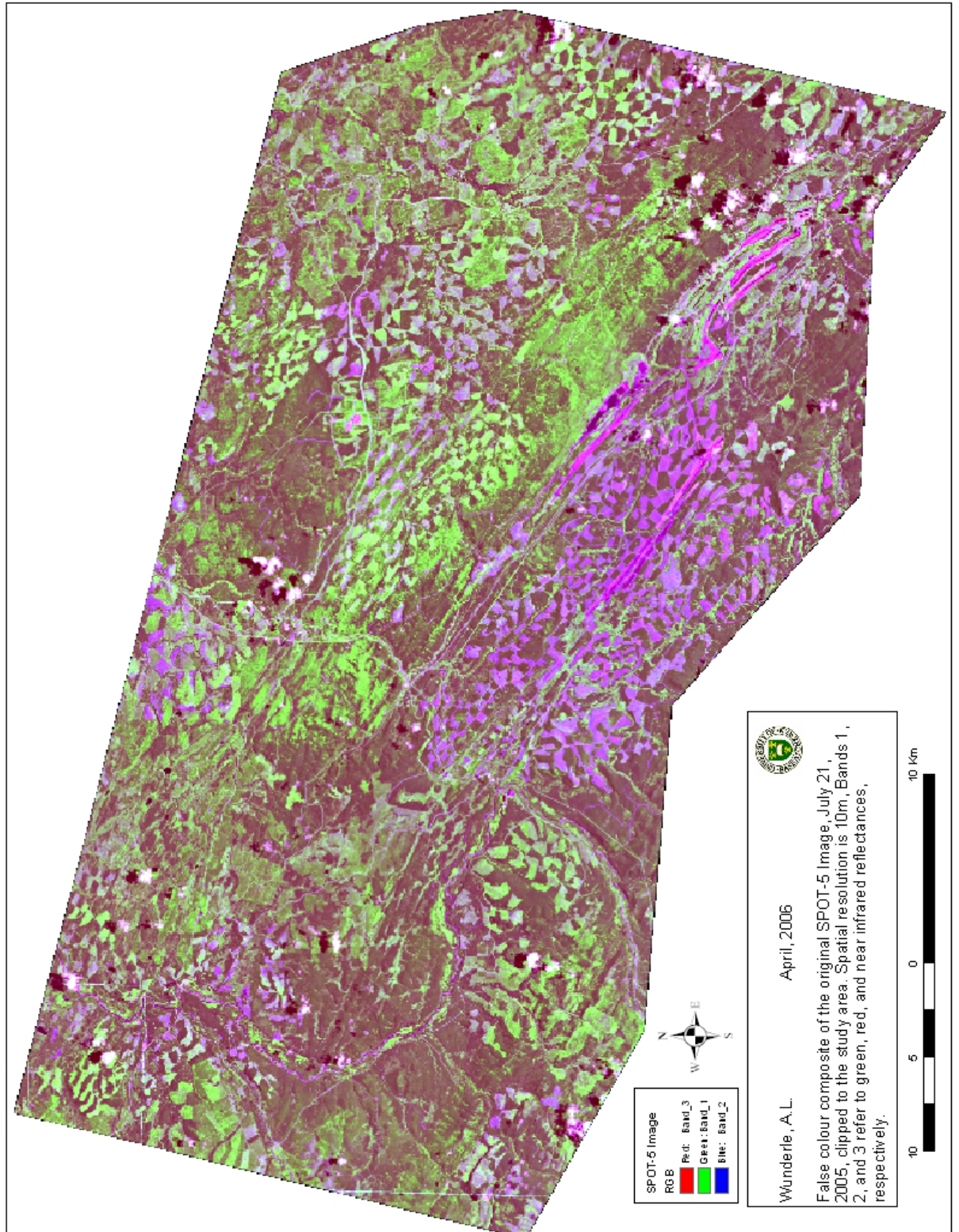
## **APPENDIX A: Communication**

The two manuscripts resulting from this research will be submitted to Remote Sensing of Environment in April of 2006 and the International Journal of Remote Sensing in May of 2006. The research will be presented at the ASPRS Annual Conference in Tampa, FL on May 7-11, 2007. To reach the second audience, the research will be presented at the Annual Conference for the Canadian Institute of Forestry 2007, as well as a departmental seminar (February 24, 2006). In addition, a formal report for the Grizzly Bear Research Project will be completed, presented in various workshops, and held on file at the Foothills Model Forest in Hinton, Alberta.

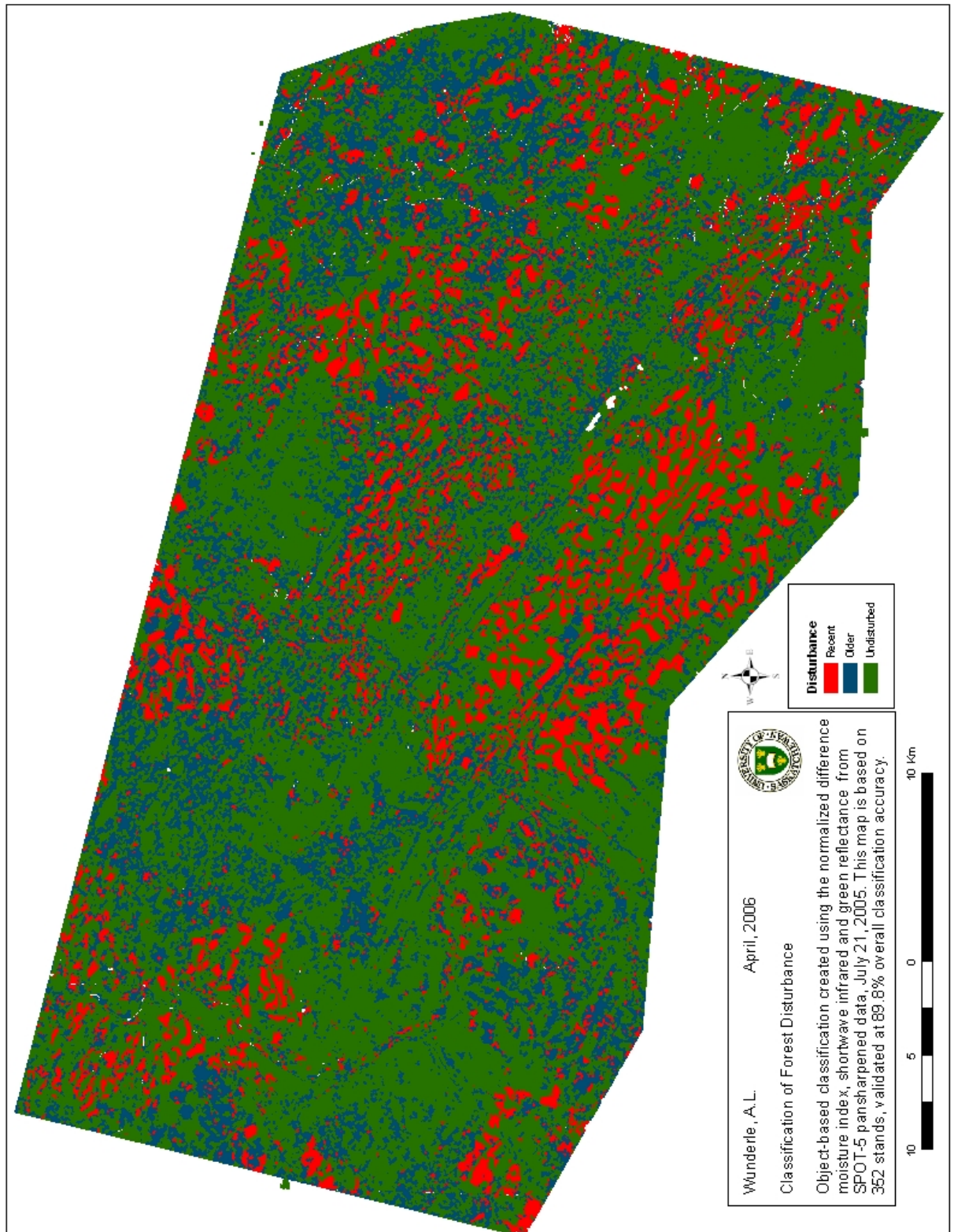
## APPENDIX B: Field sheet

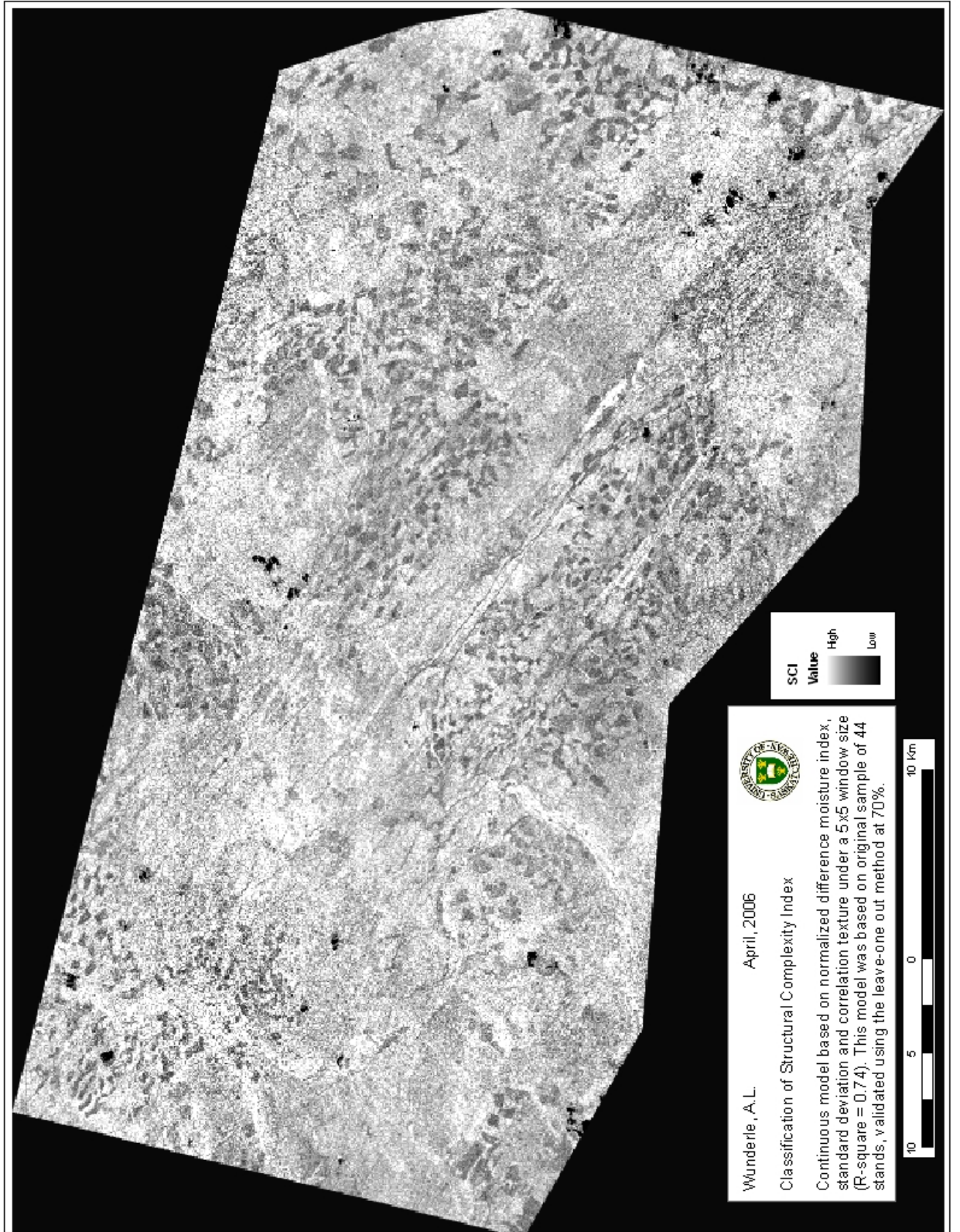
PLOT SIZE: _____ m x _____ m		
Day _____ Time arr: _____ lv: _____ Field Crew _____ _____ AVI call: _____	Easting	Northing
	GPS - office _____ GPS - field _____ Observations: _____ _____	
PLOT SIZE: _____ m x _____ m		
CC: _____	Vegetation Cover: _____	
DENSIOMETER	CEPTOMETER	
C _____	C _____	BEFORE _____
NW _____	NW _____	TIME _____
NE _____	NE _____	AFTER _____
SW _____	SW _____	TIME _____
SE _____	SE _____	_____
DBH	HEIGHT	ORDER OF PHOTOS
1 _____	_____	C _____
2 _____	_____	NW _____
3 _____	_____	SE _____
4 _____	_____	NE _____
5 _____	_____	SW _____
6 _____	_____	REP#1 _____
7 _____	_____	REP#2 _____
8 _____	_____	
9 _____	_____	
10 _____	_____	
		TREE CORE COLLECTION
11 _____	_____	No. Species DBH
12 _____	_____	1 _____
13 _____	_____	2 _____
14 _____	_____	3 _____
15 _____	_____	4 _____
16 _____	_____	5 _____
17 _____	_____	6 _____

# APPENDIX C: MAPS





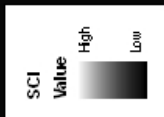


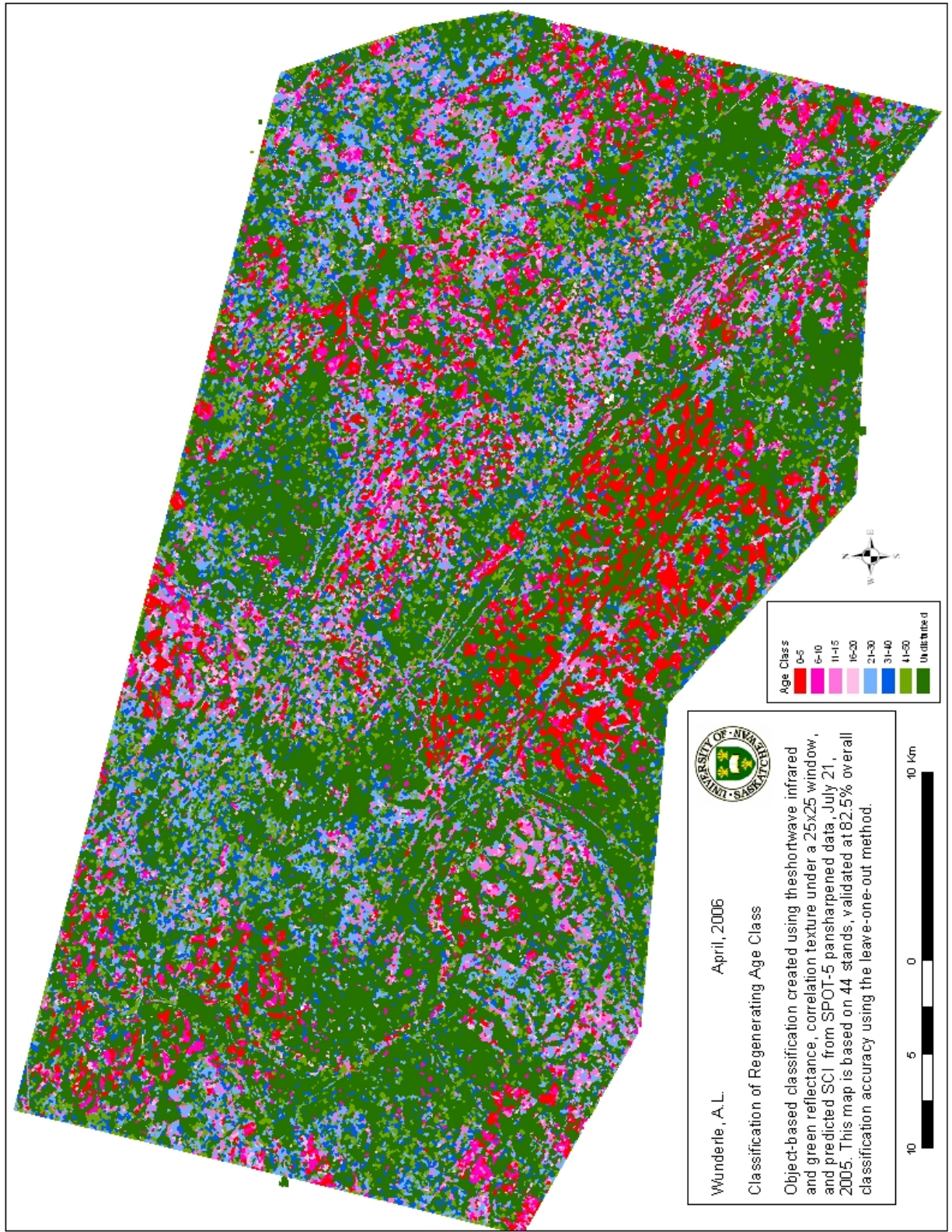



Wunderle, A.L. April, 2006

Classification of Structural Complexity Index

Continuous model based on normalized difference moisture index, standard deviation and correlation texture under a 5x5 window size (R-square = 0.74). This model was based on original sample of 44 stands, validated using the leave-one out method at 70%.






 Wunderle, A.L.      April, 2006  
**Classification of Regenerating Age Class**  
 Object-based classification created using the shortwave infrared and green reflectance, correlation texture under a 25x25 window, and predicted SCI from SPOT-5 pansharpened data, July 21, 2005. This map is based on 44 stands, validated at 82.5% overall classification accuracy using the leave-one-out method.

Age Class	Color
0-5	Red
6-10	Magenta
11-15	Pink
16-20	Light Blue
21-30	Blue
31-40	Dark Blue
41-50	Green
Unclassified	Dark Green