Investigating grizzly bear responses to spring snow dynamics through the generation of fine spatial and temporal scale snow cover imagery in Alberta, Canada

by

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Abstract

Snow dynamics influence seasonal behaviors of wildlife, such as denning patterns and habitat selection related to the availability of food resources. Under a changing climate, characteristics of the temporal and spatial patterns of snow are predicted to change, and as a result, there is a need to better understand how species interact with snow. Through the generation of fine-scale snow cover data, this thesis examines grizzly bear (*Ursus arctos*) spring habitat selection and use in the Yellowhead Bear Management Area, Alberta, Canada.

First, a new approach was developed to create a daily time-series of 30-m resolution snow cover observations (called SNOWARP). SNOWARP was derived from daily Moderate Resolution Imaging Spectroradiometer (MODIS) data to capture the temporal dynamics of snow cover and Dynamic Time Warping to re-order historical Landsat observations to account for inter-annual variability. The SNOWARP product was produced for 2000-2018 and calibrated against a network of time-lapse cameras and snow pillows. Results indicate the root mean squared error of the fractional product ranges from 31.3% to 68.3%, while F score of the binary product ranges from 87.7% to 98.6%.

Second, data from SNOWARP and other environmental variables were combined with GPS collar locations from grizzly bears to test the hypothesis that grizzly bears select for locations with less snow cover and areas where snow melts sooner during spring. Using Integrated Step Selection Analysis, a series of models were built to examine weather snow variables improved models constructed based on previous knowledge of grizzly bear selection during the spring.
Comparing four different models fit to 62 individual bear-years, it was found that the inclusion of fractional snow covered area (fSCA) improved model accuracy 60% of the time based on Akaike Information Criterion tallies. Probability of use was then used to evaluate grizzly bear habitat use in response to snow and environmental attributes. The results of this thesis provide one example of the application of newly derived daily 30-m fSCA and indicate grizzly bears select for lower elevation, snow-free locations during spring, which has important implications for management of threatened grizzly bear populations in consideration of changing climatic conditions.
Lay summary

The objectives of this research were to develop accurate maps of snow cover using satellite imagery and use the maps to investigate how snow conditions affect grizzly bears during spring in the Yellowhead Bear Management Area, Alberta, Canada. By combining data from two satellite systems, daily snow cover maps were developed for years 2000 to 2018, presenting both finer spatial and temporal resolution than has previously been available in the study region. The snow cover maps were then used in coordination with location data from collared grizzly bears to examine how bears use their habitat in relation to snow. The results of this thesis indicate that bears choose locations where there is less snow cover, and are more likely to use locations where snow melted sooner during spring. The relationship between snow and grizzly bears has important management implications for threatened bear populations in Alberta, in light of climate change.
Preface

This thesis is the compiled work of two scientific papers written for peer-review of which I am the lead author. I was responsible for refining the research objectives, defining the methodology, analyzing the data, interpreting the results, and writing and editing the manuscripts. The conceptual idea for this research was developed as part of an NSERC CRD research grant titled “Grizzly-PAW: Grizzly Population Assessment in yelloWhead”, of which Dr. Nicholas Coops is the Principal Investigator. Project oversight and editorial assistance were provided by Dr. Nicholas Coops, Dr. Daniel Moore, and Mr. Gordon Stenhouse. Additional co-authors on peer-reviewed publications gave editorial comments.

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This research was also presented as:

During my thesis work I also contributed to the development of an additional snow cover mapping methodology, warranting co-authorship:

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Table of contents

Abstract ................................................................................................................................. iii
Lay summary ......................................................................................................................... v
Preface .................................................................................................................................. vi
Table of contents ................................................................................................................ viii
List of tables ........................................................................................................................ xi
List of figures ........................................................................................................................ xii
List of abbreviations ............................................................................................................ xv
Acknowledgements ............................................................................................................. xvii
Dedication ............................................................................................................................... xviii

Chapter 1: introduction ....................................................................................................... 1
  1.1 Grizzly bears in North America ..................................................................................... 1
  1.2 Grizzly bears, snow dynamics, and climate change ....................................................... 3
  1.3 Research objectives ........................................................................................................ 5

Chapter 2: study area .......................................................................................................... 8
  2.1 Environment and climate ............................................................................................. 8
  2.2 Anthropogenic use of landscape ................................................................................ 9
  2.3 Grizzly bears in the Yellowhead BMA ......................................................................... 10

Chapter 3: daily estimates of Landsat fractional snow cover driven by MODIS and
Dynamic Time Warping ....................................................................................................... 11
  3.1 Introduction .................................................................................................................. 11
  3.1.1 Snow covered area mapping from optical satellites .............................................. 11
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1</td>
<td>Introduction</td>
<td>43</td>
</tr>
<tr>
<td>4.1.1</td>
<td>Grizzly bear spring habitat selection</td>
<td>43</td>
</tr>
<tr>
<td>4.1.2</td>
<td>Research aim</td>
<td>44</td>
</tr>
<tr>
<td>4.2</td>
<td>Methods</td>
<td>45</td>
</tr>
<tr>
<td>4.2.1</td>
<td>Grizzly bear data</td>
<td>45</td>
</tr>
<tr>
<td>4.2.2</td>
<td>Core model covariates</td>
<td>47</td>
</tr>
<tr>
<td>4.2.3</td>
<td>Snow cover variables</td>
<td>48</td>
</tr>
<tr>
<td>4.2.4</td>
<td>Integrated Step Selection Analysis</td>
<td>51</td>
</tr>
<tr>
<td>4.3</td>
<td>Results</td>
<td>54</td>
</tr>
<tr>
<td>4.4</td>
<td>Discussion</td>
<td>58</td>
</tr>
</tbody>
</table>

**Chapter 5: conclusion** | 61

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1</td>
<td>Overview</td>
<td>61</td>
</tr>
<tr>
<td>5.2</td>
<td>Key findings</td>
<td>62</td>
</tr>
<tr>
<td>5.3</td>
<td>Implications</td>
<td>62</td>
</tr>
<tr>
<td>5.4</td>
<td>Limitations</td>
<td>64</td>
</tr>
<tr>
<td>5.5</td>
<td>Future directions and applications</td>
<td>65</td>
</tr>
</tbody>
</table>

**References** | 67
List of tables

Table 1: A review of studies concerning the development of continuous time-series at Landsat spatial resolution. (*) indicates studies involving snow cover. ................................................. 17

Table 2: Compiled optical satellite imagery utilized in this study................................................. 21

Table 3: Characteristics of the ground truth sites ......................................................................... 23

Table 4: Summary of fractional statistics ....................................................................................... 33

Table 5: Summary of binary statistics ........................................................................................... 36

Table 6: Comparison of binary statistics from Landsat and MODIS-based snow products........ 37

Table 7: Covariates used in models and references to studies linking variables to grizzly bear habitat selection and use .................................................................................................... 46

Table 8: Overview of the four models assessed for each of the 62 bear-years. The AIC Tally is a record of the model that had the lowest Akaike Information Criterion score for each bear-year. 56

Table 9: A summary of the number of tallies received by each model per year. ......................... 56
List of figures

Figure 1: A flow chart displaying the overall process of this thesis. ......................................................... 7

Figure 2: A map of the Yellowhead BMA, including the general locations of time-lapse cameras used for ground validation in Chapter 3. ........................................................................................................... 9

Figure 3: Overview of the four steps of the Dynamic Time Warping (DTW) procedure (Note: Winter day of year is August 1 to July 31 of the next year). (a) The interpolation of MOD10A1 snow curves, (b) the generation of rule-sets using DTW and the MOD10A1 snow curves as inputs, (c) The application of rule-sets to the entire TMSCAG time-series, (d) The interpolation of TMSCAG snow curves resulting in SNOWARP (daily 30-m fSCA estimates). ....................... 26

Figure 4: Example results from the DTW procedure, using a single Landsat pixel (and enclosing MODIS pixel) from the Bald Hills Forested site as reference. a) MOD10A1 interpolated snow curve for target year 2013. b) Example of all MOD10A1 snow curves before the generation of DTW rule-sets. Query year values are shown in grey scale (winter years 2000 to 2017, except 2013), target year is shown in red (winter year 2013) c) Example of all MOD10A1 snow curves post-application of DTW rule-sets generated to minimize the difference between query year and target year values. d) Warping of TMSCAG historical time-series to match the target year (2013). The blue triangles are the observations from the target year, whereas the black points are values warped from other years. The dense time-series is then used to interpolate SNOWARP daily values. ............................................................................................................................................. 31
Figure 5: Example of the spatial detail of MOD10A1 versus SNOWARP in mountainous terrain on May 27, 2017. 

Figure 6: Results from the fSCA validation of the Bald Hills and Coal Valley sites during winter year 2016 (August 1, 2016 to July 31, 2017). Data were only available from March to August 2017. a), b), c), and d) compare the timing and value of fSCA from SNOWARP and ground data. e) three example time-lapse images from the Bald Hills Open site, showcasing the melt pattern.

Figure 7: Results from the fSCA validation of the Cardinal River and Portal sites during winter year 2017 (August 1, 2017 to July 31, 2018). Data were only available until early May. a), b), c), and d) compare the timing and value of fSCA from SNOWARP and ground data.

Figure 8: Binary metrics measuring the temporal performance of SNOWARP compared to ground truth from fourteen time-lapse camera sites (winter years 2016 and 2017) and two automated snow pillows (winter years 2000 to 2017) displayed by winter day of year (daily values averaged for all years in which data was available).

Figure 9: The three snow metrics derived from SNOWARP (Berman et al., 2018) at 30-m spatial resolution for years 2009 to 2017: a-c) Annual date of snow melt shown for spring 2010, 2015 and 2017. Days since snow melt (DSM) was produced by subtracting date of snow melt from the date associated with each grizzly bear telemetry location. d-f) daily binary snow
covered area (bSCA) shown on April 1, May 1, and June 1, 2017. g-i) daily fractional snow
covered area (fSCA) shown on April 1, May 1, and June 1, 2017. ........................................50

Figure 10: The date of snow melt annually by natural sub-region classification. ..................55

Figure 11: Probability of use was calculated over all available locations with both fSCA and
DSM on the x-axis. The overall trends show increased selection for locations with less snow
cover than what is available, as well as preference for locations where snow melted sooner in the
spring................................................................................................................57

Figure 12: Probability of use calculated with DSM on the x-axis and (a) categorized by elevation
(m) and (b) distance to road (m). Relative preference is shown for lower elevation locations,
especially once snow has melted. Grizzly bears generally were more likely to select for locations
closer to roads once snow has melted....................................................................................58
# List of abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>Akaike Information Criterion</td>
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<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
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<tr>
<td>bSCA</td>
<td>Binary Snow Covered Area</td>
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<td>BMA</td>
<td>Bear Management Area</td>
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<tr>
<td>CI</td>
<td>Confidence Interval</td>
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<tr>
<td>Dist(FE)</td>
<td>Distance to Forest Edge</td>
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<tr>
<td>Dist(RD)</td>
<td>Distance to Road</td>
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<tr>
<td>DSM</td>
<td>Days since Snow Melt</td>
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<td>DTW</td>
<td>Dynamic Time Warping</td>
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<td>ELEV</td>
<td>Elevation</td>
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<td>ETM+</td>
<td>Enhanced Thematic Mapper Plus</td>
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<tr>
<td>FN</td>
<td>False Negative</td>
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<tr>
<td>FP</td>
<td>False Positive</td>
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<tr>
<td>fSCA</td>
<td>Fractional Snow Covered Area</td>
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<td>INSOL</td>
<td>Solar Insolation</td>
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<td>iSSA</td>
<td>Integrated Step Selection Analysis</td>
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<tr>
<td>LiDAR</td>
<td>Light Detection and Ranging</td>
</tr>
<tr>
<td>Ln(SL)</td>
<td>Natural Log of Step Length</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
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<tr>
<td>MODSCAG</td>
<td>MODIS Snow Covered Area and Grain Size</td>
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<td>NDSI</td>
<td>Normalized Difference Snow Index</td>
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<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>-----------------------------------------------------------------------------</td>
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<tr>
<td>NSIDC</td>
<td>National Snow and Ice Data Center</td>
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<td>OLI</td>
<td>Operational Land Imager</td>
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<td>RMSE</td>
<td>Root Mean Squared Error</td>
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<td>RSF</td>
<td>Resource Selection Function</td>
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<td>SAR</td>
<td>Synthetic Aperture Radar</td>
</tr>
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<td>SCA</td>
<td>Snow Covered Area</td>
</tr>
<tr>
<td>SRTM</td>
<td>Shuttle Radar Topography Mission</td>
</tr>
<tr>
<td>SSF</td>
<td>Step Selection Function</td>
</tr>
<tr>
<td>SWE</td>
<td>Snow Water Equivalent</td>
</tr>
<tr>
<td>TM</td>
<td>Thematic Mapper</td>
</tr>
<tr>
<td>TMSCAG</td>
<td>Thematic Mapper Snow Covered Area and Grain Size</td>
</tr>
<tr>
<td>TN</td>
<td>True Negative</td>
</tr>
<tr>
<td>TOD</td>
<td>Time of Day</td>
</tr>
<tr>
<td>TP</td>
<td>True Positive</td>
</tr>
<tr>
<td>TWI</td>
<td>Terrain Wetness Index</td>
</tr>
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<td>VGF</td>
<td>Viewable Gap Fraction</td>
</tr>
<tr>
<td>USGS</td>
<td>United States Geological Survey</td>
</tr>
</tbody>
</table>
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I am grateful for the unequivocal support of my supervisor, Dr. Nicholas Coops, who was always available to provide advice and help mentor me through this process. I am also appreciative of the encouragement, assistance, and insight provided by my supervisory committee, Dr. Dan Moore and Mr. Gord Stenhouse. To my fellow lab members of the Integrated Remote Sensing Studio, I could not have asked for a more friendly, supportive, and enjoyable community of people to work alongside these last couple of years. Lastly, I would like to acknowledge my family, who form the pillars upon which all of this is built.
Dedication

This thesis is dedicated to my grandmothers, Emilia Ruducha and Ellen M. Berman. Although I may never fully grasp the hardships you experienced, I strive to embody your perseverance and am deeply grateful for the opportunities opened to me to learn, develop, and contribute.
Chapter 1: introduction

1.1 Grizzly bears in North America

Grizzly bears (*Ursus arctos*) are an important species in North America. They have a positive influence on plant and forest health (Tardiff et al., 1998) and can serve as an “umbrella” species, as habitats where viable populations exist are indicative of sustainable management and sufficiency for other species (Carroll et al., 2001). In addition, grizzly bears are socially and culturally significant. The species plays a meaningful role in Aboriginal cultures, in which respect for bears is of utmost importance (Clark & Slocombe, 2009). Growing concerns in the North and West of North America over the long-term preservation of wilderness and natural ecosystems have led to the grizzly bear being highlighted as a species-at-risk (McLellan, 1998).

In the lower 48 states, as well as Alberta and parts of British Columbia, governments have designated grizzly populations as *threatened*, implying the value of bears is high and efforts to preserve their existence important (Swanson et al., 1994; Alberta Sustainable Resource Development and Alberta Conservation Association, 2010; British Columbia Ministry of Forests, Lands, and Natural Resource Operations, 2012). The management decisions made now will likely determine the fate of these *threatened* populations (McLellan, 1998).

In Alberta, Canada the *threatened* status was designated in 2010, under the provincial Wildlife Act (Alberta Sustainable Resource Development and Alberta Conservation Association, 2010). The action took place eight years after the Endangered Species Conservation Committee recommended the status change and four years after the provincial government enacted a temporary ban on sport hunting of the species, which remains in place. A provincial population estimate of a total of 691 (No CI available for provincial estimate) grizzly bears under provincial
jurisdiction played a role in the status change determination (Alberta Sustainable Resource Development and Alberta Conservation Association, 2010). Although historical population numbers are unknown, it is accepted that provincial populations have declined in both range and numbers over the last century (COSEWIC, 2012). The prairie populations in Alberta have been extirpated, with the contemporary range spanning the Rocky Mountains and surrounding foothills to the east (Nielson et al., 2009).

Grizzly bears in Alberta live in a human-dominated landscape and remain under threat due to several interwoven factors. Within the province, bears compete for habitat with anthropogenic activities, including resource extraction (oil, gas, mining, and forestry) and public recreation (camping, hiking, mountain biking, hunting, trapping, and use of all-terrain vehicles) (Linke et al., 2005; Graham & Stenhouse, 2014). Human-caused mortality is largely considered the most detrimental factor influencing grizzly populations (Boyce et al., 2001). Mortality rates are dictated by the number and lethality of human-bear interactions (Mattson et al., 1996) and the extent and ease of human access into grizzly bear habitat, largely due to road networks. Road density has been closely linked to declining grizzly bear population numbers (Boulanger & Stenhouse, 2014) and areas of high road density continue to be developed to meet the needs of resource-extractive industries and public demand for recreational opportunities. In addition to human-caused mortality, grizzly bear populations in Alberta remain threatened by a small population size (Alberta Sustainable Resource Development and Alberta Conservation Association, 2010), habitat loss (Nielson et al., 2006), and low rates of reproduction (Garshelis et al., 2005).
1.2 Grizzly bears, snow dynamics, and climate change

The effects of climate change have the potential to increase the scale of factors that already threaten grizzly bear populations. Changing growing seasons and milder weather conditions could lead to bears adapting to shorter denning patterns, extending the possibility of negative human-bear interactions (Pigeon et al., 2016a). One environmental factor that is likely to be highly sensitive to climate change is snow, which has been less well studied within the context of grizzly bear conservation in Alberta than other environmental variables. Climate change driven transformations of snow accumulation and melt dynamics has the potential to influence the way in which bears use their habitat.

Snow dynamics are a key driver of the seasonal behaviors of a variety of wildlife species, through influencing resource availability and fitness costs (Craighead & Craighead, 1972; Magoun & Copeland, 1998; Robinson & Merrill, 2012). In landscapes with harsh seasonal conditions, snow cover can dictate food quality and distribution, and along with cold temperatures can result in patterns of hibernation and migration. For hibernators, the accumulation of snow in the fall and ablation in the spring have been linked to both spatial and temporal denning patterns (Lane et al., 2012; Pigeon et al., 2016b). Snow distribution can also adversely influence energy costs, through increased difficulty moving through a deep snowpack (Parker et al., 1984) and by dictating the timing of spring vegetation emergence (Kreyling, 2010; Noyce & Garshelis, 1998; Sherwood et al., 2017).

Grizzly bear populations in Alberta, Canada, experience a long winter, characterized by persistent snow and freezing temperatures. The hibernation period lasts from around November
to March (Graham & Stenhouse, 2014), and the timing and location of denning has been linked to snow dynamics (Evans et al., 2016; Linnell et al., 2001), with warm spring temperatures and reduced snow cover resulting in early den exit (Pigeon et al., 2016b). In addition, grizzly bears in Alberta den near high quality spring food resources (Pigeon et al., 2016a), mainly in the form of sweet-vetch roots (*Hedysarum* spp.). During the spring season, snow cover and frozen ground can restrict digging for sweet-vetch. Therefore, bears have been shown to follow a “brown-tide”, progressively following the change from winter to spring conditions in search of optimal conditions for root-digging (Coogan et al., 2012).

In a landscape dominated by anthropogenic presence and activity, changing snow dynamics due to climate change have the potential to increase the risk of negative human-bear encounters. Human-caused grizzly bear mortality is the most significant factor influencing bear population growth and long-term population sustainability (Boyce et al., 2001; Nielsen et al., 2004b). In general, snow conditions in Western Alberta are spatially and temporally heterogeneous within a given winter season, and can vary markedly inter-annually (Janz & Storr, 1977). Future climatic projections call for an increased uncertainty regarding the timing and extent of winter conditions (Barnett & Adam, 2005), and an overall decrease in days with snow cover on an annual basis (Brown, 2000), especially during spring months (Mekis & Vincent, 2011). In addition, climate models suggest higher and more frequent warmer temperatures during winter and spring, and a global average temperature rise of 1.5 °C between the 20th and 21st century (Bonsal et al., 2001; IPCC 2013). These changes in spring weather and snow patterns could lead to an earlier annual den emergence for grizzly bears, and could contribute to bears using lower elevation, snow free locations since these locations are often the first to supply food resources. Additionally, these
locations can often coincide with areas with high human population density. A better understanding of how bears use the landscape in relation to changing snow dynamics can help managers and policy-makers to sustain a healthy grizzly bear population in both the present as well as the future.

1.3 Research objectives

The overall research objective of this thesis was to develop a fine-scale remote sensing snow cover product and use it to explore the relationship between spring snow dynamics and grizzly bear habitat selection and use. To achieve this objective, two sub-objectives were defined:

1. Create a remote sensing snow cover product to improve our understanding of fine spatial and temporal scale snow dynamics in the Yellowhead Bear Management Area (BMA), Alberta, Canada.

2. Use this remote sensing snow dynamics product to inform our understanding of grizzly bear habitat selection and use post-den emergence until late spring.

A flow chart displaying the overall process of this work is shown in Figure 1. Chapter 2 characterizes the study area. Included is information about the natural environment, climate, human use of the landscape, and grizzly bears populations in the region.

Chapter 3 contains the work done to develop a new remote sensing snow cover product, called SNOWARP ("snow-warp"). SNOWARP provides daily estimates of fractional snow covered area (fSCA) at 30-m spatial resolution. The chapter details the methodology used to fuse together
data from two widely used satellite platforms and test the accuracy of the new product using a network of time-lapse cameras and government weather stations.

Chapter 4 investigates the relationship between spring snow cover and grizzly bear habitat selection and use using Integrated Step Selection Analysis (iSSA). A variety of habitat selection models are developed and tested to see how snow variables can improve model fit and how informative results can be extracted.

Chapter 5 discusses the key findings, overall conclusions, limitations, and recommendations for future research.
Figure 1: A flow chart displaying the overall process of this thesis.
Chapter 2: study area

2.1 Environment and climate

The study area is the Yellowhead Bear Management Area (BMA), which spans 28,529 km$^2$ throughout Western Alberta and includes a portion of the Rocky Mountains in the west and foothills in the east (Figure 2). It encompasses 8,694 km$^2$ of protected areas (30.5% of total area), mostly in Jasper National Park (Nielsen et al., 2009). The topography is highly mountainous and land cover, precipitation, and temperature vary from the low elevation valleys to alpine peaks reaching over 3000 m. The continental climate combined with the high latitude of the area dictate long, cold winters and cool and wet springs (DeBeer & Pomeroy, 2010). Precipitation, temperature, and wind patterns are all influenced by complex microclimates, resulting in perennial snow cover and freezing temperatures in areas of high alpine, while certain low elevation areas may remain relatively snow free (Janz & Storr, 1977). There are large variations in weather patterns on a seasonal, daily, and even hourly basis (Janz & Storr, 1977). The duration of snow generally begins with accumulation in October and ablation in late March and April, when melt begins to exceed accumulation. The melt cycle can last well into summer months. Mean annual precipitation is 450 to 800 mm and mean temperatures range from $-7.5^\circ$C in the winter to $12^\circ$C in the summer (Bourbonnais et al., 2013).

The natural sub-region classifications for the mountainous areas are alpine and subalpine, and in lower elevations consist of montane, and upper and lower foothills (Achuff et al., 1994). Coniferous forests dominate, consisting of lodgepole pine ($Pinus contorta$), spruce ($Picea$ spp.), and fir ($Abies$ spp.). Mixed forests include aspen ($Populus tremuloides$) and balsam poplar ($P. balsamifera$) (Ladle et al., 2018). Shrubs, including willow ($Salix$ spp.), are scattered throughout
the area (Nielsen et al., 2004a). Bogs, meadows, and forests regenerating from fire and harvesting are also common on the landscape (Franklin et al., 2001). Due to a history of fire suppression in the foothills, young forests and natural openings are rare (Nielsen et al., 2004a), whereas large fires have burned through parts of Jasper National Park.

![Figure 2: A map of the Yellowhead BMA, including the general locations of time-lapse cameras used for ground validation in Chapter 3.](image)

2.2 Anthropogenic use of landscape

Anthropogenic activity and disturbance vary significantly between the mountainous protected areas and lower elevation foothills. In Jasper National Park there are relatively low amounts of anthropogenic disturbance and activity (Nielsen et al., 2009), most of which consist of recreation
and tourism. The rest of the region, the “foothills”, is highly fragmented due to a history of fire, timber harvesting, coal mining, and energy exploration and development (Nielsen et al., 2006). Roads are commonplace and provide human access into grizzly bear habitat, with gravel and secondary roads comprising 96.5% of all roads in potential grizzly bear habitat in Alberta (Boulanger & Stenhouse, 2014). These roads are also used year-round by the public for a variety of recreational activities.

2.3 Grizzly bears in the Yellowhead BMA

Grizzly bear population size was estimated in the Yellowhead BMA in both 2004 and 2014. The results show an increase from 36 (CI = 27 to 45) to 74 (CI = 56 to 98) individuals, at an annual rate of 7% per year over the 10 year period (Stenhouse et al., 2015). This population increase shows promise for recovery initiatives, and is due in part to a hunting moratorium (in effect since 2006) and the relocation of around 30 bears into the region (Stenhouse et al., 2015). On the other hand, anthropogenic activity has continued to grow throughout the foothills, and more work is needed to understand the effect of management strategies and environmental changes on the grizzly bear population.
Chapter 3: daily estimates of Landsat fractional snow cover driven by MODIS and Dynamic Time Warping

3.1 Introduction

3.1.1 Snow covered area mapping from optical satellites

An understanding of seasonal snow cover is integral to ecosystem management, as it impacts a range of ecosystem services, including water supply and availability, habitat availability for wildlife species, forest fire risk assessment, as well as human use of the landscape. Under a changing climate the timing and extent of seasonal snow cover is uncertain (Barnett et al., 2005). The global extent of land covered with snow has declined in the past 30 years (Derksen & Brown, 2012; Kunkel et al., 2016; Sturm et al., 2017), as well as the number of days per year that ground is snow-covered (Brown, 2000; Clow, 2010; Stewart et al., 2005). Trends toward earlier spring snow melt at high-latitudes have been correlated to both increases and decreases in forest carbon uptake (Winchell et al., 2016; Pullianinen et al., 2017), as well as disturbances to the seasonal behaviors of certain wildlife species, such as the denning patterns of grizzly bears in North America (Pigeon et al., 2016b). The accurate mapping of the spatial extent of seasonal snow cover is therefore increasingly important to understand the effects of snow dynamics on anthropogenic and natural processes and how to prepare for, and manage, future climatic conditions.

Satellite based detection of snow dates back to the 1960’s and has enabled the quantification of broad spatial and temporal variability in snow cover on a variety of scales (Dietz et al., 2012). The global coverage available from remote sensing technologies allows detection in remote areas, where in situ measurements may not be possible (Nolin, 2010). In addition, satellite
observations in mountainous terrain provide key benefits where ground measurement networks
often do not accurately capture the spatial variability of snow cover (Rittger et al., 2016). Since
snow conditions are dictated by elevation and topography (Janz & Storr, 1977) they are difficult
to survey thoroughly in rugged, mountainous, and hard to reach grizzly bear habitat. Remote
sensing imagery can cover such areas and provide detailed information about snow dynamics at
scales relevant to wildlife studies.

Remote sensing technologies for snow cover assessment include Synthetic Aperture Radar
(SAR), Light Detection and Ranging (LiDAR) and passive optical technologies (Dietz et al.,
2012; Painter et al., 2016). Optical imagery provides reliable measurements of snow cover extent
using visible wavelengths (Clifford, 2010) across a range of spatial and temporal resolutions
(Dietz et al., 2012). The historical basis of snow covered area (SCA) mapping using optical
technology is a “binary” map (Dozier, 1989), in which each pixel is designated as “snow
covered” or “snow free” (Painter et al., 2009). This binary map is based on the normalized
difference snow index (NDSI):

\[
NDSI = \frac{R_{VIS} - R_{SWIR}}{R_{VIS} + R_{SWIR}}
\]  

(1)

In which \( R_{VIS} \) and \( R_{SWIR} \) are the spectral reflectance of a visible and short-wave infrared band
respectively (Rittger et al., 2013). The specific bands used vary by satellite platform. NDSI
exploits the unique spectral properties of snow to differentiate it from cloud and other Earth
features. Snow has a high reflectance in visible bands, and almost zero reflectance in the short-
wave infrared part of the spectrum (Hall et al., 1998). Cloud has a high reflectance in both the
visible and short-wave infrared bands. A NDSI value of 0.4 is generally the threshold set to
determine whether a pixel is classified as “snow” or “not snow” (Hall et al., 1998).
Approaches to mapping snow cover have become more sophisticated with the development of a fractional snow-covered area (fSCA) metric, a sub-pixel measurement between 0 and 100 of the percentage of a pixel’s area covered by snow (Nolin, 2010). fSCA algorithms are developed using one of two approaches: NDSI or spectral mixture analysis. fSCA is derived from NDSI using an empirical relationship between the fractional and binary snow cover measurements (Rittger et al., 2013). Using spectral mixture analysis, the reflectance of each land cover type is represented through its ‘endmember’, and the reflectance of a given pixel is said to be a linear mixture of the endmembers included (Nolin, 2010). The relative presence of snow in a pixel can be calculated based on the relative weight of its endmember in the given pixel (Painter et al., 2009). fSCA algorithms based on spectral mixture analysis have been shown to be more accurate than algorithms using NDSI, as they can detect fSCA as low as 10 to 15% (Painter et al., 2009).

3.1.2 Challenges to fine-scale optical snow mapping

A 30-m resolution daily fSCA product is desirable for wildlife movement modelling, yet it is a challenging product to develop with spatial and temporal resolution trade-offs due to pixel size and sensor swath width. No single remote sensing instrument is currently capable of producing such a high-resolution product, but a number of studies have demonstrated the ability to create 30-m daily SCA by fusing complementary optical datasets (Cristea et al., 2017; Czyzowska-Wisniewski et al., 2015; Durand et al., 2008; Li et al., 2015; Walters et al., 2014). Further work is needed to develop and validate a product that can be efficiently applied to large areas.
Snow products from optical sensors perform well in open, homogenous areas under ideal illumination and cloud-free conditions. Therefore, forested regions and winter are major limitations to accurate snow information extraction leading to underestimation of SCA, since in forests the sensor can only register snow in canopy gaps (Liu et al., 2004) and during winter there is less solar reflectance and persistent cloud cover (Deeb et al., 2017). Previous studies have improved SCA estimates by adjusting values to account for forest transmissivity (Metsämäki et al., 2012) and the percentage of canopy cover (Rittger et al., 2013). However, results have still shown underestimation of snow cover in forests. Static forest canopy adjustments are also limited in their assumption that snow cover under canopy mirrors snow cover visible in canopy gaps (Coons et al., 2014).

Cloud cover poses an additional challenge to snow cover mapping, as it is often difficult to differentiate from snow (Rittger et al., 2013). Misidentification can lead to commission errors in snow being classified as cloud, especially in high altitude areas consisting of primarily rock, snow and ice (Selkowitz & Forster, 2016). Progress has been made to adjust the standard cloud masking algorithms to improve differentiation of snow from clouds, resulting in an increase in useable data (Crawford et al., 2013; Selkowitz & Forster, 2015). However, data continuity is still a significant challenge for studies with specific spatial and temporal requirements.

3.1.3 Landsat and MODIS

The Landsat satellite series is one of the leading passive-optical platforms used for snow analysis. It is known for the depth of its historical archive, with data extending back more than 40 years in the visible and infrared wavelengths. Landsat has a medium spatial resolution (30-m)
sensor and a revisit period of 16 days. Although the spatial resolution of Landsat enables the study of snow cover at a resolution relevant to wildlife movement research, a lengthy revisit period along with distortion from cloud cover can lead to temporal gaps in data. The Thematic Mapper Snow Covered Area and Grain Size (TMSCAG) product provides fSCA data from Landsat using spectral mixture analysis (Painter et al., 2009).

Another leading platform used for optical snow sensing is the Moderate Resolution Imaging Spectroradiometer (MODIS). Launched in 1999 and 2002, the MODIS sensors collect data at 250 to 500-m spatial resolution with a daily revisit period (Vermote et al., 2011). Daily imagery from MODIS provides the means to observe temporal changes to snow cover throughout the winter, however the 250 to 500-m spatial resolution is too coarse for certain ecological applications. Several snow products exist from MODIS, including an NDSI snow cover product (Hall et al., 2002) and the MODIS Snow Covered Area and Grain Size (MODSCAG) product, which produces fSCA based on spectral mixture analysis (Rittger et al., 2013).

### 3.1.4 Data fusion

Given that the spatial resolution and archive size of Landsat provide robust data for monitoring environmental change at a local scale, much effort has been put into solving the challenges of its temporal discontinuity (see Table 1 for a review). Various studies have used a ‘data fusion’ technique, in which Landsat imagery is fused with imagery acquired at a higher temporal resolution (i.e. MODIS) to create a more continuous time-series (Hilker et al., 2009; Gao et al., 2006; White et al., 2014). Fisher et al. (2006) compiled Landsat imagery from 1984 to 2002 to map long-term phenology averages and Melaas et al. (2013) used 30 years of Landsat data to
map inter-annual variability of phenology. Dynamic Time Warping (DTW) approaches have also been applied where higher temporal resolution imagery can be used to create a set of rules used to augment finer spatial, but lower temporal resolution imagery like Landsat (Baumann et al., 2017). Baumann et al. (2017) used a DTW approach to re-order Landsat imagery from 2002 to 2012 to fit the phenology trend of each year, with annual MODIS phenology curves employed to generate the rule-sets. Methods to expand the continuity of time-series at 30-m spatial resolution have largely been focused on phenology, and less thoroughly explored in the context of snow cover. Walters et al. (2014) downscaled daily MODIS fSCA data to 30-m binary snow cover estimates using an algorithm based on various terrain factors. Additionally, Czyzowska-Wisniewski et al. (2015) utilized an Artificial Neural Network (ANN) to estimate fSCA from IKONOS 1-m imagery and scale it to 30-m, accounting for terrain features as well as spectral indices from Landsat.
### Table 1: A review of studies concerning the development of continuous time-series at Landsat spatial resolution. (*) indicates studies involving snow cover.

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Year</th>
<th>Objectives</th>
<th>Methodology</th>
<th>Location</th>
<th>Conclusions</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gao et al.</td>
<td>2006</td>
<td>Predict daily surface reflectance at daily 30-m scale.</td>
<td>Data fusion algorithm to blend MODIS 500-m and Landsat 30-m</td>
<td>Boreal forests throughout Canada</td>
<td>Approach can model surface reflectance accurately in homogenous land cover types. Accuracy deteriorates as land cover becomes mixed.</td>
<td>Approach can be used to fuse data from other satellite platforms as well.</td>
</tr>
<tr>
<td>Hilker et al.</td>
<td>2009</td>
<td>Validate new data fusion model for mapping landscape disturbances over 8-day intervals at 30-m resolution.</td>
<td>Data fusion algorithm using MODIS 500-m and Landsat 30-m</td>
<td>West-central Alberta</td>
<td>Identified disturbances at yearly time steps with 87-89% accuracy compared to validation data.</td>
<td>Limited to before/after disturbance detection.</td>
</tr>
<tr>
<td>Melaas et al.</td>
<td>2013</td>
<td>Model long-term and yearly phenology averages using 30 years of Landsat archive.</td>
<td>Compile historic Landsat archive using phenology algorithm</td>
<td>Southern New England</td>
<td>Algorithm effective to detect timing of key fall and spring dates.</td>
<td>Ground-observations used for validation.</td>
</tr>
<tr>
<td>White et al.</td>
<td>2014</td>
<td>Map landscape disturbances bi-weekly from 2001-2011 using MODIS and Landsat.</td>
<td>Data fusion algorithm using MODIS 250-m and Landsat 30-m</td>
<td>Western Alberta</td>
<td>Accuracy to 88% (Hilker et al., 2009). Found disturbances covering 3.5% of study area from 2001-2011.</td>
<td></td>
</tr>
<tr>
<td>*Walters et al.</td>
<td>2014</td>
<td>Create a spatially explicit 30-m snow covered area (binary) estimate from MODIS ISCA data.</td>
<td>Downscale MODIS to 30-m resolution using algorithm based on terrain factors</td>
<td>Southwestern Idaho</td>
<td>Downscaling model works well. Future models should use fSCA from spectral mixture analysis.</td>
<td>Landsat binary snow cover used for calibration and validation.</td>
</tr>
<tr>
<td>*Czyzowska-Wisniewski et al.</td>
<td>2015</td>
<td>Validate new approach to estimate fSCA from ground reference data at 30-m resolution.</td>
<td>Artificial Neural Network (ANN) method to estimate fSCA from IKONOS 1-m scaled up to Landsat 30-m</td>
<td>Colorado and Wyoming</td>
<td>High accuracy and precision. ANN method able to combine terrain information with spectral data from Landsat.</td>
<td>Only used three images. Unclear how much high-res data needed for entire region.</td>
</tr>
<tr>
<td>Baumann et al.</td>
<td>2017</td>
<td>Generate annual Landsat phenology curves using archive from 2002-2012.</td>
<td>Dynamic Time Warping</td>
<td>7 Landsat tiles throughout USA</td>
<td>Multi-year imagery used to create annual phenology curves is applicable to most areas with vegetation.</td>
<td>MODIS used to generate DTW rule-sets. Ground-cameras used for validation.</td>
</tr>
</tbody>
</table>
DTW is an algorithm that was originally developed for spoken word recognition (Sakoe & Chiba, 1978), but can be used for remote sensing data fusion to define patterns between complementary time-series (Baumann et al., 2017; McConnell et al., 1991; Petitjean et al., 2012; Romani et al., 2010; Weber et al., 2012). DTW can increase the temporal density of a multi-year historical data set, such as the Landsat satellite record, by shifting historical values in time to account for inter-annual variability. The shift is informed by rule-sets generated from a temporally-frequent complementary dataset, such as MODIS, which is used to normalize differences between years. Historical observations can then be re-used and applied (based on the rule-sets) to the time-series of each year. The algorithm holds promise to drive a data fusion methodology to increase the spatial and temporal resolution of SCA products.

### 3.1.5 Ground-based testing methodologies

Several methodologies exist for testing the accuracy of satellite-driven snow products using ground-based data. Varhola et al. (2010) developed a low-cost ultrasonic snow depth sensor with accuracy up to 15-cm to provide ground-based snow measurements. Despite its low cost, the bulk and weight of the storage and power equipment make such a device difficult to use in mountainous terrain. In addition, these devices are limited in spatial extent as they monitor only a single location per sensor. Raleigh et al. (2013) used a network of buried temperature sensors spaced at regular intervals to capture daily snow presence and test the MODSCAG product. Buried temperature sensors are able to detect snow cover because soil temperatures only experience diurnal fluctuations when snow is absent (Lundquist & Lott, 2008). Point data from automated snow pillow sites can also be utilized for SCA validation, though are also limited in their ability to spatially represent complex terrain (Dozier et al., 2016). Low-cost time-lapse
cameras have also proven useful in gathering snow cover data on a localized scale (Parajka et al., 2012; Hedrick & Marshall, 2014; Garvelmann et al., 2013). Images are acquired daily and processed to extract fSCA information enabling data to be gathered over larger areas and provide a visual depiction of the snow dynamics on the ground.

3.1.6 Research aim

The aim of this sub-objective is to demonstrate and test a new methodology to derive SNOWARP, a 30-m daily fSCA product covering the Yellowhead BMA. To do so the DTW algorithm is utilized, exploiting the daily re-visit period of MODIS to drive the reorganization of historical 30-m Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) imagery. SNOWARP is generated from 2000 to 2018 to examine trends in snow cover over time, and is tested using ground truth data collected through a network of time-lapse cameras along with observations from automated snow pillow sites.

3.2 Methods

3.2.1 Data

3.2.1.1 MODIS data

The Terra and Aqua MODIS sensors (launched in 1999 and 2002 respectively) collect data at 250 to 500-m spatial resolution with a daily revisit period (Vermote et al., 2011). Daily imagery from MODIS is used to predict temporal changes in snow cover globally. The National Snow and Ice Data Center (NSIDC) hosts MODIS snow products, including MOD10A1 (NDSI from the Terra sensor), which is highly correlated with snow cover (Hall & Riggs, 2016). MOD10A1 NDSI snow cover values from MODIS V6 range from 0 to 100 representing the presence of
snow in a pixel (Hall & Riggs, 2016). The NDSI snow cover value is derived from the raw NDSI ratio after applying a series of data screens to minimize snow commission errors and flag uncertainties (Hall & Riggs, 2016).

MODIS V6 MOD10A1 NDSI Snow Cover data from the Terra platform were downloaded for tiles h10v03 and h11v03 from August 1, 2000 to May 31, 2018 (Hall & Riggs, 2016). Only data from Terra were used (Aqua was excluded) to maintain data consistency starting in year 2000 and to more closely match the morning data acquisition time of Landsat in the study area (Aqua acquisition is in the afternoon). Daily images were stacked by winter day of year 1 to 365, defined as August 1st to July 31st. Leap-year days were removed to ensure a continuous 365-day stack for each year. Values were then scaled from 0.0 to 1.0.

3.2.1.2 Landsat data

The historical basis of snow cover mapping using Landsat is also NDSI (Dozier, 1989); however, recent advancements have led to the development of the TMSCAG fSCA product using spectral mixture analysis (Painter et al., 2009). TMSCAG is based on the Rosenthal & Dozier (1996) spectral mixture model, in which reflectance of each land cover type is represented through ‘endmembers’, and the overall pixel reflectance is a linear mixture of the endmembers (Nolin, 2010). The relative presence of snow in a pixel is estimated based on the relative weight of its endmember in the given pixel (Painter et al., 2009). TMSCAG is a 30-m resolution fSCA product for Landsat TM, ETM+, and OLI sensors computed every 16-days. The data values range from 0 to 10000 (re-scaled from 0 to 100%) and include a cloud mask.
TMSCAG fSCA and cloud mask for Landsat TM, ETM+, and OLI sensors were made available by the United States Geological Survey (USGS) for path/rows 43/23, 43/24, 44/23, 44/24, 45/23, and 45/24 from August 1, 2000 to July 31, 2017 (Selkowitz, 2016). Images were stacked to ensure spatial continuity amongst scenes. In addition, TMSCAG data were adjusted for forest cover using a Landsat derived 2010 30-m canopy cover map (Matasci et al., 2018). Data were adjusted based on the viewable gap fraction (VGF) (Molotch & Margulis, 2008; Raleigh et al., 2013), defined as:

$$f_{SCA_{ADJ}} = \frac{f_{SCA_{OBS}}}{1-f_{CC}}$$

(2)

In which $f_{SCA_{ADJ}}$ is the fSCA adjusted for forest canopy cover, $f_{SCA_{OBS}}$ is the observed fSCA, $f_{CC}$ is the fractional canopy cover, and $1 - f_{CC}$ is the VGF. $f_{SCA_{ADJ}}$ values were considered valid if the cloud mask contained a value of 0, 1, or 3, corresponding to “no mask”, “possible cloud cover”, or “possible water”. Values determined to be invalid were not used in the analysis. All further references to TMSCAG fSCA values refer to fSCA adjusted for forest canopy cover.

A summary of satellite imagery is shown in Table 2.

### Table 2: Compiled optical satellite imagery utilized in this study

<table>
<thead>
<tr>
<th>Data Product</th>
<th>Spatial Resolution (m)</th>
<th>Temporal Resolution</th>
<th>Path/Row / Tile</th>
<th>Average Number of Cloud-free Observations/Year</th>
<th>Dates Acquired</th>
</tr>
</thead>
<tbody>
<tr>
<td>MOD10A1</td>
<td>500</td>
<td>daily</td>
<td>h10v03, h11v03</td>
<td>102.9</td>
<td>August 1, 2000 to May 31, 2018</td>
</tr>
<tr>
<td>TMSCAG</td>
<td>30</td>
<td>16-day</td>
<td>43/23, 43/24, 44/23, 44/24, 45/23, 45/24</td>
<td>14.8</td>
<td>August 1, 2000 to July 31, 2017</td>
</tr>
</tbody>
</table>
3.2.1.3 Ground data

Two ground-based validation data sets were compiled for this analysis. First, a time-lapse camera network was established to monitor fSCA dynamics. Second, automated snow pillow data measuring snow water equivalent (SWE) and snow depth were retrieved and converted into binary snow covered area (bSCA) values representing “snow covered” or “snow free” pixels.

3.2.1.3.1 fSCA from time-lapse camera network

Fourteen time-lapse cameras were established to monitor snow cover from March 2017 to May 2018. Cameras were set-up in pairs (7 pairs total) to capture differences in snow cover between nearby forested and open areas (with the exception of the two Portal cameras, which both captured images in forests). The distance between each camera in a pair ranged from 300 to 1000-m, to ensure coverage of different Landsat pixels. Cameras were programmed to capture images between 11:00 AM and 12:30 PM each day at 30-minute intervals (4 images total per day).

Once downloaded, the single best image for each day was selected based on the consistency of light, and minimization of shadow effects, condensation, and inclement weather events. Each image was interpreted to derive fSCA (from 0 to 100% snow cover) using a semi-automated image analysis method, as described in Dickerson-Lange et al. (2015). First, the spatial extent of the ground was determined, followed by the implementation of a threshold brightness approach to convert the area of interest within each photo to a binary map of snow covered and snow free pixels (Otsu, 1979). Due to difficult lighting conditions in certain photos (either too bright or too dark), the automated threshold generated was sometimes manually changed to more accurately
quantify snow covered pixels. For each site, a reference image was selected based on the best example of 100% snow cover. For each subsequent image, fSCA was calculated by dividing the number of pixels determined to be snow covered by the number of snow covered pixels from the reference image. This value was sometimes greater than 100% (and therefore set to 100%), due to snow accumulation on tree trunks and branches that were snow-free in the reference image.

The details of the camera sites along with the data collection periods are shown in Table 3. Data collection periods vary due to camera malfunctions and additional sites placed during the second winter season.

Table 3: Characteristics of the ground truth sites

<table>
<thead>
<tr>
<th>Camera Sites</th>
<th>Latitude (degrees)</th>
<th>Longitude (degrees)</th>
<th>Elevation (m)</th>
<th>Canopy Cover (%)</th>
<th>Landsat Path/Row</th>
<th>MODIS Tile</th>
<th>Dates Acquired</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bald Hills Forested</td>
<td>52.722518</td>
<td>-117.692814</td>
<td>2059</td>
<td>71</td>
<td>45/23</td>
<td>h10v03</td>
<td>Mar 2017 to May 2018</td>
</tr>
<tr>
<td>Bald Hills Open</td>
<td>52.720635</td>
<td>-117.693201</td>
<td>2085</td>
<td>0</td>
<td>45/23</td>
<td>h10v03</td>
<td>Mar 2017 to May 2018</td>
</tr>
<tr>
<td>Cardinal River Forested</td>
<td>53.102843</td>
<td>-117.462873</td>
<td>1723</td>
<td>62</td>
<td>45/23</td>
<td>h10v03</td>
<td>Jun 2017 to May 2018</td>
</tr>
<tr>
<td>Cardinal River Open</td>
<td>53.104184</td>
<td>-117.460099</td>
<td>1768</td>
<td>0</td>
<td>45/23</td>
<td>h10v03</td>
<td>Jun 2017 to May 2018</td>
</tr>
<tr>
<td>Coal Valley Forested</td>
<td>53.115599</td>
<td>-116.981458</td>
<td>1432</td>
<td>39</td>
<td>45/23</td>
<td>h10v03</td>
<td>Mar 2017 to May 2018</td>
</tr>
<tr>
<td>Coal Valley Open</td>
<td>53.112095</td>
<td>-116.984782</td>
<td>1440</td>
<td>0</td>
<td>45/23</td>
<td>h10v03</td>
<td>Mar 2017 to May 2018</td>
</tr>
<tr>
<td>Parker Forested</td>
<td>52.189375</td>
<td>-117.117897</td>
<td>2040</td>
<td>82</td>
<td>45/23</td>
<td>h10v03</td>
<td>Jun 2017 to May 2018</td>
</tr>
<tr>
<td>Camera Sites</td>
<td>Latitude (degrees)</td>
<td>Longitude (degrees)</td>
<td>Elevation (m)</td>
<td>Canopy Cover (%)</td>
<td>Landsat Path/Row</td>
<td>MODIS Tile</td>
<td>Dates Acquired</td>
</tr>
<tr>
<td>------------------------------</td>
<td>--------------------</td>
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<td>------------------</td>
<td>------------</td>
<td>-------------------</td>
</tr>
<tr>
<td>Parker Open</td>
<td>52.190161</td>
<td>-117.113656</td>
<td>2023</td>
<td>23</td>
<td>45/23</td>
<td>h10v03</td>
<td>Jun 2017 to May 2018</td>
</tr>
<tr>
<td>Portal Forested 1</td>
<td>52.779623</td>
<td>-118.081440</td>
<td>1555</td>
<td>61</td>
<td>45/23</td>
<td>h10v03</td>
<td>Jun 2017 to May 2018</td>
</tr>
<tr>
<td>Portal Forested 2</td>
<td>52.778956</td>
<td>-118.080146</td>
<td>1515</td>
<td>51</td>
<td>45/23</td>
<td>h10v03</td>
<td>Jun 2017 to May 2018</td>
</tr>
<tr>
<td>Seabolt Forested</td>
<td>53.293881</td>
<td>-117.683826</td>
<td>1104</td>
<td>51</td>
<td>45/23</td>
<td>h10v03</td>
<td>Nov 2017 to May 2018</td>
</tr>
<tr>
<td>Seabolt Open</td>
<td>53.295228</td>
<td>-117.686382</td>
<td>1098</td>
<td>0</td>
<td>45/23</td>
<td>h10v03</td>
<td>Nov 2017 to May 2018</td>
</tr>
<tr>
<td>White Creek Forested</td>
<td>53.331939</td>
<td>-117.179698</td>
<td>1177</td>
<td>80</td>
<td>45/23</td>
<td>h11v03</td>
<td>Nov 2017 to May 2018</td>
</tr>
<tr>
<td>White Creek Open</td>
<td>53.330553</td>
<td>-117.181147</td>
<td>1178</td>
<td>0</td>
<td>45/23</td>
<td>h11v03</td>
<td>Nov 2017 to May 2018</td>
</tr>
<tr>
<td><strong>Snow Pillow Sites</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Molson Creek</td>
<td>52.216670</td>
<td>-118.216670</td>
<td>1868</td>
<td>38</td>
<td>45/24</td>
<td>h10v03</td>
<td>Aug 2000 to May 2018</td>
</tr>
<tr>
<td>Yellowhead</td>
<td>52.900000</td>
<td>-118.533330</td>
<td>1879</td>
<td>53</td>
<td>45/23</td>
<td>h10v03</td>
<td>Aug 2000 to May 2018</td>
</tr>
</tbody>
</table>

### 3.2.1.3.2 Ground binary snow cover

Time-lapse cameras were also used to calculate bSCA. From the fSCA values, any value greater than 0 was considered “snow covered”, otherwise “snow free”. In addition to time-lapse cameras, ground data were acquired from two automated snow pillow sites located within the
processed Landsat scenes but outside of the Yellowhead BMA. Daily snow depth and snow water equivalent (SWE) data from two sites, Yellowhead and Molson Creek, from August 1, 2000 to May 31, 2018, were downloaded from the online report generator of the National Water and Climate Center (United States Department of Agriculture, 2018). Daily data were stacked by winter year (August 1st to July 31st) and manually cleaned to account for sensor malfunctions and gaps and discrepancies between SWE and snow depth readings, particularly during summer months in which vegetation could distort values. A site was classified as “snow covered” when SWE was greater than 25 mm. Details of the two snow pillow sites are shown in Table 3.

3.2.2 Dynamic Time Warping algorithm

3.2.2.1 Background

For the purpose of explaining the DTW algorithm, a ‘snow curve’ is defined as a set of daily SCA values for one winter year (winter day of year 1 to 365, August 1st to July 31st) fit from either MOD10A1 NDSI or TMSCAG fSCA values. The DTW algorithm normalizes the MOD10A1 snow curve of a ‘query year’ to best match the MOD10A1 snow curve of a ‘target year’. The manipulation of the MOD10A1 query year snow curve creates a set of rules relating the dates of the query year to the corresponding dates of the target year when snow cover is most similar. By defining each winter year in turn as the target year and comparing its snow curve to each query year (all other winter years), this set of rules can then be used to temporally adjust multi-year observations of TMSCAG fSCA to match the snow dynamics of each individual year, creating an annual TMSCAG fSCA snow curve at 30-m spatial resolution (SNOWARP). The algorithm is applied on a pixel-by-pixel basis and described in detail below.
Figure 3: Overview of the four steps of the Dynamic Time Warping (DTW) procedure (Note: Winter day of year is August 1 to July 31 of the next year). (a) The interpolation of MOD10A1 snow curves, (b) the generation of rule-sets using DTW and the MOD10A1 snow curves as inputs, (c) The application of rule-sets to the entire TMSCAG time-series, (d) The interpolation of TMSCAG snow curves resulting in SNOWARP (daily 30-m fSCA estimates).

3.2.2.2 DTW procedure

Step 1 of the DTW procedure involved the generation of MOD10A1 winter year snow curves (Figure 3, top left box). Using the pre-processed MOD10A1 stacks, annual winter year data from each MOD10A1 pixel were used to generate a continuous snow curve with values for winter day of year 1 to 365. MOD10A1 values were spatially smoothed using a 3x3 low pass filter, with 50% weight on the center pixel and 50% on the neighborhood. Missing values (due to cloud cover and other factors) were temporally interpolated using a cubic smoothing spline and
Gaussian filter (Dozier et al., 2008). When the gap between valid MOD10A1 observations exceeded 7 days, a linear interpolation was used to avoid extreme values from the spline.

Step 2 involved the generation of rule-sets relating target and query years. In turn, each winter year was defined as the target year and every other year was subsequently defined as a query year. A rule-set was generated between the target year and each query year. To estimate snow curves for eighteen years (2000-2017), the eighteen years were in turn defined as the target year and for each target year, seventeen rule-sets were generated. To create the rule-set warping the query year to target year (e.g. query year 2001 to target year 2000, Figure 3, top-left box), a matrix of target year and query year values from winter day of year 1 to 365 was created with each cell containing the Euclidean distance between the NDSI Snow Cover values (Baumann et al., 2017). A rule-set was then generated based on the path which minimizes the variability between the two snow curves (Petitjean et al., 2012), restricted by some thresholds that were calibrated to best fit ground truth data. The rule-set must start at winter day of year 1 for both curves (Figure 3, top right box) and end at winter day of year 365. The algorithm was restricted by a 30 day “window” (Sakoe & Chiba, 1978), resulting in the rule-sets not being able to form a relation more than 30 days apart. After the query year was warped, if for any winter day of year the difference between the query year and target year NDSI snow cover value was > 0.3, the rule relating those two days was considered invalid.

In step 3, the rule-set generated from MOD10A1 relating the query and target year were used to warp TMSCAG iSCA observations from the query year to match the snow dynamics of the target year (Figure 3, bottom right box). All TMSCAG pixels contained within a given
MOD10A1 pixel were warped using the same rule-sets. All fSCA values from the target year itself were considered to be “true” values and were not modified. In certain cases, multiple fSCA values from the query year were shifted to the same winter day of year in the target year. When this occurred, the average of all values for that day was used. Steps two and three were replicated for each query year, adding observations to the TMSCAG time-series of the target year.

Step 4 involved the generation of TMSCAG snow curves (Figure 3, bottom left box). First, all values from the new TMSCAG time-series created in step three were rescaled to reduce underestimation of fSCA. The maximum value of fSCA from the TMSCAG time-series was set to equal the maximum value of the target year MOD10A1 snow curve. All other TMSCAG time-series values were then rescaled based on the amplitude of change from the old to new maximum value. Second, a spline interpolation was applied using the same parameters as described in section 2.3.2 to fill missing values. Lastly, a 3x3 low-pass spatial smoothing filter was applied to the resulting TMSCAG snow curve. The resulting time-series is a 30-m resolution daily fSCA snow product, from here on referred to as SNOWARP.

3.2.3 Testing SNOWARP against ground truth data

Validation tests were undertaken to assess the performance of SNOWARP fSCA and bSCA against ground truth data, as described below.

3.2.3.1 Fractional snow covered area

The agreement of SNOWARP fSCA and ground fSCA was evaluated for each winter day of year when ground fSCA values were available, including both a snow accumulation and snow melt
cycle. The metrics used were root mean squared error (RMSE), mean bias, and median bias. A positive bias indicated an overestimation of SNOWARP fSCA, whereas a negative bias indicated an underestimation when compared to ground fSCA.

3.2.3.2 Binary snow covered area

SNOWARP bSCA (0 indicating “snow free” and 1 indicating “snow covered”) were derived from SNOWARP fSCA values with a threshold of 15%, which has previously been determined as the snow detection limit for the MODSCAG algorithm (Painter et al., 2009). Ground bSCA was calculated from time-lapse imagery and automated snow pillows, as described in section 3.2.1.3.2.

SNOWARP bSCA was tested against ground bSCA using a set of binary metrics based on four outcomes in estimating whether or not a SNOWARP pixel is snow covered or snow free (Rittger et al., 2013). The possible outcomes are true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The metrics tested were:

\[
\text{Precision} = \frac{TP}{TP+FP} \quad (3) \\
\text{Recall} = \frac{TP}{TP+FN} \quad (4) \\
\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5) \\
F \text{ score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \frac{2\cdot TP}{2\cdot TP+FP+FN} \quad (6)
\]

Precision is the frequency that a pixel has snow, given that it was estimated to have snow (commission errors). Recall is the frequency that a pixel was estimated to have snow, given that it has snow (recall errors). Accuracy is the frequency that if a pixel has snow, it was estimated to
have snow, and if a pixel has no snow, it was estimated to have no snow. The F score is a balance between precision and recall. All binary metrics were multiplied by 100 to give a percentage of performance between 0 to 100%.

MOD10A1 bSCA was also calculated using two thresholds (0.15 and 0.40) and tested against ground bSCA to compare the accuracies of SNOWARP and MOD10A1. An NDSI value of 0.40 is generally the threshold set to determine whether a pixel is classified as snow covered or snow free (Hall et al., 1998), but it is a subjective threshold and therefore 0.15 was also evaluated. Lastly, MOD10A1 bSCA and pre-processed TMSCAG bSCA values were also tested against ground bSCA in order to determine any differences in accuracy between the two datasets before generating SNOWARP.

### 3.3 Results

This work resulted in the output of SNOWARP daily 30-m fSCA estimates (Figure 4) for six Landsat path/rows from August 1, 2000 to May 31, 2018. Through the application of the DTW algorithm driven by MOD10A1, the average number of cloud-free TMSCAG observations available per winter year increased from 14.8 to 136.2, creating a sufficiently dense time-series to interpolate daily values. Figure 5 shows an example of the spatial resolution of MOD10A1 and the newly generated SNOWARP, highlighting the complexity of snow dynamics in mountainous terrain and thus the value of a 30-m resolution product.
Figure 4: Example results from the DTW procedure, using a single Landsat pixel (and enclosing MODIS pixel) from the Bald Hills Forested site as reference. a) MOD10A1 interpolated snow curve for target year 2013. b) Example of all MOD10A1 snow curves before the generation of DTW rule-sets. Query year values are shown in grey scale (winter years 2000 to 2017, except 2013), target year is shown in red (winter year 2013) c) Example of all MOD10A1 snow curves post-application of DTW rule-sets generated to minimize the difference between query year and target year values. d) Warping of TMSCAG historical time-series to
match the target year (2013). The blue triangles are the observations from the target year, whereas the black points are values warped from other years. The dense time-series is then used to interpolate SNOWARP daily values.

Figure 5: Example of the spatial detail of MOD10A1 versus SNOWARP in mountainous terrain on May 27, 2017.

3.3.1 Fractional analysis results

SNOWARP fSCA and ground fSCA were compared from March 2017 to May 2018 at fourteen camera locations. Figure 6 and Figure 7 demonstrate that SNOWARP consistently underestimated fSCA throughout the winter, although the timing of transition from snow covered to snow free matches well. Early and late season snow events that only lasted a few days were challenging to capture, as well as the snow dynamics at sites that oscillated between being snow covered and snow free throughout the winter (Figure 7). RMSE ranged from 31.3% to 68.3% (Table 4). Both mean and median bias exhibit the systematic underestimation of fSCA from SNOWARP, with values ranging from -9.3% to -62.3% and 0% to -71.0% respectively. This
sometimes extreme snow underestimation bias was inherited from the original TMSCAG data as opposed to being a result of the DTW processing and MOD10A1 data. Figure 6 shows that SNOWARP values are consistently less than 100% during winter months, when time-lapse imagery clearly shows 100% fSCA. In addition, the re-scaling of TMSCAG values described in section 3.2.1.2 was applied to help reduce the underestimation bias, though it is still apparent throughout the data. No trend was inferred comparing results of forested and open sites.

Table 4: Summary of fractional statistics

<table>
<thead>
<tr>
<th>Site</th>
<th>RMSE (%)</th>
<th>Mean bias (%)</th>
<th>Median bias (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bald Hills Forested</td>
<td>35.2</td>
<td>-24.6</td>
<td>-29.0</td>
</tr>
<tr>
<td>Bald Hills Open</td>
<td>51.7</td>
<td>-39.7</td>
<td>-39.0</td>
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<tr>
<td>Cardinal River Forested</td>
<td>38.2</td>
<td>-20.4</td>
<td>-31.5</td>
</tr>
<tr>
<td>Cardinal River Open</td>
<td>31.3</td>
<td>-9.3</td>
<td>0</td>
</tr>
<tr>
<td>Coal Valley Forested</td>
<td>37.8</td>
<td>-19.4</td>
<td>-13.0</td>
</tr>
<tr>
<td>Coal Valley Open</td>
<td>41.5</td>
<td>-32.3</td>
<td>-38.0</td>
</tr>
<tr>
<td>Parker Forested</td>
<td>35.0</td>
<td>-25.8</td>
<td>-33.0</td>
</tr>
<tr>
<td>Parker Open</td>
<td>50.7</td>
<td>-38.8</td>
<td>-51.0</td>
</tr>
<tr>
<td>Portal Forested 1</td>
<td>46.8</td>
<td>-35.1</td>
<td>-45.5</td>
</tr>
<tr>
<td>Portal Forested 2</td>
<td>48.1</td>
<td>-33.1</td>
<td>-48.0</td>
</tr>
<tr>
<td>Seabolt Forested</td>
<td>52.9</td>
<td>-46.3</td>
<td>-53.0</td>
</tr>
<tr>
<td>Seabolt Open</td>
<td>68.3</td>
<td>-62.3</td>
<td>-71.0</td>
</tr>
<tr>
<td>White Creek Forested</td>
<td>57.9</td>
<td>-54.2</td>
<td>-57.0</td>
</tr>
<tr>
<td>White Creek Open</td>
<td>60.1</td>
<td>-56.3</td>
<td>-62.0</td>
</tr>
</tbody>
</table>
Figure 6: Results from the fSCA validation of the Bald Hills and Coal Valley sites during winter year 2016 (August 1, 2016 to July 31, 2017). Data were only available from March to August 2017. a), b), c), and d) compare the timing and value of fSCA from SNOWARP and ground data. e) three example time-lapse images from the Bald Hills Open site, showcasing the melt pattern.
Figure 7: Results from the fSCA validation of the Cardinal River and Portal sites during winter year 2017 (August 1, 2017 to July 31, 2018). Data were only available until early May. a), b), c), and d) compare the timing and value of fSCA from SNOWARP and ground data.

3.3.2 Binary analysis results

Four binary metrics (precision, recall, accuracy, and F score) were calculated from March 2017 to May 2018 at the fourteen camera sites and from August 2000 to May 2018 at the two snow pillow sites. All metrics performed above 80%, with 14 sites (out of 16) > 90% for precision, 11 sites > 90% for recall, 8 sites > 90% for accuracy, and 10 sites > 90% for F score (Table 5). Figure 8 highlights the difficulties of estimating snow cover during transition periods. Precision and recall errors are both common during the fall transition period, whereas recall errors are much greater than precision errors during the spring melt. Decreases in mid-winter recall were caused by the presence of false negatives in SNOWARP (at times SNOWARP estimates “snow free” in the middle of winter when ground data reads “snow covered”), and were noted to have carried over from the raw TMSCAG product. F score errors give a good indication of overall
performance, with SNOWARP generally performing better during spring transition than fall transition. No trend was inferred comparing open and forested sites.

Table 6 displays the results of SNOWARP bSCA and MOD10A1 bSCA, when tested against ground bSCA. Overall, MOD10A1 (0.15 threshold) out-performed both SNOWARP and MOD10A1 (0.40 threshold). That being said, the performance of SNOWARP was within 5% of MOD10A1 (0.15 threshold) in every metric, while greatly increasing spatial resolution. Differences between camera and pillow sites were minimal, except for MOD10A1 (0.40 threshold), in which the performance at pillow sites was generally better than at camera sites. When comparing pre-processed MOD10A1 bSCA and SNOWARP bSCA values against ground bSCA, the accuracies were 91 to 92% (for thresholds 0.15 and 0.40) and 87% respectively.

**Table 5: Summary of binary statistics**

<table>
<thead>
<tr>
<th>Camera Sites</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>Accuracy (%)</th>
<th>F Score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bald Hills Forested</td>
<td>94.7</td>
<td>98.4</td>
<td>94.7</td>
<td>96.5</td>
</tr>
<tr>
<td>Bald Hills Open</td>
<td>97.7</td>
<td>80.3</td>
<td>82.6</td>
<td>88.2</td>
</tr>
<tr>
<td>Cardinal River Forested</td>
<td>84.0</td>
<td>91.8</td>
<td>84.6</td>
<td>87.7</td>
</tr>
<tr>
<td>Cardinal River Open</td>
<td>85.4</td>
<td>93.1</td>
<td>86.7</td>
<td>89.1</td>
</tr>
<tr>
<td>Coal Valley Forested</td>
<td>94.7</td>
<td>86.6</td>
<td>88.5</td>
<td>90.4</td>
</tr>
<tr>
<td>Coal Valley Open</td>
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<td>96.0</td>
<td>93.9</td>
<td>96.4</td>
</tr>
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<td>98.2</td>
<td>98.1</td>
<td>98.6</td>
</tr>
<tr>
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<td>87.2</td>
<td>85.7</td>
<td>89.9</td>
</tr>
<tr>
<td>Portal Forested 1</td>
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<td>92.6</td>
<td>94.3</td>
</tr>
<tr>
<td>Portal Forested 2</td>
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<td>87.2</td>
<td>85.7</td>
<td>89.9</td>
</tr>
<tr>
<td>Seabolt Forested</td>
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<td>94.1</td>
<td>96.4</td>
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<td>89.7</td>
</tr>
<tr>
<td>White Creek Forested</td>
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<td>91.7</td>
<td>92.0</td>
<td>95.7</td>
</tr>
<tr>
<td>White Creek Open</td>
<td>100.0</td>
<td>94.0</td>
<td>94.3</td>
<td>96.9</td>
</tr>
<tr>
<td>Snow Pillow Sites</td>
<td>Precision (%)</td>
<td>Recall (%)</td>
<td>Accuracy (%)</td>
<td>F Score (%)</td>
</tr>
<tr>
<td>------------------</td>
<td>---------------</td>
<td>------------</td>
<td>--------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Molson Creek</td>
<td>93.5</td>
<td>93.1</td>
<td>90.4</td>
<td>93.3</td>
</tr>
<tr>
<td>Yellowhead</td>
<td>92.8</td>
<td>91.1</td>
<td>89.6</td>
<td>91.9</td>
</tr>
</tbody>
</table>

Table 6: Comparison of binary statistics from Landsat and MODIS-based snow products

<table>
<thead>
<tr>
<th>Product</th>
<th>Metric</th>
<th>Camera Sites</th>
<th>Snow Pillow Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNOWARP</td>
<td>Precision (%)</td>
<td>94.5</td>
<td>93.1</td>
</tr>
<tr>
<td></td>
<td>Recall (%)</td>
<td>90.7</td>
<td>92.1</td>
</tr>
<tr>
<td></td>
<td>Accuracy (%)</td>
<td>89.3</td>
<td>90.0</td>
</tr>
<tr>
<td></td>
<td>F Score (%)</td>
<td>92.6</td>
<td>92.6</td>
</tr>
<tr>
<td>MOD10A1 (0.15 threshold)</td>
<td>Precision (%)</td>
<td>96.5</td>
<td>95.1</td>
</tr>
<tr>
<td></td>
<td>Recall (%)</td>
<td>92.8</td>
<td>97.5</td>
</tr>
<tr>
<td></td>
<td>Accuracy (%)</td>
<td>92.3</td>
<td>94.9</td>
</tr>
<tr>
<td></td>
<td>F Score (%)</td>
<td>94.6</td>
<td>96.3</td>
</tr>
<tr>
<td>MOD10A1 (0.40 threshold)</td>
<td>Precision (%)</td>
<td>99.6</td>
<td>98.5</td>
</tr>
<tr>
<td></td>
<td>Recall (%)</td>
<td>76.2</td>
<td>91.3</td>
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<tr>
<td></td>
<td>Accuracy (%)</td>
<td>82.3</td>
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</tr>
<tr>
<td></td>
<td>F Score (%)</td>
<td>86.3</td>
<td>94.8</td>
</tr>
</tbody>
</table>
Figure 8: Binary metrics measuring the temporal performance of SNOWARP compared to ground truth from fourteen time-lapse camera sites (winter years 2016 and 2017) and two automated snow pillows (winter years 2000 to 2017) displayed by winter day of year (daily values averaged for all years in which data was available).
3.4 Discussion

Through applying the DTW algorithm and using daily MOD10A1 observations to characterize the inter-annual dynamics of snow cover, this study demonstrates a new methodology to construct a high spatial and temporal resolution snow product. As a proof of concept, DTW can be used to map snow cover at a daily time step and 30-m spatial resolution, which is required for applications in hydrology, wildlife ecology, environmental monitoring, and industrial and recreational planning. This approach increased the average number of valid TMSCAG observations available per year from 14.8 to 136.2, enabling the interpolation of annual snow curves and the production of a large dataset of fSCA values spanning almost two decades.

SNOWARP shared strong agreement with binary ground truth data. Binary metrics derived in Table 6 show the performance of SNOWARP at both camera and snow pillow sites to be around 90% or greater (the lowest value being 89.3%). The F score for both camera and snow pillow sites was 92.6%. Although previous studies have highlighted the limitations of point estimate data to accurately represent the snow dynamics in mountainous environments (Rittger et al., 2016), this study found comparable results between camera and snow pillow data. One exception to this finding is the discrepancy between the performance of MOD10A1 (0.40 threshold) at camera and snow pillow sites (Table 6). Snow pillow sites have been used for MODIS snow product validation by many studies (Klein & Barnett, 2003; Huang et al., 2011; Parajka & Blöschl, 2006; Simic et al., 2004), and the implication of this discrepancy for MODIS snow cover mapping may be that snow pillow sites show inflated performance when compared to time-lapse camera sites.
Figure 7 demonstrates the difficulty of capturing snow dynamics during seasonal transitions. During the fall transition period, decreases in performance were due to both precision and recall (SNOWARP commission and omission errors). During the spring transition, recall was a much more significant factor. In terms of overall accuracy (Figure 8), SNOWARP performed better during the spring transition than fall transition, possibly because of the slower changes in SCA during melt than accumulation. Mid-winter false negatives were noted in the TMSCAG dataset and led to decreased recall performance during winter months.

The binary validation results also indicate that the performance of SNOWARP is comparable to MOD10A1 (within 5%), though the performance of MOD10A1 (0.15 threshold) was higher in every metric (Table 6). It was hypothesized that SNOWARP would demonstrate a stronger correlation to ground truth data than MOD10A1, as it provides a finer spatial resolution depicting more localized snow conditions around the ground sites. In reality the 30-m TMSCAG fSCA data was more noisy than MOD10A1, leading to a slightly lower performance but a significantly higher spatial resolution. The analysis of pre-processed bSCA values from TMSCAG and MOD10A1 (section 3.3.2) also supports the conclusion that SNOWARP performance is comparable to MOD10A1 but resolution is effectively much higher. Given the limited number of pixels tested, a more extensive spatial validation is needed to draw stronger conclusions about the relative performance of SNOWARP estimates.

The results from the fractional analysis demonstrate a consistent underestimation of SNOWARP fSCA, with mean bias ranging from -9.3 to -62.3%. The varying extent of this systematic underrepresentation is visible in Figure 6 and Figure 7. TMSCAG may be underestimating snow
cover due to seasonal fluctuations in Landsat reflectance caused by solar zenith angle (Roy et al., 2016), which has been hypothesized to cause the same issue with MODSCAG data (Raleigh et al., 2013). Further research is needed to quantify the influence of solar zenith angle on TMSCAG fSCA estimations, which could lead to an adjustment in reflectance values for winter months to increase fSCA agreement. Although the general trends of snow seasonality were captured well by SNOWARP, early and late season snow events (in which snow persists for a short period of time) were challenging to capture. This is likely because the magnitude and duration of such events vary from year to year, and are therefore difficult to match inter-annually. In addition, the Cardinal River site (Figure 7) demonstrates the difficulty of estimating mid-winter oscillations in snow cover (when snow melts and accumulates at various times throughout the winter). The spline used to interpolate SNOWARP may be over-smoothing fSCA values, and further work may investigate alternative interpolation methods.

The fractional (Table 4) and binary (Table 5) analysis results did not demonstrate an identifiable trend in performance between forested and open sites. It was hypothesized that accuracy at forested sites would be lower than open sites, due to the difficulty of observing snow conditions under forest canopies. The similar performance between sites could be a result of camera sites only reaching 60 to 70% canopy cover (with two sites above 80%), as opposed to denser forests found in other ecosystems. In certain instances, the algorithm predicted snow on the ground much earlier in the fall than observed at snow pillow sites (Figure 7). This is probably the result of a combination of false positives from TMSCAG, the misalignment of random early season snow events, and the spline interpolation.
This study builds upon a growing popularity of time-lapse photography for snow monitoring (Dickerson-Lange et al., 2015; Garvelmann et al., 2013; Parajka et al., 2012) due to the low cost and weight of equipment, and the greater spatial representation of a camera image than a point observation. Throughout this study, time-lapse imagery provided a good representation of the temporal trends of snow accumulation and snow melt, which was useful for comparison against the temporal trends of SNOWARP in a limited number of example pixels. On the other hand, time-lapse imagery is limited in its spatial representation of the study area, and therefore further work is needed to perform an extensive validation of SNOWARP throughout the Yellowhead BMA and in other areas if the product is to be expanded.
Chapter 4: grizzly bear response to fine spatial and temporal scale spring snow cover

4.1 Introduction

4.1.1 Grizzly bear spring habitat selection

To date, most wildlife habitat selection studies focused on the influence of snow dynamics use seasonally averaged data, or data at a spatial or temporal resolution too coarse to represent the influence of snow on selection and movement. In areas where snow dynamics fluctuate seasonally and inter-annually, using these averaged or coarse data may result in underrepresentation or ambiguity with regards to selection, whereas incorporating fine-scale data may be key to gathering a better understanding of habitat use (Gilbert et al., 2017). Through the development of SNOWARP in Chapter 3, fine-scale snow cover data is now available and can be used to model grizzly bear habitat selection and use in response to a dynamic environment.

Although snow cover dynamics are largely unstudied in relation to grizzly bear spring habitat selection, a large body of work exists characterizing grizzly bear spring habitat selection in relation to a variety of other environmental and landscape variables. Elevation, solar insolation, topographic wetness, and land cover influence vegetation productivity and food availability and have been linked to grizzly bear habitat selection (Mace et al., 1996; Nielsen, 2005; Nielsen et al., 2004a). Bears also select for both natural and anthropogenic edges (Stewart et al., 2013; Larsen et al., 2019), related to an abundance of important habitat resources. Previous work has shown negative and positive selection for roads, due to both high food productivity and high risk (Boulanger & Stenhouse, 2014; Ciarniello et al., 2007; Kite et al., 2016; Northrup et al., 2012; Roever et al., 2010). Roads create forest edge habitat but also increase the risk of human-caused
grizzly bear mortality, especially within 500-m of a road or 200-m of a trail (Benn & Herrero, 2002; Nielsen et al., 2004b). Snow interacts with these variables and previous studies have commented on the potential influence of snow on spring habitat selection due to snow creating undesirable landscape conditions for bears (Mace et al., 1996; Noss et al., 1996; Coogan et al., 2018). Fine-scale snow data, such as SNOWARP, may be key to better understanding spring selection (Gilbert et al., 2017).

4.1.2 Research aim

By incorporating fine-scale remote sensing snow cover data (Berman et al., 2018; Mityok et al., 2018), this research aims to build upon the existing body of knowledge surrounding the drivers of grizzly bear spring habitat selection and use in the Yellowhead BMA. Integrated Step Selection Analysis (iSSA) (Avgar et al., 2016, Ladle et al., 2018, Prokopenko et al., 2017; Scrafford et al., 2018) is used to build a core model with variables previously shown to explain grizzly bear spring habitat selection and snow cover data is added to test if it improves the fit of the model. Probability of use is then calculated to examine the average effect of snow cover, elevation, and distance to roads on grizzly bear habitat use. Elevation and distance to roads are known to be key indicators of whether snow is driving bears to locations with higher risk of human encounters. Through this process a hypothesis is tested that bears are selecting for locations with lower percentages of snow cover during spring, and once snow has melted they are selecting for locations where it melted sooner on the landscape. In addition, SNOWARP data is used to analyze year-to-year variability in snow melt and how these trends may affect model accuracy. This chapter demonstrates the utility and flexibility of iSSA in examining and
evaluating wildlife selection in response to spatially and temporally dynamic environmental variables derived from developments in remote sensing technology.

4.2 Methods

The methods section contains details on grizzly bear telemetry data, core model covariates, and snow covariates. The iSSA modelling approach is then described, beginning with the development of a core model built using covariates previously shown to influence habitat selection during spring (Table 1). Snow covariates were added to the core model in three configurations to assess whether the inclusion of snow improved model accuracy. The best fitting model was evaluated to determine average effects of individual snow covariates on probability of use by grizzly bears.

4.2.1 Grizzly bear data

Global Positioning Systems (GPS) telemetry data from 47 grizzly bears were used from years 2009 to 2017. Bears were captured during the spring (May to June) using culvert traps and aerial darting from helicopters (Cattet et al., 2008; Cattet et al., 2003). Followit (Lindesberg, Sweden) GPS radiocollars (Televilt Simplex and Tellus models) were fitted on captured bears and collected location data at one hour intervals for up to two years. Locations with positional dilution of precision values greater than 10 were removed in order to increase positional accuracy (D’Eon & Delparte, 2005). All grizzly bears captures were authorized under the permitting authority of Alberta Environment and Parks (provincial jurisdiction lands, provincial parks, and protected areas jurisdiction lands), and Parks Canada (federal jurisdiction lands). Research and collection permits were obtained each year from all regulatory agencies. All
capture and handling efforts followed guidelines created by the Canadian Council of Animal Care (Canadian Council on Animal Care, 2003) and the American Society of Mammologists (Sikes et al., 2016). Capture protocols were approved annually by both the University of Saskatchewan’s Committee on Animal Care and Supply and the Alberta Environment and Parks Animal Care Committee.

The period of interest for this research spans from the date of den emergence until May 31st each year, and therefore data used were from the spring following the year of collaring. Data from the 47 bears resulted in 62 bear-years of data, defined as unique years of data from each individual, since some individuals were collared during multiple years. Of the 62 bear-years, 19 were adult females (>= 5 years old), 6 sub-adult females (< 5 years old), 3 females with dependents or cubs, 26 adult males (>= 5 years old), and 8 sub-adult males (< 5 years old). Certain individual grizzly bears changed age-reproductive class as their age increased or reproductive status changed.

**Table 7: Covariates used in models and references to studies linking variables to grizzly bear habitat selection and use**

<table>
<thead>
<tr>
<th>Covariate Name</th>
<th>Covariate Acronym</th>
<th>Spatial resolution</th>
<th>Temporal resolution</th>
<th>Previous work indicating relation to grizzly bear habitat selection and use</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural log of step length</td>
<td>Ln(SL)</td>
<td>n/a</td>
<td>Hourly</td>
<td>Munro et al., 2006</td>
</tr>
<tr>
<td>Time of day</td>
<td>TOD</td>
<td>n/a</td>
<td>Hourly</td>
<td>Munro et al., 2006</td>
</tr>
<tr>
<td>Elevation</td>
<td>ELEV</td>
<td>30-m</td>
<td>Static</td>
<td>Mace et al., 1996; Nielsen, 2005; Nielsen et al., 2004a; Noss et al., 1996</td>
</tr>
<tr>
<td>Distance to road</td>
<td>Dist(RD)</td>
<td>30-m</td>
<td>Static</td>
<td>Boulanger &amp; Stenhouse, 2014; Ciarniello et al., 2007; Kite et al., 2016; Mace et al., 1996; Northrup</td>
</tr>
<tr>
<td>Covariate Name</td>
<td>Covariate Acronym</td>
<td>Spatial resolution</td>
<td>Temporal resolution</td>
<td>Previous work indicating relation to grizzly bear habitat selection and use</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------------</td>
<td>--------------------</td>
<td>---------------------</td>
<td>--------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Terrain wetness index</td>
<td>TWI</td>
<td>30-m</td>
<td>Static</td>
<td>Nielsen, 2005</td>
</tr>
<tr>
<td>Distance to forest edge</td>
<td>Dist(FE)</td>
<td>30-m</td>
<td>Yearly</td>
<td>Laberee et al., 2014; McLellan, 1990; Nielsen et al., 2004a; Nielsen et al., 2006; Stewart et al., 2013; Theberge, 2002; Graham et al. 2010</td>
</tr>
<tr>
<td>Land cover</td>
<td>Land cover</td>
<td>30-m</td>
<td>Yearly</td>
<td>Mace et al., 1996; McLellan &amp; Hovey, 2001; Munro et al., 2006</td>
</tr>
<tr>
<td>Solar insolation</td>
<td>INSOL</td>
<td>30-m</td>
<td>Static</td>
<td>Nielsen, 2005; Nielsen et al., 2004a; Nielsen et al., 2006; Roever et al., 2010</td>
</tr>
<tr>
<td>Days since snow melt</td>
<td>DSM</td>
<td>30-m</td>
<td>Daily</td>
<td>Pigeon et al., 2016b; Mace et al., 1996; Noss et al., 1996; Coogan et al., 2018</td>
</tr>
<tr>
<td>Binary snow covered area</td>
<td>bSCA</td>
<td>30-m</td>
<td>Daily</td>
<td>Mace et al., 1996; Noss et al., 1996; Coogan et al., 2018</td>
</tr>
<tr>
<td>Fractional snow covered area</td>
<td>fSCA</td>
<td>30-m</td>
<td>Daily</td>
<td>Mace et al., 1996; Noss et al., 1996; Coogan et al., 2018</td>
</tr>
</tbody>
</table>

4.2.2 Core model covariates

A variety of environment and landscape covariates were used to characterize grizzly bear habitat selection and use (see Table 7 for a list of all covariates and references to previous work linking variables to grizzly bear selection and use). Data for elevation (ELEV), solar insolation (INSOL), and a topographic wetness index (TWI) were calculated at 30-m spatial resolution from the NASA Shuttle Radar Topography Mission (SRTM) digital elevation model. INSOL represents the amount of primary energy received from the sun, accounting for terrain variation. TWI represents surface water flows and accumulation. These three static variables have been linked to grizzly bear habitat selection (Nielsen, 2005) and have been used in other step-selection analyses.
in the study area (Roever et al., 2010). An annual land cover classification at 30-m spatial resolution from Hermosilla et al., (2015) was adapted to represent four distinct classes: forested, forbs, shrubs, and non-vegetated. From the forested class, annual distance to forest edge (dist(FE)) layers were generated, with negative distances representing locations inside of the forest. Road network data was downloaded from the Government of Alberta web portal (https://geodiscover.alberta.ca/) and distance to road (dist(RD)) calculated. All values greater than 1000 m were revalued to 1000 m (Graham et al., 2010), to account for the diminishing effect of roads at large distances.

The rate of travel of grizzly bears is an important indicator of movement behavior and therefore the natural log of step length (ln(SL)) was calculated from the Euclidean distance between consecutive telemetry locations. Movement of grizzly bears has also been linked to a strong diurnal pattern throughout the day (Munro et al., 2006; Graham and Stenhouse, 2014). For this reason, time of day (TOD) was calculated at the end of each step to correspond to four periods: dawn (one hour before civil dawn until sunrise), day (sunrise until sunset), dusk (sunset until one hour after dusk), and night (one hour after dusk until one hour before dawn).

### 4.2.3 Snow cover variables

Daily 30-m snow cover data from SNOWARP (Berman et al., 2018) was used from 2009 to 2017 (Table 7 and Figure 9). Using this fSCA dataset, two additional snow variables were derived: bSCA and date of snow melt. bSCA designates a pixel as either “snow covered” or “snow free”, and was calculated using a threshold of 15% on the SNOWARP fSCA product (Berman et al., 2018). Date of snow melt is an annual layer, which estimates the date each spring
in which a pixel transitions from snow covered to snow free. It was derived from the bSCA dataset by taking the average of a 31-day moving window (15 days before, and 15 days after a given date), and choosing the latest day in the spring (moving backwards from July 31st) which had 50% of days “snow covered”, and 50% of days “snow free” within the surrounding window. From the annual date of snow melt layers, daily date since snow melt (DSM) was calculated by subtracting the date of snow melt from the date of each grizzly bear telemetry location (negative values indicating number of days until snow melt, zero indicating the day of snow melt, and positive values indicating the number of days since snow melt).

In addition to using the snow cover variables to model grizzly bear habitat selection and use, the annual date of snow melt layers were used to examine trends in the timing to snow melt. Spatially, the landscape was separated into the 5 natural sub-region classifications (alpine, subalpine, upper foothills, lower foothills, and montane) and for each spring season from 2009 to 2017 average date of snow melt statistics were extracted by natural sub-region.
Figure 9: The three snow metrics derived from SNOWARP (Berman et al., 2018) at 30-m spatial resolution for years 2009 to 2017: a-c) Annual date of snow melt shown for spring 2010, 2015 and 2017. Days since snow melt (DSM) was produced by subtracting date of snow melt from the date associated with each grizzly bear telemetry location. d-f) daily binary snow covered area (bSCA) shown on April 1, May 1, and June 1, 2017. g-i) daily fractional snow covered area (fSCA) shown on April 1, May 1, and June 1, 2017.
Integrated Step Selection Analysis (iSSA) (Avgar et al., 2016, Ladle et al., 2018, Prokopenko et al., 2017; Scrafford et al., 2018) is an extension of Resource Selection Function (RSF) theory (Ciarniello et al., 2007; Graham et al., 2010; Laberee et al., 2014; Nielsen et al., 2004a) and Step Selection Function (SSF) theory (Gilbert et al., 2017; Northrup et al., 2012; Potts et al., 2014; Roever et al., 2010) used to model the likelihood that an animal uses an available location, given its resource value quantified through model covariates. SSFs define the domain available to an animal using the empirical distributions of steps taken, where a step is the linear connection of two telemetry locations, defined with the attributes of step length and turning angle (Thurfjell et al., 2014). Each step taken is evaluated against a series of randomly generated available steps using conditional logistic regression to determine the likelihood of an animal choosing from available options (Fortin et al., 2005). The generation of available steps corresponding to a specific time and location allows for the inclusion and evaluation of temporally dynamic variables, such as fSCA and DSM. Whereas traditional SSFs exclude movement parameters in the models, iSSA includes either step length or turning angle or a combination of the two, which allows for simultaneously estimating movement and selection parameters (Avgar et al., 2016).

The implementation of iSSA is described below.

First, grizzly bear location information was transformed into used steps, distinguished by time, location, step length and turning angle. Step length is the Euclidean distance between two consecutive telemetry locations registered at a regular interval (Turchin, 1998). Turning angle is the angular change in direction between steps. Three consecutive telemetry locations are required to calculate turning angle, and therefore steps were only generated for three or more linked
locations (Thurfjell et al., 2014). Over the 62 bear-years from 2009 to 2017, 36,645 steps were created to analyze during the period of interest.

Second, five available steps were generated for each used step using a gamma distribution for step length and a von Mises distribution using maximum likelihood for turning angle, both fit from distributions built upon the used steps from each individual bear-year (Avgar et al., 2016). Once all used and available steps were created, environmental, landscape, and movement variables were extracted (Table 7). Spatial variables were extracted from the end location of each step, as opposed to the start location.

Third, four conditional logistic regression models (Table 8) were fit to the data for each individual bear-year, using the used and available steps generated. The first model fit was a core model, which included variables that have previously been shown to influence bear movement and selection in the spring. These variables included the log of step length, an interaction between log of step length and time of day, elevation, distance to road, terrain wetness index, distance to forest edge, and solar insolation. Both linear and quadratic terms were included in the model for INSOL, TWI, dist(FE) and dist(RD) to account for non-linear relationships.

By fitting three additional models built by adding various snow indicators to the core model, it was possible to assess whether snow cover variables improved the model fit, and therefore test the hypothesis predicting snow as an important factor in characterizing spring habitat selection and use. The “DSM model” included the core model and DSM. The “bSCA model” included the core model, bSCA, and DSM. The “fSCA model” included all variables from the core model,
fSCA, an interaction between fSCA and ln(SL), as well as DSM. Both linear and quadratic terms were included for DSM in all three snow models and for fSCA in the fSCA model.

Next, model fit was evaluated for each model and each individual bear-year to assess the best fitting model and see which of the three snow models, if any, would outperform the core model. To do this, the Akaike Information Criterion (AIC) was calculated for each model run and the model with lowest AIC for each bear-year received a tally, resulting in 62 total tallies. In addition, the average AIC weight (Wagenmakers & Farrell, 2004) was calculated for each model by taking the mean of the AIC weight from each model run. The AIC tally and average AIC weight were used to select the best candidate model, and subsequently that model was used to calculate probability of use.

Probability of use is used to visualize the average effect of covariates, or resource types (such as fSCA) on the probability of space use by grizzly bears (Avgar et al., 2017). It was generated by computing the predicted probability of selection values of the fitted model outputs from each individual bear-year over all available steps, and smoothing the results using a cubic spline function with 4 knots and 95% confidence intervals. Since the curve was fit over all available points, it represents the average probability of selection conditional on the availability of all resources, and therefore represents the probability of use (Avgar et al., 2017; Lele et al., 2013).

Probability of use was calculated using the fSCA model in response to both fSCA and DSM. Additionally, data points were stratified by elevation categories (from the ELEV layer) and
distance to road in response to DSM. In all analyses, DSM was truncated at -50 and 50 to restrict analysis to the period of transition.

Organization of data, model fitting, and analyses were undertaken using the AMT (version 0.0.5.0) (Signer, 2018) package in R (version 3.5.1) (R Core Team, 2018). ArcGIS Pro (version 2.2.3) (ESRI, 2018) was used to pre-process model variables.

4.3 Results

The average trends in the date of snow melt on the landscape are shown in Figure 10. Overall, snow in alpine environments melted the latest, whereas snow in montane and lower foothills melted earliest. The timing of snow melt at lower elevations, in upper foothills, lower foothills, and montane environments, fluctuated more year-to-year than at higher elevations in alpine and subalpine regions. Additionally, the years of 2010, 2015, and 2016 can be characterized as years with early snow melt in lower elevation areas.
Through the process of fitting the four candidate models to the individual bear-years, the fSCA model received 37 out of 62 AIC tallies (Table 8), indicating the importance of snow variables in explaining spring movement and selection. The core model received 11 tallies, which is indicative of the variation amongst individual bears and the covariates that influence their selection. The bSCA and DSM models received 5 and 9 tallies respectively, underlying the importance of fine-scale fractional snow mapping (from the fSCA model) when compared to more coarse indicators of snow dynamics. In terms of AIC weight, the fSCA model also significantly outperformed the other models. By dividing the AIC weights, we can determine that the fSCA model is 3.89 times more likely to be the best model than the core model, and 3.76 times more likely to be the best model than the DSM model, the next best performing model that includes snow variables (Wagenmakers & Farrell, 2004).
Table 8: Overview of the four models assessed for each of the 62 bear-years. The AIC Tally is a record of the model that had the lowest Akaike Information Criterion score for each bear-year.

<table>
<thead>
<tr>
<th>Model</th>
<th>Covariates</th>
<th>AIC Tally</th>
<th>Average AIC Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Core</td>
<td>Ln(SL) + ln(SL):TOD + ELEV + dist(RD)^2 + TWI^2 + dist(FE)^2 + Land cover + INSOL^2</td>
<td>11</td>
<td>0.1460</td>
</tr>
<tr>
<td>Days since snow melt (DSM)</td>
<td>Core + DSM^2</td>
<td>9</td>
<td>0.1508</td>
</tr>
<tr>
<td>Binary snow covered area</td>
<td>Core + bSCA + DSM^2</td>
<td>5</td>
<td>0.1357</td>
</tr>
<tr>
<td>Fractional snow covered</td>
<td>Core + fSCA + fSCA:ln(SL) + DSM^2</td>
<td>37</td>
<td>0.5675</td>
</tr>
</tbody>
</table>

Comparing the number of AIC tallies received by each model per year (Table 9), a disproportionally high number of tallies were received by the core model for the early snow melt years of 2010, 2015, and 2016. Out of 11 tallies received by the core model, 72.8% were for early snow melt years, whereas the total number of tallies for the early snow melt years account for only 54.8% of the total tallies from 2009 to 2017.

Table 9: A summary of the number of tallies received by each model per year.

<table>
<thead>
<tr>
<th>Tallies received/year</th>
<th>Core</th>
<th>DSM</th>
<th>bSCA</th>
<th>fSCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>2010</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>2011</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2012</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2013</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>2014</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>2015</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>2016</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>2017</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>8</td>
</tr>
</tbody>
</table>
Probability of use was explored in response to various snow indicators from the top performing model (fSCA model). In response to fSCA (Figure 11, a), there was a strong overall correlation between increased probability of use and lower percentages of snow cover. Probability of use was most negatively affected at high percentages of fSCA, between 60 to 100%. In response to DSM (Figure 11, b), probability of use increased as the number of days since snow melt increased. In response to DSM and stratified by elevation (Figure 12, a), the effect of DSM was stronger at lower elevations (steeper curve with higher probability) than at higher elevations (flatter curve with lower probability). Use did not vary significantly by elevation prior to snow melt, and reached a maximum effect between 10 to 25 days after snow melt. When probability of use was tested in response to DSM and stratified by distance to road, a similar trend was present in each distance category, yet locations closer to roads were preferred (Figure 12, b).

Figure 11: Probability of use was calculated over all available locations with both fSCA and DSM on the x-axis. The overall trends show increased selection for locations with less snow cover than what is available, as well as preference for locations where snow melted sooner in the spring.
Figure 12: Probability of use calculated with DSM on the x-axis and (a) categorized by elevation (m) and (b) distance to road (m). Relative preference is shown for lower elevation locations, especially once snow has melted. Grizzly bears generally were more likely to select for locations closer to roads once snow has melted.

4.4 Discussion

This chapter has demonstrated the application of fine scale daily remote sensing data in evaluating a hypothesis relating snow cover variables to spring habitat selection and use of grizzly bears in the Yellowhead BMA. Based on the AIC tally and average AIC weights, the inclusion of fSCA improved the predictive model over both a core model and other models which contained more coarse spatial and temporal representations of snow on the landscape. Temporally dynamic covariates such as snow depth have previously been introduced into iSSA (Prokopenko et al., 2017), however these were shown to demonstrate a weak or variable response, possibly due to low spatial resolution. The advancement of both the resolution and reliability of fine scale remote sensing datasets, such as daily fSCA values at 30-m spatial resolution, hold promise in investigating a range of hypotheses related to wildlife habitat selection, movement, and use.
The key findings of this study support the hypothesis that during spring (den emergence to May 31st) grizzly bears display preference for using locations with less snow cover (Figure 11, a), as well as locations where snow melted sooner (Figure 11, b). When bears emerge from denning, spring food resources are often “locked” in the snowpack and are not available until snow melt occurs and the ground thaws (Coogan et al., 2002). The exception is when bears find or kill ungulates in the spring, which might provide reason to stay in a snow covered location (Munro et al., 2006). Our results further validate studies focused on the availability of spring food resources in relation to the probability of bear occurrence (Nielsen et al., 2017; Pigeon et al., 2014). Areas where snow melts sooner in the spring provide the first opportunities for feeding, specifically in this study area, where digging for the roots of *Hedysarum* provides the main staple of the spring diet (Munro et al., 2006). Earlier snow melt can also result in earlier emergence of other vegetation consumed by bears, and these locations with early food sources are also likely to attract prey species, such as deer and other ungulates.

The results in Table 9 provide insights into why the core model outperformed the snow models in certain instances. The core model received a disproportionately high number of AIC tallies during the years with earliest snow melt (2010, 2015, and 2016). When snow melts earlier on the landscape, it could be a less important factor determining grizzly bear habitat selection during spring, and therefore the variables in the core model would be sufficient for modelling selection.

The results in Figure 12 demonstrate how fine-scale modelling can lead to a better understanding of grizzly bear use of the landscape. When probability of use is stratified by elevation (Figure 12,
a), grizzly bears show a strong preference for use of lower elevation locations where snow has already melted. Negative human-bear encounters are the most important factor influencing grizzly bear survival in the study region (Benn & Herrero, 2002; Nielsen et al., 2006). These results link spring snow melt dynamics to the probability of bears using lower elevation locations, which are also the locations that have higher levels of human use. In addition, road networks have strong links to human-caused grizzly bear mortality, especially within 500-m (Benn & Herrero, 2002; Nielsen et al., 2006). It was interesting to investigate if bears were more likely to use locations closer to roads when snow was present or absent. The results indicate that locations closer to roads (between 0 to 500-m) were more preferable after snow melted (Figure 12, b), possibly due to food availability along road edges, which may melt sooner than other locations. The probability of bears using locations closer to roads is also linked to elevation, as road networks are denser at lower elevations.
Chapter 5: conclusion

5.1 Overview

The objective of this thesis was to investigate the relationship between fine-scale snow dynamics and grizzly bear habitat selection and use during spring. This was accomplished through: (1) the development of SNOWARP, a daily 30-m fSCA remote sensing product and (2) modelling grizzly bear spring habitat selection in relation to snow and other variables.

The process undertaken to develop a new fine-scale remote sensing snow cover product resulted in SNOWARP, daily estimates of 30-m fSCA for the entire Yellowhead BMA from 2000 to 2018. The DTW algorithm was used to fuse together satellite imagery from MODIS and Landsat, where daily MODIS values produced a rule-set that was then applied to rearrange historical Landsat values. Ground truth data from time-lapse cameras and automated snow pillows were then used to test the validity of SNOWARP.

Next, using iSSA, four models were built from a variety of environmental and landscape variables to test whether the inclusion of snow variables would improve model fit. The models were fitted to grizzly bear GPS telemetry data from 2009 to 2017 and were compared using an AIC tally and average AIC weights. The best fitting model, which included fSCA and DSM variables, was then used to calculate probability of use and explore the impact of spring snow dynamics on grizzly bear habitat use.
5.2 Key findings

The development of SNOWARP is a proof of concept that DTW can be implemented to derive daily 30-m values of fSCA. The data used were freely available and open-access and therefore the methods are reproducible globally. In terms of results, SNOWARP strongly agreed with ground truth data from time-lapse cameras and snow pillows. The binary metrics calculated showed the performance of SNOWARP to be around 90% or greater in terms of precision, recall, accuracy, and F score (the lowest value being 89.3%).

Through modelling grizzly bear spring habitat selection and use, this research has shown that the inclusion of fine-scale snow variables improved model accuracy 60% of the time and the best performing model with snow was on average 3.89 times more likely to be the best model than a core model that did not include snow variables. By calculating probability of use in response to fSCA, days since snow melt, elevation, and distance to roads, this work has established a baseline relationship between grizzly bear habitat use and spring snow dynamics. Results indicated that grizzly bears are more likely to use lower elevation, snow-free locations during spring, which has important implications for management of threatened grizzly bear populations in consideration of changing climatic conditions.

5.3 Implications

The increase in spatial and temporal resolution of fSCA data as demonstrated by SNOWARP in Chapter 3 has implications for a variety of applications. The resolution of this product has the potential to increase the accuracy of snow water equivalent estimates in mountainous terrain, which has been highlighted as a pressing issue in snow hydrology (Dozier et al., 2016).
Additionally, the scale of SNOWARP can improve our understanding of the influence of fine-scale environmental variables on wildlife habitat selection, use and movement (Neumann et al., 2015), forestry operations dependent on the dynamics of localized spring snow melt patterns, fine-scale mapping of run-off due to snow and glacial melt (Schaper et al., 1999), forest-fire risk assessment (O’Leary et al., 2016), as well as recreational planning.

The results from Chapter 4 have important management implications for bear conservation related to future climatic projections and human-bear encounters during spring in snow free areas. Future climate predictions suggest that winters will have a higher level of uncertainty, with more inter-annual variation in both the timing and extent of winter conditions (Barnett & Adam, 2005). In addition, projections show a decline in the number of days with snow cover (Mekis & Vincent, 2011; Price et al., 2013; Zhang et al., 2000) and warmer winter and spring temperatures (IPCC 2013). As winter and snow conditions change, bears will adapt. One implication of changing winter conditions could be a shorter denning season, resulting in more bears on the landscape in the spring, which would increase the risk of negative human-bear encounters (Pigeon et al., 2016b). Worldwide, humans are the main cause of grizzly bear mortality (Can et al., 2014). If lower elevation locations are preferred by bears during this time of year due to snow melt dynamics, earlier snowmelt could also be driving bears into locations with higher risk of human-caused mortality. Future work should apply fine-scale snow maps to develop probability of bear occurrence layers during spring snow melt. These layers could help to identify key locations where snow consistently melts sooner, and these areas could then be designated as target areas for grizzly bear conservation initiatives, such as seasonal access closures to roads and trails.
5.4 Limitations

SNOWARP requires information on canopy cover to minimize the underestimation bias caused by the difficulty of seeing the ground in dense forested areas. In this research, Landsat fSCA values were adjusted by a static 2010 canopy cover map, which is a potential limitation because in some areas of the Yellowhead BMA there are high annual levels of anthropogenic landscape change (outside of parks and protected areas). This means that the static 2010 values used may not correctly account for canopy cover in other years. Future versions of SNOWARP would benefit from an annually derived canopy cover map, though some disparities may still exist due to differences in the detectability of snow before and after disturbance events. In addition, forest disturbances can alter the snow accumulation and melt dynamics on the landscape (Micheletty et al., 2014), which could lead to challenges in accurately capturing inter-annual patterns within individual pixels.

Limitations of the iSSA methodology used include the fact that grizzly bear telemetry locations were only evaluated at an hourly rate. Effects of snow dynamics on grizzly bear habitat selection probably occur at a variety of temporal scales, including both sub-hourly locations and broader trends in home-range usage inter-annually and throughout different seasons (Mace et al., 1996). In addition, data on snow depth was not included, since the spatial resolution of available data was too coarse to match the other fine-scale data of this study. Snow depth can influence activity levels in bears during den entry and emergence periods (Evans et al., 2016) and in the future could be compared to spring resource selection and movement rates. Date of snow melt is
potentially a proxy for snow depth, as snow will melt later in locations with greater snow depth, especially if other environmental and terrain factors are accounted for.

5.5 Future directions and applications

Although this first iteration of SNOWARP is a historical time series, a future version could include an operational product, functioning in near real-time. Further assessment is needed to determine the extent of operational latency, which could span several days to several weeks. Although the MOD10A1 dataset worked well as the driver of the DTW algorithm, future analyses may consider using a fSCA product such as MODSCAG, as it could better align with the temporal dynamics of the TMSCAG fSCA product, due to both utilizing a spectral mixture analysis approach. Alternatively, MOD10A1 could be used to re-order Landsat NDSI snow cover (calculated from raw Landsat surface reflectance values), which may provide an opportunity to reduce the underestimation bias (since raw values could be manipulated), but would only result in a binary snow product.

Further testing is also needed to validate the SNOWARP product. This could be achieved by withholding TMSCAG images from the target year and testing their values against those generated by SNOWARP, or comparing imagery from other satellite platforms, such as Sentinel 2, which is available from 2015 until present at 20-m resolution. Additional fSCA datasets could be utilized from temperature sensors (Raleigh et al., 2013), high-resolution imagery (Selkowitz & Forster, 2016), and LiDAR (Bair et al., 2016).
In terms of modelling grizzly bear selection in relation to snow dynamics, future research could focus on an analysis of grizzly bear denning location and date of den entry and emergence, which has been linked to snow dynamics and food availability (Pigeon et al., 2016b). Future analyses may also further stratify the landscape based on year-to-year snow melt patterns within individual grizzly bear home ranges, to examine how bears use their home-ranges in different years with regards to snow dynamics.

Snow conditions are an integral habitat component for a number of species, including grizzly bears, wolverine (McKelvey et al., 2011), elk (Telfer, 1978), deer (Gilbert et al., 2017), and caribou (Stuart-Smith et al., 1997). Although the relationships that exist between grizzly bears and their natural environments are complex, this research has succeeded in linking grizzly bear habitat selection and use to spring snow dynamics. This success is in large part due to advances in remote sensing technology, which enables users to create datasets with higher spatial and temporal resolution than have ever been available before. High-resolution data can facilitate a better understanding of how grizzly bears use the landscape, and a better understanding of how bears use the landscape in relation to changing environmental and climatic variables can help resource managers and policy-makers to maintain a sustainable grizzly bear population for present and future generations.
References


