Glacier change assessment of the Columbia Icefield in the Canadian Rocky Mountains, Canada


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Glaciers adjust their sizes as a response to changing climatic conditions which make them a good indicator of climate change. Remote-sensing based glacier monitoring provides a robust way to inventory the health of glaciers and are estimated as a measure of changes in their area, length, volume and mass balance over a period. This research uses remote sensing methods to map glacier extents from satellite images and explores the efficacy of three machine learning algorithms for accurate glacier classification. The results indicated that the Columbia icefield lost 42 km² of its area cover between 1985 and 2018. It was observed that smaller glaciers lost more of their area at a faster pace than larger ones. Change analysis showed the Columbia glacier experienced the highest area loss (-5.62 km²) and retreat (-3.37 km) while the Athabasca glacier recorded the highest mass ice lose (-2.54 m w.e.) over the study period.
DEDICATION

This dissertation is dedicated to the Almighty God for providing me with grace in completing such an awesome opportunity. Secondly, to my family and friends who have offered their encouragement and support throughout my graduate study. Special Thanks to my friend, Harry Tetteh who encouraged me to take on this bold step. Thank you to my father, Kwadjo Intsiful, aunt, Monica Owusu and friend, Yayra Yaa Davor for their constant encouragement throughout my journey in graduate school.
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CHAPTER I
INTRODUCTION

The presence of the cryosphere on the earth makes life bearable as it balances the energy budget between the earth and the sun. Every aspect of the cryosphere has some snow and ice. However, depending on the size, shape, thickness, location and behavior of an ice, it can be classified as either sea ice, glaciers, ice shelves and icebergs, frozen ground or permafrost. Notable among the various aspects of the cryosphere is glaciers which play the most significant role in climate studies (Ambinakudige, 2010; Inamdar and Ambinakudige 2016): and as such, act as a sensitive indicator for climatic variations. They have been tagged by the Intergovernmental Panel on Climate Change (IPCC) as an overall temperature indicator. Currently, glaciers cover about 10% of land area on earth. They are typically found in climatic and topographic conditions where snow can accumulate over long periods of time and gradually metamorphose into what is termed as firn. After a period, the firn may persist for a while and finally become ice and are then forced downward to elevations with higher temperatures. At this stage some of the ice may melt during the summer season.

Glaciers remain the largest reservoir of freshwater on earth serving more than 1.3 billion people (Brown et al, 2010). Meltwater especially from mountain glaciers make significant contributions to general streamflow especially in the late summer when there are warm periods with dry weather (Zappa and Kan, 2007; Jost et al., 2011). Surface runoff from these glaciers
during summer regulate stream temperature making it conducive to be effectively used for irrigation, tourism, industry, hydro power, domestic consumption and to support aquatic life (Granshaw and Fountain, 2006; Stahl and Moore, 2006). The twentieth century has seen an accelerated wastage of glacier ice especially in mountainous regions (Barry, 2006). During recent years, many glaciers around the globe have lost significant amounts of ice with smaller glaciers experiencing relatively higher rates of shrinkage compared to larger glaciers (Tennant and Menounos, 2013). The ramifications of these processes may include, increased contributions to global sea-level rise (Berthier et al., 2004) and negative socio-economic impacts on communities which rely on them for recreational and tourism activities. Glacier mass wastage can cause an increased volumes of late summer discharge which could lead to long-term loss of natural fresh water. The aftermath of the rapid discharge could lead to glacial lake outburst flood (GLOF) which are mostly catastrophic to surrounding regions.

Annual fluctuations in snow precipitation and energy balance affect snow accumulation and ablation. During the end of an ablation season, several factors may account for the loss of glacier ice to exceed the snow accumulation it received during the previous winter period. Two main sources that feed the accumulation area are; (i) refreezing of water and (ii) annual snow precipitation. On the other hand, ablation is the results from higher temperatures causing snow and other components of ice to melt into surface runoff. They may also happen with calving or sublimation of ice toward the land or into a water body. A significant anomaly of both accumulation and ablation may be attributed to winds and avalanches. The balance between the ablation and the accumulation of snow precipitation primarily determines the mass balance of glaciers. The equilibrium line of altitude (ELA) is a major indicator of determining whether a glacier has increased or decreased. The ELA is the separation between accumulation area and
ablation area. At this line, ablation over the annual snow season is equally balanced by the snow/ice accumulations and the mass balance is zero.

The vitality of mountain glaciers requires a close monitoring of changes in their area, volume and length periodically. Glacier studies require precise glacier outlines to produce accurate mass balance estimations. Various algorithms have been applied to glacier mapping using traditional and automated techniques (Berthier et al., 2004; Bolch et al., 2010; Tennant et al., 2012; Dixon and Ambinakudige, 2015). Summaries of proceedings from most of these studies have been compiled into various databases (e.g: World Glacier Inventory, Randolph Glacier Inventory, etc). However, glacier studies have been biased towards glaciers that are easily accessible and those with less complex topography. This has left a lot of mountain glaciers to be undocumented. For instance, the Columbia Icefield in Canada has limited existing knowledge on mass balance estimations. The broader objectives of this study were to apply data fusion approaches and band ratios on Landsat and ASTER imagery over four decades to classify glaciated areas, measure the rate of retreat, changes in glacial extent and estimate mass balance in the Columbia Icefield located in the Canadian Rocky Mountains.

Background

For glacier studies and monitoring, the World Glacier Inventory (WGI) was the first to have existed and been built on by others including the Randolph Glacier Inventory (RGI) which was more detailed on many levels and very extensive (Arendt et al., 2012). In the new inventory, total glacier volumes and masses were determined by applying ice-dynamical considerations and simple scaling relations. Two main limitations of these monitoring services included (i) lack of details in their glaciological information (WGS, 1989) and, (ii) glaciers were represented by points instead of polygon shapes based on knowledge of glacier outlines (Racoviteanu et al.,
The Global Land Ice Measurements from Space (GLIMS) initiative supplements this pitfall by providing a more comprehensive documentary of global glacier boundaries (GLIMS; http://www.glims.org). The IPCC (2015) stated with evidence the bias of glacier monitoring programs towards glaciers that are smaller in size, easily accessible, and easily interpreted as compared to glaciers with complex terrain and those with thick debris cover.

Studies on velocity change (Heid and Kääb, 2012, Inamdar and Ambinakudige 2016) and accumulation (Bolch et al., 2010) have indicated that, current climate anomaly and glacier trends are out of balance and climate may continue to impact glaciers even without further changes. ‘Glacier changes are generally variable across the globe. In recent times, most glaciers have recorded higher thinning rates, whiles a few ones have experienced the opposite of a positive mass balance, such as those in Norway, and Southern Patagonia (Aniya, 2007). The expansion of existing lakes and the potential of glacial lake outburst floods (GLOFs) are a result of melting high-altitude glaciers (Fujita et al., 2008; Bajracharya et al., 2009; Ambinakudige and Joshi, 2015). While glacier melt can be useful for social and economic gains, it can over the years contribute a significant amount of water and increase global sea-level rise (Granshaw and Fountain, 2006; Stahl and Moore, 2006; Tennant and Menounos, 2013). A few studies (Schiefer et al., 2008 for BC glaciers, Berthier et al., 2010 for Alaskan glaciers) which focused on glacier volume change analyzed their potential contribution to global sea-level rise. Consistent monitoring of glaciers especially those in mountainous regions is key for hazard preparedness, projections of impacts on global warming and sea-level rise. This information is also necessary for decision makers including land managers and stakeholders to make informed decisions regarding consequences of glacier cover change (Schiefer et al., 2007).
Earlier monitoring of glaciers began with the use of maps, photographs, paintings of dated moraines and other *in-situ* techniques (Davies and Glasser, 2012; Leclercq and Oerlemans, 2012) to determine glacier changes from the terminus position. For instance, Kite & Reid (1976) used a combination of existing radio-interferometry and photogrammetry, electrical gravity, drill holes, seismic and radar surveys to measure the volumetric change of the Athabasca Glacier which is the second largest glacier in the Columbia icefield. Their work was built on earlier studies done by Reid and Charbonneau (1972), Paterson (1962) and Kanasewich (1963). Based on evidence of lateral moraines, they (Kite & Reid, 1976) estimated the volume of the glacier in 1870 over a period of 100 years. Their study was limited to only the Athabasca glacier due to the difficulties imposed by *in-situ* data collection on the other glaciers which had a more complex terrain.

**Remote sensing of glaciers**

The advent of airborne and spaceborne remote sensing has become more robust in advancing the creation of glacier inventory. Information from several satellites including Landsat (Ambinakudige, 2010), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER; Kääb et al., 2002), Satellite Pour l'Observation de la Terre, (SPOT; Berthier et al., 2007) and Shuttle Radar Topography Mission (SRTM; Berthier et al., 2006), among others have been widely used to map changes in glacial extent, retreat and mass balance. Precise delineation of glacier extents is paramount for accurate measurements of glacier mass changes. The use of manual heads-up digitizing was the commonest practice for glacier extents. Recently, data from multispectral sensors allows for an automated classification of glacial extents by leveraging the absorption characteristics of snow and ice in the short-wave infrared (SWIR, 1.5 µm – 1.8 µm) band. Snow and ice have a relatively low spectral reflectivity in that portion of the
electromagnetic spectrum as compared to their high reflectivity in the visible portion of the spectrum (Paul et al., 2015). Table 2.1 shows the spectral bands widely used in glacier studies in Landsat Thematic Mapper (TM) bands equivalent. The latest Landsat Operational Land imager/Thermal infrared Sensor is referred to as OLI in subsequent mentions of this project.

Table 1.1 Landsat spectral bands and their application to remote-sensing based glacier studies.

<table>
<thead>
<tr>
<th>Wavelengths (µm)</th>
<th>Common Name</th>
<th>TM Band</th>
<th>OLI Band</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.45 - 0.51</td>
<td>Blue</td>
<td>1</td>
<td>2</td>
<td>Snow/ice discrim. in shadow, mapping glacier lakes</td>
</tr>
<tr>
<td>0.53 - 0.59</td>
<td>Green</td>
<td>2</td>
<td>3</td>
<td>Part of NDSI, snow/ice discrim. in shadow</td>
</tr>
<tr>
<td>0.64 - 0.67</td>
<td>Red</td>
<td>3</td>
<td>4</td>
<td>Part of NDVI, useful in some band ratios</td>
</tr>
<tr>
<td>0.85 - 0.88</td>
<td>NIR</td>
<td>4</td>
<td>5</td>
<td>Part of NDVI, useful in some band ratios</td>
</tr>
<tr>
<td>1.57 - 1.65</td>
<td>SWIR</td>
<td>5</td>
<td>6</td>
<td>Key band for auto classification (ratio, NDSI)</td>
</tr>
<tr>
<td>2.11 - 2.29</td>
<td>SWIR</td>
<td>7</td>
<td>7</td>
<td>Noise in shadow areas limits effectiveness</td>
</tr>
<tr>
<td>10.60 - 12.51</td>
<td>TIR</td>
<td>6</td>
<td>10/11</td>
<td>Some use for mapping thin debris-covered areas</td>
</tr>
<tr>
<td>0.50 - 0.68</td>
<td>Panchromatic</td>
<td>-</td>
<td>8</td>
<td>Manual delineation, sharpening of multispec. bands</td>
</tr>
</tbody>
</table>

Adapted from Pellika and Rees (2009)

Creating an accurate glacier extent largely depends on obtaining suitable images collected at the end of the ablation season (August, September). This is to avoid obscuring of glacier extents by late-lying snow. Freely available satellite data commonly obtained from the United States Geological Survey (USGS) on their EarthExplorer website and Earth Resources Observation Satellite (EROS) websites among others, allow for a preview of images which enables good knowledge of scenes to be selected. After downloading images, the files are converted to the format usable in any required image processing software. Most important step of any image processing techniques is the application of atmospheric and topographic correction.
To enhance visualization for manual editing and subsequent processing, it is advised to create false-color composite of the multiple bands using TM equivalent bands 432, 321 and 543 as red, green, blue (RGB) bands respectively. Each of these band combinations may be appropriate for proper identification of glaciers with peculiar instances. For instance, the 543 band combination does a proper separation between snow and clouds while the 321 band combination does a good job in identifying ice and snow under cast shadows. The 432 band combination is known for its ability to identify different water surfaces. Several band ratios for glacier classification can be employed which largely is based on conditions of the study area and determines the accuracy of the results. Due to local variations of terrain, an ideal threshold to be applied to single band ratios may be selected based on site inspection of the image scene. Band ratio techniques rely mainly on the low reflectivity of ice and snow in the SWIR wavelengths for separation from surrounding bare rock, vegetation or rock (Racoviteanu et al., 2008). Paul et al. (2002) evaluated the use of image segmentation of TM3/TM5 and TM4/TM5 band ratios for mapping glaciers in the Weissmies Group Switzerland as part of a GLIMS-led project. TM4/TM5 performed a greater mapping in the test area especially for regions with cast shadow. TM3/TM5 band ratio worked well in the case of extracting glaciers in the BC and Alberta region (Bolch et al., 2010). The normalized difference snow index (NDSI; Equation 1.1) has proven to be more successful in rough topography where ice and other land coves can cause confusion (Biddle, 2015).

\[
\text{NDSI} = \frac{(TM2 - TM5)}{(TM2 + TM5)} \tag{1.1}
\]

For improved glacier extent mapping, several studies have adapted supervised and unsupervised classification (Aniya et al., 1996; Paul, 2002). However, these techniques hardly
can detect debris-covered ice which may be ice-cored marginal moraine, supraglacial moraine or buried ice. Poor contrast in aerial photography and satellite images pose some large uncertainties in glacier extent measurements due to snow cover in the accumulation zones. (Schiefer et al., 2007). Post processing may be necessary include (i) extraction of topographic parameters from DEMs, (ii) manual correction of glacier boundaries and (iii) using digital intersection of drainage divides (Paul et al., 2015) for correction. In manual correction of misclassified ice, all gross errors are removed with the classified image in vector format. More detailed correction is required for misclassified polygons in debris-covered, shadowed area and thick clouds portions of an image. To correctly map debris-cover which are major sources of error (Racoviteanu et al., 2008), the classified image is laid beneath a false color composite image of the scene. The use of high-resolution image from Bing and google maps, best-guess interpretation of a shaded relief from DEMs (Paul et al., 2015) are helpful and useful for correction of misinterpreted glacier outlines.

**Multitemporal analysis of glacier extents in Western Canada.**

Monitoring of glaciers in the Canadian Cordillera began in the 1980s when a federal mapping commenced as part of Canada’s contribution to the International Hydrological Decade. The mapping was however limited to select glaciers which were easily accessible with smoother features. Earlier glaciologists employed the use of photogrammetric methods for glacier change assessments due to the size and remoteness of glaciers in the Canadian Cordillera (Ventura et al., 1987; W. Haeberli, 1990). Aerial photographs were used alongside, moraine positions, and dates maps to estimate glacier lengths which were related to glacier -areas and mass volumes. (Luckman et al., 1987; 2007, Raup et al., 2007). These techniques were however laborious and time consuming. Errors could stem from misinterpretations of high reliefs regions and low-lying
reliefs (Ommanney, 1986). Howarth and Ommanney (1986) performed a supervised classification on Landsat MSS imagery to map the steady ice cap and Kaskawulsh glacier. The challenges associated with their study involved the very low spatial resolution of imagery and the limited use of the multispectral image processing methods. Sidjak and Wheate (1999) improved the technique using integration of Landsat image classification with high resolution DEMs to map the Illecillewaet Icefield. In their subsequent studies, they employed geocoding and orthorectification techniques to improve the accuracy of the integrated database. However, two challenges that surfaced were (i) topographic shadows and ice in cast shadow were difficult to distinguish and (ii) misclassification of ice under thick clouds. They suggested a more thorough accuracy assessment and classification techniques to improve glacier extent mapping which may include proper consideration of accumulation-area ratio (AAR), ELA and hypsography as well as the average, maximum and minimum of both accumulation and ablation area. This is also necessary for documentation of the attributes of these glaciers into an inventory (Paul et al., 2015). The above techniques including both automatic and manual delineations of ice have been used and built upon to make reliable recurrent projections for the future of these glaciers (Huss et al., 2010).

Gratton and others (1994) used the Landsat TM imagery to characterize glaciers of the Canadian Cordillera which spans across the two western provinces of BC and Alberta. They employed the NDSI, semi-automated multispectral mapping and thresholding of ratio images. The limitation to the semi-automated drainage basin delineation is that, it is close to failing in steep terrain (Bolch et al., 2010) especially when working on mountain glaciers. Landsat TM scenes were compared with extents derived with high altitude aerial photos from mid-1980s.
While applying three results to a 25m DEM, they divided the glaciers into their appropriate drainage basins and to also identify debris-covered ice.

**Area loss and retreat**

At a regional scale, smaller glaciers in Western Canada are said to be shrinking faster than larger ones while debris-covered glaciers have a lesser thinning rate than non-debris covered ones. This causes variations in the thinning rates of glaciers even within the same mountainous rage. Beedle and others (2014), reviewed the use of DEMs and other space borne imagery to estimate the rate of glacier thinning and retreat occurring in the Canadian Cordillera between 1965 and 2005. According to the study, glaciers in the BC, Alberta and Yukon territory lost 11.1 ± 3.8% of their area representing an annual shrinkage of 0.55% comparable to the rates recorded by Bolch and others (2010) 1985 – 2005. Bolch and others (2010) recorded a total ice loss of 3,336 km\(^2\) (11%) of the total glacier area, with an average rate of 0.55% /yr between 1985 and 2005. They also noticed trends of larger glaciers experiencing the most absolute percentage loss than smaller sized glaciers. The smaller glaciers however experienced a higher percentage of relative lost and mostly by the continental glaciers in the region.

Tennant and others (2012) studied the impact of local topography and climate on area change of glaciers in the Canadian Rocky Mountains between 1919 to 2006. Satellite data were supplemented with Interprovincial Boundary Commission Survey (IBCS) maps and Terrain Resource Information Management (TRIM) data. The authors report glacier area decrease by 590 ± 70 km\(^2\) during the study period. Out of 523 documented glaciers, a total of 17 had disappeared and about 124 glaciers developed crevasses and had become unstable. They found that glaciers less than 1 km\(^2\) lost the greatest cover of their area which is also confirmed in other studies (Kääb et al., 2002; Paul et. al., 2004; Demuth et. al., 2008). Glacier area change is
influenced by its size, local topography and climate with larger glaciers having the most absolute
lose and the smaller glaciers having the most relative area lose.

**Mass balance estimation**

Mass balance is the link pointing to climate changes and topographical setting of a glacier
which influences its retreat or advance. Individual glaciers respond to climate change differently
(Bolch et. al 2010) which asserts that current glacier changes may not only be a direct reflection
of current climatic conditions but may have some influences from past climatic conditions. The
relationship between climate anomalies and glacier recession may be measured using several
correlations between multiple climate variables (including temperature and precipitation) and
glacier change (Tennant and Menounos, 2013). Factors that may affect glacier change may also
be associated with the morphometric and topographical characteristics of the glaciers. Glacier
changes are often depicting significant correlations with glacier terrain aspect, and other
topographic influences (Bishop et al., 2001, Schiefer et al., 2007). This often result in glaciers
with the same elevation and spatial range experiencing variations in rates of change over the
same period. Tennant and Menounos (2013) estimated glacier mass balance in the Columbia
Icefield using statistical data (mean, maximum, minimum, median) of glacier slope and surface
changes by comparing absolute and relative glacier changes. Their results indicated a moderate
correlation between glacier area and both minimum values of elevation and slope among large
glaciers. They therefore concluded that local topography extensively influences smaller glaciers
better and at lower elevations and slopes. An observed increase in temperature from 0.4 °C to 0.5
°C from 2001 to 2006 resulted in a rapid rate of area change for the region. During the same
period, the region received a lesser amount of annual snow precipitation. This may be an
obvious indication of the influence of climate anomalies on glacier change.
A glacier in good shape is determined by its mass balance which is the change in a glaciers’ mass overtime. When annual snow accumulation surpasses the amount of ice lost during the summer without any major calving or basal ablation, the glacier gains extra mass which results in a positive mass balance. In instances where the amount of ice or snow lost exceeds its gains, a negative mass balance is said to occurred. Glacier mass balance measurements is either extracted directly (\textit{in-situ} measurements) or indirectly (remote sensing). The use of DEMs from space-borne instruments is important for larger spatial coverages and possibility to measure glacier volume and mass balance. SRTM has a wider coverage and a high resolution which makes them ideal terrain product to measure glacier volume change (Vanlooy et al., 2006). Their use for measuring glacier volume change is widely accepted even though they are prone to systematic errors due to radar penetration of snow cover glaciers (Berthier et al., 2006). The altitudinal biases in the measure of volume loss can be corrected using a thorough comparison of satellite data with other topographic data (Berthier et al., 2006) before further calculations of mass balance. Altimetry and planimetric biases are also encountered in SPOT 5-HRS DEMs which are automatically derived from stereo imagery.

ASTER satellite promises new discoveries for world glacier monitoring and have been widely used by glaciologists (Raup et al., 2007; Bolch et al., 2008; Paul et al., 2004) for glacier elevation change. Kääb and others (2002) used repeated ASTER orthoimages and DEMs to analyze glacier hazard assessment through glacier velocity measurements. Total volume of glacier loss was calculated as the difference between DEMs from BC provincial maps and STRM terrain model between 1985 - 1999. They noticed the introduction of errors in high-mountain conditions using ASTER which need to be accounted for in final mass balance budget. The results showed an annual thinning rate of 0.78 ± 0.19 m/yr and volume loss of 22.48 ± 5.53
km$^3$(w.e). Earlier estimations of the Yukon territory documented between 1958 and 2008 were a reduction of 22% of total glaciated area at a -0.4 m/yr (w.e) mass balance rate with greatest thinning occurring at lower elevations. Unlike complex glacier changes in parts of Alaska due to surging and tidewater, the Yukon changes are not homogenous. The paper summarizes the potential for repeat altimetry to estimate glacier change and mass balance in the Western Canada Region. It was noted that the area received limited summer precipitation, and supply of runoff water due to glacier thinning and retreat.

**Glacier Lake Expansion and Hazards**

Common glacier hazards may include GLOF, creation of crevasses and landslides. The most common of them is GLOF which occurs when the moraine dammed lakes are broken and let out catastrophic discharge of large volume of water or runoff from glaciers. Reasons which have led to GLOF include the avalanche or calving of glaciers, weakened walls of moraine dams and earthquake. A common and recurrent cause may be attributed to the constant melting of high mountain glaciers due to higher temperatures (Huggl et al., 2002). For instance, on August 12, 1997, a huge displacement wave outstripped and incised the moraine dam of the Queen Bless Lake sitting in the Southern Coast Mountains which caused a rapid draining of approximately 6,000,000 m$^3$ tons of water (Wheate et al., 2014). This event was directly linked with climate warming which caused the diadem glacier to lose ice, weaken and became unstable: triggering the incision of the moraine dam (Kershaw et al., 2005). The underlying cause was the calving of a large icefall from the Diadem Glacier. Similar events occurred when the Salmon glacier had its surface melt runoff flowing into the adjacent towns of Hyder and Alaska where it made its ways to the Portland Canal. Record showed that the salmon glacier which contain few icebergs had been stable until late 1961 when it had weakened from prolonged thinning. The latter years of
1965 and 1967 saw two more major damages from the Salmon River valley which destroyed the road systems. Western Canada has on record one of the largest landslides in history which occurred on Capricorn creek in 2010 (Wheate et al., 2014). It has the record of the third and fifth largest landslide in the Capricorn creek and meager creek respectively which is evident of global warming.

**Why study glaciers in the Canadian cordillera**

The Canadian cordillera comprises of the Coast Mountains to the west and the Rocky Mountains on the east and spans into Alberta and the Northern territories from BC-Alberta border and Yukon. Most large glaciers in North America are hosted in these rugged mountains and include St. Elias, a major contributor to global sea-level rise (Arendt et al., 2002; Berthier et al., 2010). Interactions between local as well as regional topography and frontal systems cause variations in winter precipitations which influences glacier mass balance in the region. By the mid-1980s, the glaciers approximately covered an area of 28,800 km² (Schiefer et al., 2007) and represented 23% of the total contiguous North American glacier cover. Studies on these mountain glaciers are necessary to understand their response to climate change and to predict the long-term impacts on water availability, global sea-level rise and hazard risk assessments that may be associated with them. Glacier run off in the region is heavily relied upon for hydroelectric power generation in parts of BC. Due to the important role these mountain glaciers play in supplementing streams required for human and aquatic consumptions; it is imperative to monitor them periodically. The glaciers in the Canadian Cordillera like glaciers worldwide have been experiencing a rapid level of shrinkage since the middle the end of the little ice age (Stahl and Moore, 2006). The need to monitor these glaciers led to a federal mapping which has progressed over the years. The Peyto Glacier located in the Banff National Park has the longest
standing mass balance documented (Ostrem, 2006). Current status of most glaciers in the region still need period measurements and documentation.

**Study Area**

The Columbia Icefield is the largest icefield in the Canadian Rockies lying partly in the northwestern tip of Banff National Park and partly in the southern end of Jasper National Park. Meltwater from glaciers in the icefield flow into various watersheds and subsequently into the Atlantic, Arctic and Pacific oceans. Meltwater from the Athabasca glacier flows into Athabasca river and then into Lake Athabasca and thence by the slave rivers and subsequently through the Mackenzie river and then finally into the Arctic ocean (Kite & Reid, 1976). Meltwater from the Saskatchewan glacier flows into Saskatchewan river and passes across the Alberta, Manitoba and Saskatchewan provinces into the Hudson Bay and finally into the Atlantic Ocean. Runoff from the Columbia glacier flows via the Columbia and Fraser rivers into the Pacific Ocean. The icefield comprises twenty-five glaciers and maybe either of individual ice bodies or outlet based on glacial drainage.

The six major glacier outlets include; Stutfield to the north, Dome to the northeast, Athabasca and Saskatchewan to the east, Castleguard to the south and Columbia to the West. The Athabasca, Dome and Saskatchewan are located nearest to the Highway 93. The main glacier body has a steep nature which drops off through the lower glacier tongues into deep canyons. The region is also characterized by lakes and thick, low-level forests in the fringing valley areas.

With a mean sea-level of 2300 m a.s.l, its elevation ranges between 1000 to 3700 m a.s.l with a mean elevation of the peak ice cap close to 3000 m. The highest peaks of the icefield are Mt. Athabasca (3,491 m) and Mt. Columbia (3,745 m). The lower elevation regions experience
the development of alpine tundra in regions above ~2500 m a.s.l creating what is termed as Engelmann-Spruce-Subalpine fir ecosystem (Tennant and Menounos, 2009). The region has an average annual temperature of -40° C and an annual snow precipitation of 1277mm. Climate of the region is characterized by cyclonic storms which occur because of maritime polar air masses from the west (between September and June) and continental polar air masses from the east (winter), (Tennant & Menounos, 2009).

Figure 1.1 Study Area. A 5,4,3 false composite bands of Landsat TM 5 scene obtained on September 10, 1999 showing the Columbia Icefield.
Research objectives

The objectives of this research are:

1. To estimate the spatio-temporal retreat of six major glacier outlets and delineate area
cover of 25 glaciers in the Columbia Icefield using Landsat data (TM and OLI).
2. To evaluate the efficacies of machine learning classifiers including Random Forest (RF),
   Support Vector Machine (SVM) and Maximum Likelihood Classification (MLC) for
   automated glacier classification.
3. To estimate the mass balance of the major glaciers in the Columbia Icefield between
   2001 and 2018.

The following chapters are organized as follows. Chapter II will cover measurement of
glacial retreat and changes in glacial extent of the icefield between 1985 and 2018 using satellite
images from Landsat (Thematic Mapper 5 and OLI). Chapter III details the leveraging of thermal
information, morphometric features with multispectral bands of ASTER using three RF, SVM
and MLC algorithms for glacier classification of the entire icefield. Results will be used to
determine mass balance estimations of the major glaciers. Chapter IV will cover an in-depth
discussion of the proceeding from this study.
CHAPTER II
GLACIAL RETREAT AND CHANGE IN GLACIAL EXTENTS IN THE COLUMBIA ICEFIELD

Abstract

To expand our knowledge on the status of the Columbia icefield, a continuous glacier monitoring will enhance our understanding of the impacts of global warming on the glaciers and changes in their topographical features. In this study, band ratios are applied to Landsat (TM 5 and OLI) imagery to delineate the glacier extents for 1985, 1999 and 2018 in the Columbia icefield. The study also analyzed the retreat of the Athabasca, Castleguard, Columbia, Dome, Saskatchewan and Stutfield glaciers. The total area covered by the icefield in 1985 was 227 km$^2$. By 2018, the Icefield had lost approximately 42 km$^2$ of its area coverage representing 18% percent of its previous coverage at a rate of -$1.28$ km$^2$ a$^{-1}$ between the period of 1985 and 2018. The Columbia glacier lost the most absolute area coverage (-5.62 km$^2$) while G13 had the least absolute and relative area loss during the study period. G8 glacier completely disappeared by 2018. The terminus of the Columbia glacier which falls out into a lake retreated the most by 3.37 km at a rate of 0.10 km a$^{-1}$ between 1985 and 2018.

Introduction

Glaciers in the icefield like other mountain glaciers have been shrinking more rapidly over the last few years (Bolch et al., 2010). The Athabasca, Columbia and Saskatchewan glaciers were the first to receive most attention and documentation on their retreat by surveyors and
mountaineers. Most of these earlier studies focused on glacier length while a few included glacier thickness and width. Monitoring of the Athabasca and Saskatchewan were continued from the 1940s - 1980s by the Water Survey department of Canada who expanded the glacier studies to include mapping of glacier terminus changes, elevation and volume changes and mass balance (Luckman, 1986; Tennant and Menounos, 2013) and continued by individual studies (Schiefer et al., 2007; Demuth et al., 2008; Bolch et al., 2010) in the 21st century. However, not enough exclusive studies exist of the Columbia Icefield in terms of mass balance and volume measurements.

The use of optical remote sensing to map glacier extent in glacial environments is a very robust and common application. The procedure may involve manual delineation via heads-up digitization or automated classification of glacier extents using multispectral data. The Columbia icefield as reported by Tennant and Menounos (2013) recorded a mean retreat of 1150 ± 34 m at a rate of -12.8 ± 0.4 m representing -0.28 ± 0.01 a⁻¹ between 1919 and 2009. Estimated average thinning was 49 ± 25 m w.e. at a rate of -0.6 ± 25 m w.e. a⁻¹. Although, these studies have analyzed earlier retreat rates, very recent estimations are lacking. The objective of this chapter was to analyze changes in area extents and retreat at the terminus of glaciers in the Columbia Icefield between the period 1985 and 2018.

Data and methodology

Data

Image data

For the objective of estimating glacier boundary and area changes, I used Landsat TM scenes acquired on September 5, 1985; September 8, 1999 and Landsat OLI scene acquired on September 10, 2018. Both TM and OLI bands have a nominal spatial resolution of 30 meters.
The visible and near-infrared (VNIR) regions make up five spectral bands with two SWIR bands. OLI has a cirrus cloud detection bands, two thermals bands (TIRS) and a 15-meter panchromatic band (USGS 2015). Tables 2.1 and 2.2 show the spectral bands of Landsat TM and OLI.

Table 2.1 Landsat OLI bands

<table>
<thead>
<tr>
<th>Bands</th>
<th>Wavelength (micrometers)</th>
<th>Resolution (meters)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 1 - Coastal aerosol</td>
<td>0.43-0.45</td>
<td>30</td>
</tr>
<tr>
<td>Band 2 - Blue</td>
<td>0.45-0.51</td>
<td>30</td>
</tr>
<tr>
<td>Band 3 - Green</td>
<td>0.53-0.59</td>
<td>30</td>
</tr>
<tr>
<td>Band 4 - Red</td>
<td>0.64-0.67</td>
<td>30</td>
</tr>
<tr>
<td>Band 5 - Near Infrared (NIR)</td>
<td>0.85-0.88</td>
<td>30</td>
</tr>
<tr>
<td>Band 6 - SWIR 1</td>
<td>1.57-1.65</td>
<td>30</td>
</tr>
<tr>
<td>Band 7 - SWIR 2</td>
<td>2.11-2.29</td>
<td>30</td>
</tr>
<tr>
<td>Band 8 - Panchromatic</td>
<td>0.50-0.68</td>
<td>15</td>
</tr>
<tr>
<td>Band 9 - Cirrus</td>
<td>1.36-1.38</td>
<td>30</td>
</tr>
<tr>
<td>Band 10 - Thermal Infrared (TIRS) 1</td>
<td>10.6-11.19</td>
<td>100</td>
</tr>
<tr>
<td>Band 11 - Thermal Infrared (TIRS) 2</td>
<td>11.50-12.51</td>
<td>100</td>
</tr>
</tbody>
</table>

The World Reference System (WRS2) path 44 and row 24 Landsat scenes from were downloaded from the USGS EROS center using the Earth Explorer web interface. They came orthorectified and projected in the Universal Transverse Mercator (UTM) coordinate zone 11 north and in a Geotiff format. The scenes covered the full extent of the icefield with minimal cloud coverage (<20) on dates near the ablation season to avoid late-lying snow which could obscure glacier extents (Racoviteanu et al. 2009).
Table 2.2  Landsat TM 4-5 spectral bands

<table>
<thead>
<tr>
<th>Landsat 4-5</th>
<th>Wavelength (micrometers)</th>
<th>Resolution (meters)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 1</td>
<td>0.45-0.52</td>
<td>30</td>
</tr>
<tr>
<td>Band 2</td>
<td>0.52-0.60</td>
<td>30</td>
</tr>
<tr>
<td>Band 3</td>
<td>0.63-0.69</td>
<td>30</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.76-0.90</td>
<td>30</td>
</tr>
<tr>
<td>Band 5</td>
<td>1.55-1.75</td>
<td>30</td>
</tr>
<tr>
<td>Band 6</td>
<td>10.40-12.50</td>
<td>120 (30)</td>
</tr>
<tr>
<td>Band 7</td>
<td>2.08-2.35</td>
<td>30</td>
</tr>
</tbody>
</table>

Reference data

The primary reference data was glacier boundaries selected from the Northern Cordillera region collection from the GLIMS inventory. GLIMS is an international initiative whose goal is to join world-wide collaborators to primarily use satellite imagery and a wide range of techniques for glacier studies and monitoring to create comprehensive database of current extents of world glaciers. The primary data for the collection is from ASTER and Landsat TM Plus (ETM+) imagery and historical data derived from aerial photographs and maps. The GLIMS Map Server website allows for viewing and application of queries to multiple layers, resulting in specific GIS-compatible formats for download. The second source of reference for the manual digitization was high resolution images from Google map and Bing Maps™.
Manual Delineation

All bands were resampled to 30 meters. For the main processing, a threshold was applied to NDSI ratio of each year and glacier boundaries were manually digitized. In areas where there were cast shadows, a TM3/TM5 band ratio was used to help identify ice in those areas (Paul et al., 2015) at pixel level. After the first classification, detailed digitization was done on areas that appeared to be debris-covered with guidance from google maps and Bing images to help identify previously mapped extents. and ice in cast shadow. The glacier outlines were overlaid on the false-color composite of TM band equivalent of 543 and 321 as RGB (red, green, blue) which were created for proper identification of glacier and clouds for further corrections. All work was done in ArcGIS v10.6. Glacier retreat at the tongues of Athabasca, Stutfield, Columbia, Castleguard, Saskatchewan and Dome were calculated as the difference between the terminus of a previous study year and the terminus of the following study year.

Error Estimation

For error in glacier area, a buffer of the size of one pixel (30 m) was created around each individual glacier (Granshaw and Fountain, 2006). The area was calculated and subtracted from the area of the digitized boundaries using the ‘raster calculator’. The sum of each year’s error was noted and the total error in glacier change measurements was computed as:

\[ E\Delta = \sqrt{E^2i + E^2j + \cdots + E^2n} \] (2.1)

Where \( E\Delta \) is the total error calculated, \( E_i^2 \) is the error of one year and so on. Absolute length error was based on the combined mean horizontal RMSE and half of the resolution of the data (15m) of a scene. Error in retreat between two years was calculated using equation 2.1.
Results

Glacier retreat

The estimated error in length change measurements using Equation 2.1 is ± 0.05 km. Results from this study on glacier area and length changes indicated a significant recession of the glaciers in the Columbia Icefield from 1985 to 2018. Each glacier experienced some amount of retreat and loss in area coverage area. The Columbia glacier experienced the most absolute retreat (3.37 km) but terminates into a lake at its terminus. The least retreated glacier was the Athabasca (0.56 km) over the period. Mean retreat recorded for the Athabasca, Columbia, Stutfield, Dome, Castleguard and Saskatchewan glaciers was 1.43 km at a rate of 0.04 km a$^{-1}$ as shown in figure 2.1. Results indicate a recession in glacier tongues in the Icefield over the period of 1985 and 2018.

Figure 2.1  Glacier length retreat overlaid on a 5,4,3 false composite band of the 1999 Landsat. *Glacier names: a = Saskatchewan, b = Athabasca, c = Castleguard, d = Columbia, e = Stutfield, f = Dome. Glacier extents: Green = 1985, Blue = 1999, Red = 2018.
All glaciers but Dome and Stutfield recorded lower retreat between 1985 – 1999 than between 1999 – 2018. The total mean for all six glaciers between the first half of the study period increased about 400% in the second half of the study period.

Table 2.3    Glacier retreat of Athabasca, Castleguard, Dome, Saskatchewan, Columbia and Stutfield glaciers between 1985 and 2018.

<table>
<thead>
<tr>
<th>Glacier</th>
<th>Glacier_ID</th>
<th>1985 - 1999 L (km)</th>
<th>1999 - 2018 L (km)</th>
<th>1985 - 2018 L (km)</th>
<th>Rate L (km a⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dome</td>
<td>G4</td>
<td>0.64</td>
<td>0.09</td>
<td>0.73</td>
<td>0.02</td>
</tr>
<tr>
<td>Stutfield</td>
<td>G2</td>
<td>1.49</td>
<td>0.43</td>
<td>1.92</td>
<td>0.06</td>
</tr>
<tr>
<td>Athabasca</td>
<td>G5</td>
<td>0.21</td>
<td>0.35</td>
<td>0.56</td>
<td>0.02</td>
</tr>
<tr>
<td>Columbia</td>
<td>G18</td>
<td>1.59</td>
<td>1.78</td>
<td>3.37</td>
<td>0.1</td>
</tr>
<tr>
<td>Castleguard</td>
<td>G14</td>
<td>0.11</td>
<td>0.82</td>
<td>0.93</td>
<td>0.03</td>
</tr>
<tr>
<td>Saskatchewan</td>
<td>G10</td>
<td>0.48</td>
<td>0.60</td>
<td>1.08</td>
<td>0.03</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td>0.17</td>
<td>0.68</td>
<td>1.43</td>
<td>0.04</td>
</tr>
</tbody>
</table>

**Area change**

The total area changes from 1985 to 2018 (Table 2.4 and Table 2.5) was -42.56 km² for the entire icefield. The Columbia glacier lost the largest absolute area of -5.62 km² at a rate of -1.02 % a⁻¹ while G13 lost the smallest relative area (-4.58) at a rate of -0.27% a⁻¹. The least absolute and relative area loss changes was recorded by G13 and G8 glaciers respectively.
Table 2.4 Characteristics and spatial extents of glaciers in the Columbia Icefield.

<table>
<thead>
<tr>
<th>Glacier ID</th>
<th>Glacier Name</th>
<th>Watershed</th>
<th>Flowsed</th>
<th>Glacier Type</th>
<th>Length m</th>
<th>EL m a.s.l</th>
<th>ELhi m a.s.l</th>
<th>ELlo m a.s.l</th>
<th>Slope °</th>
<th>Aspect</th>
<th>Area (1985) km²</th>
<th>Area (1999) km²</th>
<th>Area (2018) km²</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>Athabasca</td>
<td>DA</td>
<td>2140.2</td>
<td></td>
<td>2322</td>
<td>1829</td>
<td>2997</td>
<td>24</td>
<td>E</td>
<td>1.19</td>
<td>0.75</td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>G2</td>
<td>Saskatchewan</td>
<td>DA</td>
<td>2875.1</td>
<td></td>
<td>2308</td>
<td>1707</td>
<td>3115</td>
<td>24</td>
<td>N</td>
<td>2.53</td>
<td>1.94</td>
<td>1.60</td>
<td></td>
</tr>
<tr>
<td>G3</td>
<td>Deese</td>
<td>DA</td>
<td>5198.4</td>
<td></td>
<td>2557</td>
<td>1985</td>
<td>3409</td>
<td>20</td>
<td>NE</td>
<td>9.15</td>
<td>7.88</td>
<td>5.73</td>
<td></td>
</tr>
<tr>
<td>G4</td>
<td>Athabasca</td>
<td>DA</td>
<td>8378.4</td>
<td></td>
<td>2661</td>
<td>1941</td>
<td>3600</td>
<td>18</td>
<td>NE</td>
<td>19.02</td>
<td>17.44</td>
<td>16.67</td>
<td></td>
</tr>
<tr>
<td>G5</td>
<td>Little Athabasca</td>
<td>CI</td>
<td>2272.9</td>
<td></td>
<td>2744</td>
<td>2258</td>
<td>3301</td>
<td>25</td>
<td>N</td>
<td>2.70</td>
<td>2.30</td>
<td>2.19</td>
<td></td>
</tr>
<tr>
<td>G6</td>
<td>Athabasca</td>
<td>DA</td>
<td>2396.7</td>
<td></td>
<td>2707</td>
<td>2292</td>
<td>3300</td>
<td>24</td>
<td>NE</td>
<td>1.23</td>
<td>1.09</td>
<td>0.80</td>
<td></td>
</tr>
<tr>
<td>G7</td>
<td>Saskatchewan</td>
<td>DA</td>
<td>2142.9</td>
<td></td>
<td>2426</td>
<td>2338</td>
<td>2526</td>
<td>18</td>
<td>E</td>
<td>0.92</td>
<td>0.21</td>
<td>0.09</td>
<td></td>
</tr>
<tr>
<td>G8</td>
<td>Saskatchewan</td>
<td>DA</td>
<td>3245.7</td>
<td></td>
<td>2369</td>
<td>2082</td>
<td>2786</td>
<td>25</td>
<td>NE</td>
<td>2.59</td>
<td>0.90</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>G9</td>
<td>Saskatchewan</td>
<td>DA</td>
<td>12494.9</td>
<td></td>
<td>2513</td>
<td>1776</td>
<td>3534</td>
<td>16</td>
<td>E</td>
<td>42.70</td>
<td>39.36</td>
<td>37.31</td>
<td></td>
</tr>
<tr>
<td>G10</td>
<td>Saskatchewan</td>
<td>DA</td>
<td>2570.5</td>
<td></td>
<td>2627</td>
<td>2325</td>
<td>3020</td>
<td>16</td>
<td>E</td>
<td>2.28</td>
<td>2.14</td>
<td>2.01</td>
<td></td>
</tr>
<tr>
<td>G11</td>
<td>Castle guard I</td>
<td>Saskatchewan</td>
<td>991.5</td>
<td></td>
<td>2624</td>
<td>2482</td>
<td>2809</td>
<td>19</td>
<td>SE</td>
<td>1.46</td>
<td>1.01</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>G12</td>
<td>Castle guard II</td>
<td>Saskatchewan</td>
<td>1322.9</td>
<td></td>
<td>2609</td>
<td>2483</td>
<td>2782</td>
<td>12</td>
<td>SE</td>
<td>1.52</td>
<td>1.79</td>
<td>1.45</td>
<td></td>
</tr>
<tr>
<td>G13</td>
<td>Castle guard III</td>
<td>Saskatchewan</td>
<td>10188.8</td>
<td></td>
<td>2429</td>
<td>1973</td>
<td>3031</td>
<td>12</td>
<td>SE</td>
<td>17.34</td>
<td>17.01</td>
<td>15.33</td>
<td></td>
</tr>
<tr>
<td>G14</td>
<td>Castle guard IV</td>
<td>Saskatchewan</td>
<td>10552.5</td>
<td></td>
<td>2460</td>
<td>1630</td>
<td>3208</td>
<td>18</td>
<td>SW</td>
<td>21.61</td>
<td>20.77</td>
<td>19.59</td>
<td></td>
</tr>
<tr>
<td>G15</td>
<td>Columbia</td>
<td>DA</td>
<td>3114.0</td>
<td></td>
<td>2440</td>
<td>1810</td>
<td>3122</td>
<td>16</td>
<td>SE</td>
<td>11.52</td>
<td>11.07</td>
<td>10.55</td>
<td></td>
</tr>
<tr>
<td>G16</td>
<td>Columbia</td>
<td>OA</td>
<td>3009.6</td>
<td></td>
<td>2684</td>
<td>1787</td>
<td>3416</td>
<td>22</td>
<td>SW</td>
<td>6.79</td>
<td>6.36</td>
<td>6.41</td>
<td></td>
</tr>
<tr>
<td>G17</td>
<td>Columbia</td>
<td>OA</td>
<td>8951.0</td>
<td></td>
<td>2738</td>
<td>1511</td>
<td>3587</td>
<td>22</td>
<td>W</td>
<td>32.37</td>
<td>30.79</td>
<td>28.75</td>
<td></td>
</tr>
<tr>
<td>G18</td>
<td>Manitoba</td>
<td>DA</td>
<td>2875.1</td>
<td></td>
<td>2508</td>
<td>1707</td>
<td>3115</td>
<td>24</td>
<td>N</td>
<td>5.83</td>
<td>4.04</td>
<td>3.12</td>
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</tr>
<tr>
<td>G19</td>
<td>Athabasca</td>
<td>DA</td>
<td>1330.2</td>
<td></td>
<td>2228</td>
<td>2139</td>
<td>2803</td>
<td>20</td>
<td>NE</td>
<td>0.43</td>
<td>0.59</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>G20</td>
<td>Athabasca</td>
<td>DA</td>
<td>2800.3</td>
<td></td>
<td>2301</td>
<td>2018</td>
<td>3009</td>
<td>13</td>
<td>N</td>
<td>3.35</td>
<td>3.15</td>
<td>1.99</td>
<td></td>
</tr>
<tr>
<td>G21</td>
<td>Athabasca</td>
<td>DA</td>
<td>2789.7</td>
<td></td>
<td>2904</td>
<td>2232</td>
<td>3604</td>
<td>27</td>
<td>SE</td>
<td>6.22</td>
<td>6.46</td>
<td>5.41</td>
<td></td>
</tr>
<tr>
<td>G22</td>
<td>Athabasca</td>
<td>DA</td>
<td>3202.2</td>
<td></td>
<td>2666</td>
<td>2141</td>
<td>3374</td>
<td>24</td>
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<td>3.21</td>
<td>2.18</td>
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</tr>
<tr>
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<td>Athabasca</td>
<td>DA</td>
<td>4883.1</td>
<td></td>
<td>2738</td>
<td>1776</td>
<td>3685</td>
<td>23</td>
<td>NW</td>
<td>7.46</td>
<td>6.04</td>
<td>5.41</td>
<td></td>
</tr>
<tr>
<td>G24</td>
<td>Athabasca</td>
<td>OA</td>
<td>3249.9</td>
<td></td>
<td>2985</td>
<td>2551</td>
<td>3416</td>
<td>31</td>
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<td>1.87</td>
<td>1.74</td>
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</tr>
<tr>
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<td>Athabasca</td>
<td>OA</td>
<td>4427.0</td>
<td></td>
<td>2593.6</td>
<td>2021.8</td>
<td>3217.96</td>
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<td>8.30</td>
<td>7.39</td>
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<td>Mean</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>227.38</td>
<td>207.58</td>
<td>184.81</td>
</tr>
</tbody>
</table>

*D is a detached glacier, O is an outlet glacier, I is glaciers with at least one icefall, and A means the glaciers is avalanche-fed. (Glacier ID, flowshed, watershed, type, elevation, slope and aspect adapted from GLIMS inventory).

The estimated error in area change measurements using Equation 2.1 is ± 28.9 m which is less than one-pixel size of the data, so it is negligible. The overall mean glacier area change was -1.70 km² at a rate of -1.87% a⁻¹ for the entire study period. The mean area changes for the entire icefield increased from -0.79 km² between 1985 and 1999 to -1.70 km² by 1999 to 2018.
Table 2.5  Glacier area change between 1985 and 2018.

<table>
<thead>
<tr>
<th>Glacier Id</th>
<th>Glaciers</th>
<th>Flowshed</th>
<th>1999-1985</th>
<th>1999_2018</th>
<th>Total Change</th>
<th>Thinning rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td></td>
<td></td>
<td>-0.44</td>
<td>-0.15</td>
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<td>-0.02</td>
</tr>
<tr>
<td>G2</td>
<td>Stutfield</td>
<td></td>
<td>-2.51</td>
<td>-2.61</td>
<td>-5.12</td>
<td>-0.16</td>
</tr>
<tr>
<td>G3</td>
<td></td>
<td></td>
<td>-0.62</td>
<td>-0.25</td>
<td>-0.87</td>
<td>-0.03</td>
</tr>
<tr>
<td>G4</td>
<td>Dome</td>
<td></td>
<td>-1.27</td>
<td>-1.14</td>
<td>-2.41</td>
<td>-0.07</td>
</tr>
<tr>
<td>G5</td>
<td>Athabasca</td>
<td></td>
<td>-1.59</td>
<td>-0.76</td>
<td>-2.35</td>
<td>-0.07</td>
</tr>
<tr>
<td>G6</td>
<td>Little Athabasca</td>
<td></td>
<td>-0.40</td>
<td>-0.11</td>
<td>-0.51</td>
<td>-0.02</td>
</tr>
<tr>
<td>G7</td>
<td></td>
<td></td>
<td>-0.14</td>
<td>-0.29</td>
<td>-0.43</td>
<td>-0.01</td>
</tr>
<tr>
<td>G8</td>
<td></td>
<td></td>
<td>-0.71</td>
<td>-0.21</td>
<td>-0.92</td>
<td>-0.03</td>
</tr>
<tr>
<td>G9</td>
<td>Hilda</td>
<td></td>
<td>-1.48</td>
<td>-0.50</td>
<td>-1.99</td>
<td>-0.06</td>
</tr>
<tr>
<td>G10</td>
<td>Saskatchewan</td>
<td></td>
<td>-3.34</td>
<td>-2.04</td>
<td>-5.39</td>
<td>-0.16</td>
</tr>
<tr>
<td>G11</td>
<td>Castleguard I</td>
<td></td>
<td>-0.13</td>
<td>-0.13</td>
<td>-0.26</td>
<td>-0.01</td>
</tr>
<tr>
<td>G12</td>
<td>Castleguard II</td>
<td></td>
<td>-0.44</td>
<td>-0.67</td>
<td>-1.12</td>
<td>-0.03</td>
</tr>
<tr>
<td>G13</td>
<td>Castleguard III</td>
<td></td>
<td>0.26</td>
<td>-0.33</td>
<td>-0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>G14</td>
<td>Castleguard IV</td>
<td></td>
<td>-0.33</td>
<td>-1.67</td>
<td>-2.00</td>
<td>-0.06</td>
</tr>
<tr>
<td>G15</td>
<td></td>
<td></td>
<td>-0.84</td>
<td>-1.26</td>
<td>-2.11</td>
<td>-0.06</td>
</tr>
<tr>
<td>G16</td>
<td></td>
<td></td>
<td>-0.45</td>
<td>-0.52</td>
<td>-0.97</td>
<td>-0.03</td>
</tr>
<tr>
<td>G17</td>
<td></td>
<td></td>
<td>-0.42</td>
<td>0.04</td>
<td>-0.38</td>
<td>-0.01</td>
</tr>
<tr>
<td>G18</td>
<td>Columbia</td>
<td></td>
<td>-1.58</td>
<td>-4.03</td>
<td>-5.62</td>
<td>-0.17</td>
</tr>
<tr>
<td>G19</td>
<td>Manitoba</td>
<td></td>
<td>-1.79</td>
<td>-0.93</td>
<td>-2.71</td>
<td>-0.08</td>
</tr>
<tr>
<td>G20</td>
<td></td>
<td></td>
<td>0.15</td>
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<td>-0.25</td>
<td>-0.01</td>
</tr>
<tr>
<td>G21</td>
<td></td>
<td></td>
<td>-0.20</td>
<td>-1.16</td>
<td>-1.36</td>
<td>-0.04</td>
</tr>
<tr>
<td>G22</td>
<td></td>
<td></td>
<td>0.24</td>
<td>-1.05</td>
<td>-0.81</td>
<td>-0.02</td>
</tr>
<tr>
<td>G23</td>
<td></td>
<td></td>
<td>-1.03</td>
<td>-1.62</td>
<td>-2.65</td>
<td>-0.08</td>
</tr>
<tr>
<td>G24</td>
<td></td>
<td></td>
<td>-1.42</td>
<td>-0.63</td>
<td>-2.05</td>
<td>-0.06</td>
</tr>
<tr>
<td>G25</td>
<td></td>
<td></td>
<td>0.68</td>
<td>-0.33</td>
<td>0.35</td>
<td>0.01</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td>-0.79</td>
<td>-0.91</td>
<td>-1.70</td>
<td>-0.05</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>-19.80</td>
<td>-22.76</td>
<td>-42.56</td>
<td>-1.29</td>
</tr>
</tbody>
</table>

For further analysis, the glaciers were divided into classes by their sizes based on the 1985 image; < 1 km$^2$, 1-5 km$^2$, 5-10 km$^2$, 10-15 km$^2$, 15-20 km$^2$ and >20 km$^2$. Glaciers between 1.0 – 5.0 km$^2$ had the largest composite of glaciers per class (Table 2.6). It was observed that larger glaciers (>20 km$^2$) tend to have the greatest absolute area loss (-18.23 km$^2$; -15.3%) at a rate of -0.5% while the smaller glacier classes (<1 ) experience the opposing trend of the greatest
relative area loss (-86.18% ; 1.17 km$^2$) at a rate of -2.6% for the entire study period. Mean glacier change was seen in all class sizes from 1985 – 1999 and 1999 - 2018 as shown in table 2.6.

Table 2.6  Changes in class sizes of the glaciers between 1985 and 2018

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>km$^2$</td>
<td>km$^2$ (%)</td>
<td>km$^2$ (%)</td>
<td>km$^2$ (%)</td>
<td>km$^2$ (%)</td>
</tr>
<tr>
<td>&lt; 1</td>
<td>2</td>
<td>0.68</td>
<td>-0.55 (-40.86)</td>
<td>-0.61 (-76.63)</td>
<td>-1.17 (-86.18)</td>
<td>-0.04 (-2.61)</td>
</tr>
<tr>
<td>1.0 - 5.0</td>
<td>11</td>
<td>2.17</td>
<td>-3.94 (-16.50)</td>
<td>-5.55 (-27.85)</td>
<td>-9.49 (-39.76)</td>
<td>-0.29 (-1.20)</td>
</tr>
<tr>
<td>5.1-10</td>
<td>5</td>
<td>7.09</td>
<td>-4.66 (-13.16)</td>
<td>-3.70 (-12.04)</td>
<td>-8.37 (-23.61)</td>
<td>-0.25 (-0.72)</td>
</tr>
<tr>
<td>10.0 - 15.0</td>
<td>1</td>
<td>11.52</td>
<td>-0.45 (-3.89)</td>
<td>-0.52 (-4.70)</td>
<td>-0.97 (-8.41)</td>
<td>-0.03 (-0.25)</td>
</tr>
<tr>
<td>15.0 - 20.0</td>
<td>2</td>
<td>18.18</td>
<td>-1.92 (-5.27)</td>
<td>-2.43 (-7.06)</td>
<td>-4.35 (-11.95)</td>
<td>-0.13 (-0.36)</td>
</tr>
<tr>
<td>&gt; 20</td>
<td>4</td>
<td>29.71</td>
<td>-8.28 (-6.97)</td>
<td>-9.95 (-9.00)</td>
<td>-18.23 (-15.34)</td>
<td>-0.55 (-0.46)</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td>11.56</td>
<td>-3.30 (-8.71)</td>
<td>-3.79 (-10.97)</td>
<td>-10.97 (-30.87)</td>
<td>-0.05 (-1.82)</td>
</tr>
<tr>
<td>Total</td>
<td>25</td>
<td></td>
<td>-19.80 (-22.76)</td>
<td>-22.76 (-42.56)</td>
<td>-42.56 (-18.72)</td>
<td>-1.29 (-1.10)</td>
</tr>
</tbody>
</table>

Discussions

The terminus of the six major glaciers in the Columbia icefield retreated with a mean distance of 1.43 km at a rate of 0.04 km a$^{-1}$ and decreased in area by 1.3 km$^2$ on average between 1985 and 2018. The total area loss for the entire icefield was 42.56 km$^2$ at a rate of -1.29 km$^2$ per annum during the study period. All glaciers retreated and decreased in area cover over the study period. The pattern observed in this study is one of general ice lose in the Columbia icefield which mirrors patterns observed in other mountain glaciers in Western Canada (Tennant et. al., 2012; Paul et. al., 2015). Analysis of change in glacier cover and ice lose show a greater percentage consistently for larger glaciers as compared to smaller ones. This is because the larger glaciers have the greatest ice cover to lose. The smaller glaciers which also are usually the detached glaciers, however, recorded lower relative area loss than the larger glacier bodies which are avalanche-fed. The number of glaciers increased within the Columbia Icefield from 1985.
through to 2018 mainly because a few the larger glaciers disintegrated into smaller portions as they become weak and unstable.

As seen in some previous studies (Bolch et. al 2010; Tennant and Menounos, 2013), when glacier changes were compared by their class values, smaller-sized glaciers experienced higher relative area loss rates as compared to larger-sized glaciers which had the largest absolute retreat. From the mean glacier changes calculated for each class between 1985 and 2018, it was observed that the mean rate of area lose for each class-size increased over the subsequent time period (1985-1999; 1999-2018). Other studies (Tennant and Menounos, 2013) have shown variability in glacier parameters between the mid-1990s and 2000 but the general pattern is one of ice loss and it is dependent on climate changes.

Previous literature existing in the 21st century for the entire Columbia Icefield exclusively are very limited. The rate of glacier area changes for this study (0.57% a\(^{-1}\)) is comparable to that of Bolch et. al (2010) in their study of Western Canada which recorded rate of area loss 0.6 ± 0.19% a\(^{-1}\) for the southern Canadian Rockies which includes the Columbia Icefield between 1985 and 2005. A perfect comparison is not expected due to differences in the time span of study periods and the extent of spatial coverage between studies. For this study, the highest absolute glacier retreat was recorded for the Columbia glacier (1.94 ± 0.05 km) which agrees to the results of Tennant and Menounos (2013) the same glacier recorded the highest retreat with 3.7 ± 0.03 km between 1919 and 2006. This may be attributed to the fact that its terminus into a lake and may cause an expedited melting of the tongue. Saskatchewan glacier had the largest absolute area loss which is also in agreement with the findings of Tennant and Menounos (2013).
CHAPTER III

SUPERVISED CLASSIFICATIONS OF GLACIER AND MASS BALANCE ANALYSIS

Abstract

In recent times, the availability of computer hardware and sophisticated processing techniques have made it possible to develop complex machine learning algorithms which can be applied to satellite and aerial image classification for glacier monitoring. The objectives of this study were to evaluate the application of three most commonly used machine learning algorithms; random forest, support vector machine and maximum likelihood classifications for semi-automated glacier classifications from satellite imagery. Accuracy assessments of initial classification on Landsat TM and OLI imagery indicated high accuracies for all the classifiers. For all classes and overall accuracies, SVM performed the highest. It was applied to ASTER imagery using data fusion for a second classification. The high accuracy obtained was beneficial for measuring specific mass balance of the glaciers. Mass balance measurements were estimated from the resulting classified image for four major outlet glaciers in the Columbia icefield between 2001 and 2018. Results indicated that, the Athabasca glacier experienced the highest thinning (-2.54 m w.e.) at a rate of -0.10 m w.e.a\(^{-1}\) while the Columbia glacier recorded the lowest absolute thinning (0.77 m w.e) at a rate of -0.01 m w.e.a\(^{-1}\).

Introduction

Mass balance provides an understanding into the dynamics of glacier change over a given period (Tennant and Menounos, 2013). Mass balance calculations aid in creating models for
projecting predictions on global sea-level rise and to also make informed decisions on preparedness for freshwater limitations to regions which are supplied freshwater by these glaciers (Singh et al., 2018). The geodetic method which involves differencing of surface elevations from two time periods is a widely used measurement for mass balance. A major advantage of the geodetic method is the large extent of coverage it allows (Berthier et al., 2010; Bolch et al., 2011; Schiefer et al., 2007) for mapping. An alternative technique for mass balance calculation is repeat track method from satellite altimetry. In this technique, data from past missions are used as constraints on mission grounds. (Paul et al., 2015). The method involves the use of ground tracks of closely repeated satellite orbits (Remy and Blarel, 2006; Pritchard et al., 2009) and the use of interpolated elevation difference at crossing points of orbits on the ground (Paul et al., 2015). Mass balance is estimated from the measured elevation differences.

To improve the accuracy of the mass balance estimation, precise measurement of ice and snow extent is required. The use of automated machine learning (ML) algorithms for glacier facies mapping is gaining weight over the past few years as an effort into the research of new techniques for better classification of glaciers using remote sensing (Zang et al., 2019). Classifiers used in ML remote sensing of glaciers are either supervised, unsupervised or tree-based classifiers. Over recent years, ML approaches have proven to be an efficient image classification procedure (Jensen, 2016). In this study, I analyzed the efficacies of the RF, SVM and MLC classifiers in classifying water bodies, bare rock/moraines, vegetation, ice, snow/firn and debris-covered/ice-in-cast shadows. Based on the initial classification accuracy assessments, data fusion was employed by adding new parameters such as slope and curvature from DEMs (Biddle, 2015) to supplement the visible and thermal bands to train the classifiers and test the models for better performance. The use of these algorithms for the classifications in this study
was a way of testing the efficiency of the new technique of data fusion in efficiently mapping debris-covered terminus of glaciers.

Previous studies on the Columbia icefield focused on the glacial extents and recession leaving a gap for mass balance and volume assessments. The objectives of this study was therefore (i) to evaluate the performance of the RF, SVM and MLC classifiers by employing morphometric features from an ASTER DEM and thermal information with multispectral bands in glacier image classification in the Columbia icefield and (ii) to estimate mass balance of the six major outlet glaciers of the icefield between 2001 and 2018.

Data and Methods

Data

Image data

Two ASTER level 2 data images were obtained on July 3, 2001 and July 27, 2018 from the USGS EROS earth explorer website. The estimation of mass balance for this project did not involve years prior to 2000 because the ASTER sensor was launched on December 18, 1999 and have been available for global ice observations. ASTER sensors capture images in three bands in the VNIR with a 15 m resolution and six bands in the SWIR bands in a 30 m resolution. It has five bands in the TIR at a resolution of 90m. The stereo band 3B and nadir band 3N cover the same spectral range (0.76 µm – 0.86 µm) which allows for the creation of DEMs. The NIR band of the satellite has a 15m resolution. For glacial studies, the high spatial resolution of the Visible, NIR and the stereo bands are of high interest (Kaab, 2002). The swath width of an ASTER scene is 60 X 60 km. Only two years were analyzed in this study because data was limited for the study area as most of the scenes had heavy cloud cover. The ASTER level 2 data products are of a higher order which come atmospherically corrected to surface reflectance and at sensor
radiance. The two DEMs were projected to NAD 83 UTM zone 11 and some bands of resolutions other than 15m were resampled to 15m in ArcGIS v10.6 using a bilinear algorithm to avoid sub-pixel horizontal misalignments. The resampling was necessary to create a uniform data of pixel sizes and locations. (Kaab et al., 2002). Using the spatial analyst toolbar in ArcGIS, a slope raster (in degrees) and a curvature raster (in radians/meter) were derived from the DEM.

Table 3.1 ASTER band designations. (Source: ASTER Reference Guide Version1.0)

<table>
<thead>
<tr>
<th>Radiometer</th>
<th>Band</th>
<th>Wavelength (μm)</th>
<th>Spatial resolution</th>
<th>Quantum number</th>
</tr>
</thead>
<tbody>
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<td>0.52 - 0.60</td>
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<td>8 bits</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.63 - 0.69</td>
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<td>3N</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>3B</td>
<td>0.78 - 0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SWIR</td>
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<td>1.600 - 1.700</td>
<td>30 m</td>
<td>8 bits</td>
</tr>
<tr>
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<td></td>
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<td>6</td>
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</tr>
<tr>
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<td>7</td>
<td>2.235 - 2.285</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>8</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>2.360 - 2.430</td>
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</tr>
<tr>
<td>TIR</td>
<td>10</td>
<td>8.125 - 8.475</td>
<td>90 m</td>
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</tr>
<tr>
<td></td>
<td>14</td>
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</tr>
</tbody>
</table>

**Topographic map**

Digital copy of the topographic map of the region was obtained from the open source website of the Natural Resources Canada. The map has a scale of 1:50,000 with a contour interval of 40 meters. It was rectified in ArcGIS v10.1 using a first-order polynomial transformation and by using evenly distributed ground control points (GCPs) along the highway 93, mountain ridges and stable bedrocks which were free of snow or vegetation from the Landsat imagery on the 2001 ASTER imagery.
Image preprocessing

Previously obtained Landsat scenes used in Chapter II were used here for the initial classification. Comparing images two different times required that they be brought to a common scale before any analysis performed on them. This is usually necessary as differences and degradation of sensors could prevent an accurate comparison of spectral differences (Ambinakudige et al., 2003). All bands of the Landsat scenes were first converted in the raster calculator in ArcGIS from Digital numbers (DNs) to radiance (at-sensor radiance) manually using the equation:

\[ L_i = \left( (L_{\text{MAX}} - L_{\text{MIN}}) \right) \left( Q_{\text{CALMAX}} - Q_{\text{CALMIN}} \right) \left( Q_{\text{CAL}} - Q_{\text{CALMIN}} \right) + L_{\text{MIN}} \]  

(3.1)

Rescaling factors used in the equation were derived from each band located in the MTL file that accompanied the images. Atmospheric correction was performed to obtain surface reflectance values since comparisons were being made across multiple images (Carswell et al., 2017). The equation used was: (Radiance to TOA reflectance)

\[ \rho_\lambda = \pi L_\lambda d^2 / ESUN_\lambda \cos \theta_z \]  

(3.2)

After thoughtful consideration of the satellite data size, a conclusion was drawn on the extraction of the Columbia Icefield region from the entire satellite scene by creating a 100 m buffer around the study region and masking out the icefield after a layer stacking of the bands. This was done to concretize the study region and to reduce the processing time of the classifiers.
**Initial image classification**

The next procedure was feature extraction in order to obtain sample data for training classifiers. For this step, different polygons for cloud, bare rock, vegetation, water, debris-cover, snow and firn were manually selected from the 2018 Landsat image. Computations such as NDSI, normalized difference vegetation index (NDVI) and normalized difference water index (NDWI) were employed to aid in the proper selection of snow and ice, vegetation and water samples respectively for training data. The training sample tool in ArcGIS v 10.6 was used to collect training sample by creating several smaller polygons. For the main classification, a comprehensive comparison of RF, SVM and MLC algorithms were performed in R studio to evaluate the most efficient classifier for glaciers by computing their error matrix. To ensure the uniformity in the sample sizes, a sample partition was created in the algorithms.

The RF technique, a non-parametric machine learning algorithm applied to classification is based on creation of multitudes decision trees at training time that decide the class of a pixel (Jensen, 2016). Different samples and subsets are used in creating each tree. The trees output a class prediction for a pixel and the class with most votes becomes the model’s prediction of the pixel. Training data are randomly selected before fitting the trees to allow for tree variations. SVM is a non-parametric classifier based on statistical goal of determining the greatest margin between classes. This margin maximization determines the optimal separating hyperplane between classes (Jensen, 2016). It determined by the closest points that separates two classes and are referred to as support vectors. SVMs have high demonstrated capabilities to interpret hyperspectral data (Gualtieri et al., 1999). The most widely used parametric classifier is MLC due to its robust abilities. (Lu and Weng, 2007). It based on the selection of the largest posterior probability (Aktinsson and Lewis, 2000). The MLC assumes that each class has a normal
distribution of its statistics and calculates the probability that a pixel belongs to a class based on this assertion. Pixels are assigned the classes with the high probability.

For a comprehensive summary of the above described procedures, the R code used for the algorithms have been included in Appendix A. SVM and MLC use the same algorithm other than the RF algorithm.

**Second classification**

Based on the accuracies returned by the three algorithms, SVM recorded higher performances than RF and MLC. The SVM algorithm was then applied to the ASTER images. All three algorithms performed poorly in areas of debris-cover in the initial classification, hence, additional parameters including slope and curvature (Bolch et. al., 2010) which were created from the ASTER DEM and combined with the thermal band, VIR and SWIR bands for the second classification.

**Accuracy assessment**

To evaluate the accuracies of the classifiers, a code for computation of full error matrices (user’s and producer’s accuracy and overall accuracy statistics) was included in the R scripts for each classification step. The error matrix represents expected classification (reference/validation) against predicted classification results (Congalton, 1991).

\[
Producer's\ Accuracy = \frac{\text{# of objects correctly classified as class } y}{\text{Total of objects of class } y \text{ in reference data}} \quad (3.3)
\]

User’s accuracy is the errors of commission (per-class basis) and is calculated as:

\[
User's\ Accuracy = \frac{\text{# of objects correctly classified as class } y}{\text{Total # objects classified as } y} \quad (3.4)
\]
The overall accuracy statistics is the overall classifications across classes and is calculated as:

$$\text{Overall Accuracy} = \frac{\text{# of objects correctly classified in all classes}}{\text{Total number of objects classified}} $$

(3.5)

Kappa statistic is an additional accuracy metric which includes all information with a matrix error. This makes it a comprehensive measure of accuracy across multiple data (Congalton, 1991). \( R \) is the number of rows in the matrix, \( x_{ii} \) is the number of cases in row \( i \) and column \( i \), \( x_i \) and \( x_i+ \) being the marginal totals of row \( i \), and column \( i \). \( N \) is the total of cases (Congalton, 1991). Kappa statistic is computed as:

$$ K = \frac{N \sum_{i=1}^{R} x_{ii} - \sum_{i=1}^{R} (x_{i+} x_{++})}{N^2 - \sum_{i=1}^{R} (x_{i+} x_{++}) + 1} $$

(3.6)

**DEM differencing**

The geodetic method was employed to obtain changes in elevation values, between the 2001 and 2018 DEMs. Both images were converted to points shapefile with a minimum distance of 21.22 m between any two points which is the hypotenuse of one-pixel cell size (15m X 15m). That distance was chosen so that each pixel should contain only one random point. Using the “Extract Multi Values to Points” tool, elevation values were extracted for both DEMs and the 2018 values were subtracted from the 2001 values. Visual inspection of the elevation differences showed outrageous numbers in the areas where clouds were present in either of the images. Those points were excluded. Points with elevation differences greater than 150 and lesser than -150 were also removed to avoid any influence of cloud in the analysis (Dixon and Ambinakudige, 2015). The main challenge was that most of these excluded points were found at
the terminus of Columbia, Castleguard and Saskatchewan glaciers and that could affect the results for the overall mass balance estimation since those were ablation zones.

The expectation was to find zero elevation difference in areas assumed to be stable terrain. However, most points in such regions had non-zero elevation differences which could be an indication of some level of vertical bias also in the glaciated areas and could affect the overall mass balance. The statistical error modelling involving the use of estimates based of stable terrain was employed. This procedure assumes that non-glaciated regions with bare terrain should remain the same over years in the absence of any natural alteration of the region. GCPs were manually selected from the topographic map for this step.

De-trending of the 2018 image was necessary to correct for vertical biases. To do this, values of manually selected 70 random points on stable terrain were extracted from both images and a topographic map. A regression analysis was done with elevation values from non-glaciated areas in the topographic map as the dependent variable and elevation values from the same points in DEM as independent variables. RMSE, $R^2$ and standard coefficients were determined from the plot. Results showed that 2001 DEM was more accurate with respect to the topographic map with standard coefficient of 1. To remove the vertical bias, only the 2018 image was detrended using the raster calculator in ArcMap by multiplying the image by the standard coefficient obtained from the regression results. No detrending was done on 2001 DEM since it showed a coefficient other than 1. Elevation differencing was calculated again using the 2001 image and the detrended 2018 image.

**Uncertainty Estimation**

Random error for individual elevation can be estimated from using the standard deviation (STDV) from GCPs selected on stable terrain with the assumption that no major changes will
happen to the terrain in the case of no natural disaster. The relative uncertainty \( (e; \text{Equation 3.8}) \) in the change in elevation differences is computed using individual standard error (SE; Equation 3.7) and the mean elevation difference (MED) in non-glaciated areas in accordance with the law of error of propagation (Bloch et. al 2011). The equation for SE is indicated below where ‘n’ is the number of pixels. Some studies (Paul et al., 2004) include mean vertical bias in the total error budget obtained from the triangulating residual of the co-registration vectors. The formulas for standard error (SE) and uncertainty (e) are:

\[
SE = \frac{STDV_{\text{non-glaciated}}}{\sqrt{n}}
\]  

(3.7)

Uncertainty (e) is calculated using the SE and MED as shown in the equation below.

\[
e = \sqrt{(SE)^2 + (MED)^2}
\]

(3.8)

**Mass balance estimation.**

For areas with both ice and snow, the mean elevation difference was multiplied by the density of ice (900 kg m\(^{-3}\)) and the density of snow (600 kg m\(^{-3}\)) respectively to determine the total mass balance of each glacier and divided by 17 (the number of years in between 2001 and 2018) resulting in the specific mean mass balance per year (kg m\(^{-2}\) yr\(^{-1}\)). The mass balance is finally divided by the density of water (1000 kg m) and presented as the meter water equivalent per annum (m w. e. a\(^{-1}\)).
Results

Initial classification

The initial classification of the 2018 Landsat OLI image resulted in high performance accuracies returned by the algorithms. A visual look at the classified images suggest an equal performance. All three classifiers were within the general acceptable level (85% by the USGS). A closer look at the error matrix however indicates higher performances by the SVM for all classes (Figure 3.1). All three classifiers performed lower for water and debris-covered ice. Experiments (Jensen, 2016) including the initial classification in this project have shown that SVMs have a higher ability to interpret multispectral and hyperspectral data better. A summary of the error matrix is included in Appendix B.
Figure 3.1  Classified images of a 2018 Landsat OLI scene with RF, SVM and MLC classifiers.

**Second classification**

SVM was applied to the ASTER surface reflectance images with thermal information, slope and curvature for better accuracies in the final classification. Error matrix showed high performances of the algorithm in the two years (2001, 2018) but still with some misclassified
(figure 3.2) pixels. With reference to the GLIMS database, it could be seen that, the debris-covered regions were still not accurately classified. This was expected as most promising algorithms for debris-covered glaciers still fail when debris-thickness exceeds 0.5 m (Bolch et al., 2010). A summary of the error matrix included in Appendix B.

Figure 3.2 SVM classified images of 2001 and 2018 ASTER scene of the Columbia Icefield)

**Uncertainty in mass balance**

Estimation of accuracy of the DEM was done by validating it with a topographic map. Uncertainty was calculated using the STDV, MED and SE as presented in tables 3.2 and 3.3. The
relative STDV, MED and SE and uncertainty were computed using elevations values from the non-glaciated area of the two DEMs. Table 3.2 and 3.3 shows the results below.

Table 3.2 Uncertainty calculation of master DEM with respect to topographic map

<table>
<thead>
<tr>
<th>Error Analysis of 2001 DEM with respect to Topographic Map</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of elevations points(n)</td>
</tr>
<tr>
<td>Mean Elev. Difference (m)</td>
</tr>
<tr>
<td>Avg. STDV</td>
</tr>
<tr>
<td>Standard Error (SE)</td>
</tr>
<tr>
<td>Uncertainty (e)</td>
</tr>
<tr>
<td>Minimum Elevation</td>
</tr>
<tr>
<td>Maximum Elevation</td>
</tr>
</tbody>
</table>

The MED and STDV were used to calculate relative SE and uncertainty between the two DEMs. Results is presented in table 3.3 below.
Table 3.3  Descriptive statistics of non-glaciated area

| Description                        | Value  
|------------------------------------|--------
| Mean                               | -8.41  
| Std. Error of Mean                 | 2.44   
| Std. Deviation                     | 22.48  
| Number of random points            | 85     
| Uncertainty                        | 3.89   
| Minimum Elevation                  | -45    
| Maximum Elevation                  | 85     

Inaccurate classification of the heavily debris-covered tongues of the Stutfield and Dome glaciers led to their removal from the final mass balance estimations. Based on the non-glaciated region parameters, the uncertainty in the mass balance calculation was 0.04 m w.e.a\(^{-1}\) between 2001 and 2018.

**Specific mass balance estimation**

Results of mass balance estimation expressed as specific mass balance for the four glaciers (Athabasca, Castleguard, Columbia and Saskatchewan) over the study period is presented in table 3.4. All glaciers obtained a negative mass balance of the study period except Castleguard. Athabasca glacier recorded the largest absolute mass ice loss -2.54 m w.e at a rate of -0.10 m w.e.a\(^{-1}\) between 2001 and 2018. The least recorded ice loss was from the Columbia glacier with -0.29 m w.e a\(^{-1}\) mass loss at a rate of -0.01 m w.e a\(^{-1}\).
Table 3.4 Individual mean specific mass balance.

<table>
<thead>
<tr>
<th>Glacier Name</th>
<th>Size (sq. km)</th>
<th>Mean Elev. Diff (2001-2018; m)</th>
<th>Specific Mass Balance (m w.e.a(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Athabasca</td>
<td>19.02</td>
<td>-2.82</td>
<td>-0.10</td>
</tr>
<tr>
<td>Castleguard</td>
<td>17.34</td>
<td>0.86</td>
<td>0.03</td>
</tr>
<tr>
<td>Columbia</td>
<td>32.37</td>
<td>-0.29</td>
<td>-0.01</td>
</tr>
<tr>
<td>Saskatchewan</td>
<td>42.70</td>
<td>-1.75</td>
<td>-0.06</td>
</tr>
</tbody>
</table>

**Discussions**

The progress from in-situ measuring of glaciers to the widespread use of remote sensing for glacier mapping is a promising feet. In employing ML algorithms to classify glaciers in the study region, performances for some rare classes (water and debris-cover) were very low partly due to small sampling size as they did not cover a large portion of the study area. However, a lot of the poor classification was in debris-cover areas. This is an indication that the efficiency of the use of surface temperatures in data fusion procedures used in this study can only be helpful to an extent. The thermal information from surface temperatures could be problematic in areas of deep cast shadow as they depict lower surface temperatures for bare rocks in cast shadows and debris-covered ice under direct radiation, tend to be warmer.

The DEM resolution may have been too coarse to clearly be able to reflect individual surface differences. This can be problematic for determining glacier extents and mass balance calculations especially for the Columbia Icefield as it has approximately 70% (Tennant and Menounos) of area covered with debris. The use of ASTER thermal information, morphometric
parameters such as slope and curvature seem to be promising to some extent and they can be used as additional information. But the progress is only great when the debris-cover does not exceed 0.5m (Ranzi et al., 2004). To reduce potential errors from inconsistencies in mass balance estimations, these problematic glaciers were excluded before final mass balance estimations. This was a major challenge in this study that resulted in the removal of the Dome and Stutfield glacier from the mass balance estimation. In future studies, field data may be the single most reliable source of data for mass balance estimations.

Results of mass balance estimation expressed as specific mass balance for the four glaciers (Athabasca, Castleguard, Columbia and Saskatchewan) over the study period is presented in table 3.4. All glaciers obtained a negative mass balance of the study period except Castleguard. Athabasca glacier recorded the largest absolute mass ice loss -2.54 ± 0.75 m w.e at a rate of -0.10 ± 0.04 m w.e.a⁻¹ between 2001 and 2018. The least recorded ice loss was from the Columbia glacier with -0.29 ± 0.75 mass loss at a rate of -0.01 ± 0.04 m w.e a⁻¹. There is a slightly less confidence in the mass balance results since most of the points in the ablation zone of the glacier tongues for Columbia, Saskatchewan and Castleguard glaciers were removed initially. This may have had a significant impact on the mean elevation difference of the glaciers. The Columbia lake showed a considerable increase in length from 1985 to 2018 which may be an indication of how much ice melted from the Columbia glacier. The Castleguard glacier showed a positive mass balance which could mean that not all glaciers experienced a linear trend of ice loss between 2001 and 2018. Results of mass balance is graphically presented in Appendix C.
Conclusion

Data integration from different sources are integral in providing accurate mass balance estimation. This study analyzed the use of machine learning algorithms for glacier mapping in the Columbia icefield. The support vector machine as experimented in this study performed higher the random forest and maximum likelihood. This results maybe subjective to the study area and other parameters used to train models. Over a period of seventeen years, the Athabasca, Columbia, Castleguard and Saskatchewan glaciers shrank at a mean rate of -0.14 m w. e.a⁻¹. There is no doubt that glaciers in the Columbia icefield are losing much ice at a faster than previously estimated. Constant monitoring will be necessary to measure their response to increasing climate changes.
CHAPTER IV

CONCLUSIONS AND RECOMMENDATIONS

There is limited literature existing for studies on the entire Columbia Icefield as most of the studies in the region are focused on individual glaciers (Athabasca, Columbia, Saskatchewan and Manitoba). Remote sensing alone of glaciers in this region may not be reliable as it may need to be supplemented with in-situ data for accurate glacier parameter measurements. Current glacier cover studies in the region have been documented in the GLIMS inventory. However, the region is limited in mass balance studies. Reasons are unknown but maybe due to the rugged terrain of the region which could account for lower accuracies in mass balance calculation. There is the need for more studies involving volume and mass balance changes in the icefield. The objectives of this study were to:

1. To determine change in glacier cover and length retreat of glaciers in the Columbia icefield from 1985 to 2018 using Landsat (TM and OLI) imagery.

2. To evaluate the efficiency of three commonly used machine learning classifiers (RF, SVM and MLC) for glacier classification.

3. To estimate the mass balance of the major glacier outlets in the Columbia icefield between 2001 and 2018 using ASTER imagery.

In this project, three Landsat images (1985 & 1999 Landsat TM 5 and 2018 Landsat OLI) were used to measure the area change and retreat of the entire icefield and major glacier outlets respectively. Manual heads-up digitizing was used to create glacier outlines for glaciers in the
Columbia Icefield and glacier retreat and area cover were subsequently computed. The Columbia glacier, the second largest in the icefield lost the largest area of 5.62 km$^2$. The terminus of this glacier calves into the Columbia lake and this was evident as the lake increased voluminously and in area between 1985 to 2018. The research was not validated with *in-situ* data, but accuracy was determined using a topographic map and the GLIMS boundary as references. The icefield covered an area of 227 km$^2$ in 1985 and by 2018, it had lost 42.56 km$^2$ of its area. The smaller glaciers were seen to have lost more of their area than the larger ones. However, the larger glaciers experienced the highest loss of mass ice since they have more ice to melt. One glacier (G8) disappeared completely by 2018. Both thinning rates and area change among individual glaciers were variable as some glaciers advanced between 1985 and 1999. To obtain glacier mass balance, a data fusion approach was applied to ASTER DEMs leveraging on the thermal information for accurate classification of glacier extents. The SVM classifier performed the better with relatively higher accuracies than RF and MLC classifiers. Heavily debris-covered in some parts of the icefield could prevent accurate mass balance estimation in the area.

More detailed mass balance studies could be done in future to include all the glaciers and also extended to involve glacier velocity and most importantly, developing new algorithms to properly delineate debris-covered ice. The contribution of climate forcing to glacier recession in this region is also a potential field of interest in the future. Despite the challenges faced in this work, it is of significance to the documentation of mass balance of individual glaciers in the Columbia Icefield. This will enhance the existing knowledge of the mountain glaciers in the Canadian Rockies.
REFERENCES


APPENDIX A

MACHINE LEARNING CLASSIFICATION ALGORITHMS
### Algorithm 1: Random Forest

```r
## importing libraries
library(rgdal)
library(raster)
library(caret)
library(snow)

## setting working environment and image
setwd("working directory")
img <- brick("image")
names(img) <- paste0("B", c(1:4))

## training data
trainData <- shapefile("sample.shp")
responseCol <- "Classvalue"

dfAll = data.frame(matrix(vector(), nrow = 0, ncol = length(names(img)) + 1))
for (i in 1:length(unique(trainData[[responseCol]]))){
    category <- unique(trainData[[responseCol]])[i]
categorymap <- trainData[trainData[[responseCol]] == category,]
dataSet <- extract(img, categorymap)
if(is(trainData, "SpatialPointsDataFrame")){
    dataSet <- cbind(dataSet, class = as.numeric(rep(category, nrow(dataSet))))
    dfAll <- rbind(dfAll, dataSet[complete.cases(dataSet),])
}
if(is(trainData, "SpatialPolygonsDataFrame")){
```
dataSet <- dataSet[!unlist(lapply(dataSet, is.null))]

dataSet <- lapply(dataSet, function(x){cbind(x, class = as.numeric(rep(category, nrow(x))))})

df <- do.call("rbind", dataSet)

dfAll <- rbind(dfAll, df)

print(i)

} nsamples <- 10000 sdfAll <- dfAll[sample(1:nrow(dfAll), nsamples), ]

## create data partition
inBuild <- createDataPartition(y = dfAll$class, p = 0.7, list = FALSE)

training <- dfAll[inBuild,]

dim(training)

testing <- dfAll[-inBuild,]

## fitting model
modFit_rf <- train(as.factor(class) ~ B1 + B2 + B3 + B4, method = "rf", data = training)

beginCluster()
preds_rf <- clusterR(img, raster::predict, args = list(model = modFit_rf))

endCluster()

writeRaster(preds_rf, "classifiedRF.tif", format="GTiff")
## predict on the test dataset and calculate confusion matrix: predicted <- predict(preds_rf, testing)

confusionMatrix(predicted, as.factor(testing$class))

### Algorithm 2: Support Vector machine/Maximum Likelihood

# import image to be classified and extract band values

library(raster)

setwd("working directory")

img <- brick("image")

### extracting band values

myvar1 <- getValues(raster(img, 1))

myvar2 <- getValues(raster(img, 2))

myvar3 <- getValues(raster(img, 3))

# import shapefile with training polygons

shp <- shapefile(Samples.shp")

shp$class.int <- as.numeric(shp$Classvalue)

# rasterize shapefile

r <- rasterize (shp, img, field = 'class.int')

# extract values of the response variable

mysample <- getValues(r)

# create data.frame with all variables

dataF <- data.frame(mysample, myvar1, myvar2, myvar3)

# Prepare a rasclass object using the dataframe and specifying raster properties

library(rasclass)
object <- new('rasclass')

object <- setRasclassData(dataF, ncol = ncol(), nrow = nrow(), xllcorner = extent(), yllcorner = extent(), cellsize =(), NAvalue =, samplename = '')

# Classify using maximum likelihood algorithm/support vector machine
outlist <- list()

system.time(outlist[['algorithm']] <- classifyRasclass(object, method = '))

summary(outlist[['algorithm']])

# export to esri ascii grid, it may lack CRS
rasclass::writeRasclass(outlist[1]@predictedGrid, path = "predicted.asc")

# read ascii grid file back into R, define CRS if needed and export as .tif
result <- raster("predictedGrid.asc")

crs(result) <- crs(img)

raster::writeRaster(result, "predictedGrid.tif")
APPENDIX B

ERROR MATRICES OF MACHINE LEARNING CLASSIFIER
Error matrices for classifiers

RF classifier

Table B. 1 Error matrix for 2018 OLI Landsat classification by Random Forest

Confusion Matrix and Statistics

<table>
<thead>
<tr>
<th>Reference</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction</td>
<td>74</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>829</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
<td>139</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>585</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>4</td>
<td>1338</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Overall Statistics

- Accuracy : 0.989
- 95% CI : (0.9846, 0.9924)
- No Information Rate : 0.4486
- P-Value [Acc > NIR] : < 2.2e-16
- Kappa : 0.9838

McNemar's Test P-Value : NA

Statistics by Class:

<table>
<thead>
<tr>
<th>Class: 1</th>
<th>Class: 2</th>
<th>Class: 3</th>
<th>Class: 4</th>
<th>Class: 5</th>
<th>Class: 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>1.00000</td>
<td>0.9952</td>
<td>0.97887</td>
<td>0.9915</td>
<td>0.9948</td>
</tr>
<tr>
<td>Specificity</td>
<td>0.99932</td>
<td>0.9921</td>
<td>0.99965</td>
<td>0.9971</td>
<td>0.9970</td>
</tr>
<tr>
<td>Pos Pred Value</td>
<td>0.97368</td>
<td>0.9799</td>
<td>0.99286</td>
<td>0.9882</td>
<td>0.9963</td>
</tr>
<tr>
<td>Neg Pred Value</td>
<td>1.00000</td>
<td>0.9981</td>
<td>0.99895</td>
<td>0.9979</td>
<td>0.9958</td>
</tr>
<tr>
<td>Prevalence</td>
<td>0.02468</td>
<td>0.2779</td>
<td>0.04736</td>
<td>0.1968</td>
<td>0.4486</td>
</tr>
<tr>
<td>Detection Rate</td>
<td>0.02468</td>
<td>0.2765</td>
<td>0.04636</td>
<td>0.1951</td>
<td>0.4463</td>
</tr>
<tr>
<td>Detection Prevalence</td>
<td>0.02535</td>
<td>0.2822</td>
<td>0.04670</td>
<td>0.1975</td>
<td>0.4480</td>
</tr>
<tr>
<td>Balanced Accuracy</td>
<td>0.99966</td>
<td>0.9937</td>
<td>0.98926</td>
<td>0.9943</td>
<td>0.9959</td>
</tr>
</tbody>
</table>
SVM classifier

Table B. 2 Error matrix for 2018 OLI Landsat classification by Support vector machine.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Predicted 1</th>
<th>Predicted 2</th>
<th>Predicted 3</th>
<th>Predicted 4</th>
<th>Predicted 5</th>
<th>Predicted 6</th>
<th>Producer Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample 1</td>
<td>6093</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0</td>
<td>1.000000e+00</td>
</tr>
<tr>
<td>Sample 2</td>
<td>0</td>
<td>7.660200e+04</td>
<td>7.200000e+01</td>
<td>1.400000e+02</td>
<td>0.000000e+00</td>
<td>0</td>
<td>0.9972401</td>
</tr>
<tr>
<td>Sample 3</td>
<td>0</td>
<td>2.430000e+02</td>
<td>1.300000e+04</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0</td>
<td>0.9817718</td>
</tr>
<tr>
<td>Sample 4</td>
<td>0</td>
<td>1.300000e+02</td>
<td>0.000000e+00</td>
<td>5.625600e+04</td>
<td>8.470000e+02</td>
<td>0</td>
<td>0.9829294</td>
</tr>
<tr>
<td>Sample 5</td>
<td>0</td>
<td>4.000000e+00</td>
<td>0.000000e+00</td>
<td>6.200000e+02</td>
<td>1.280521e+05</td>
<td>0</td>
<td>0.9951506</td>
</tr>
<tr>
<td>Sample 6</td>
<td>0</td>
<td>1.464000e+03</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0</td>
<td>0.9999999</td>
</tr>
</tbody>
</table>


MCL classifier

Table B. 3 Error matrix for 2018 OLI Landsat classification by Maximum likelihood.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Predicted 1</th>
<th>Predicted 2</th>
<th>Predicted 3</th>
<th>Predicted 4</th>
<th>Predicted 5</th>
<th>Predicted 6</th>
<th>Producer Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample 1</td>
<td>6082</td>
<td>5.000000e+00</td>
<td>0.000000e+00</td>
<td>6.000000e+00</td>
<td>0.000000e+00</td>
<td>8.000000e+00</td>
<td>0.9981946</td>
</tr>
<tr>
<td>Sample 2</td>
<td>0</td>
<td>6.408300e+04</td>
<td>2.030000e+02</td>
<td>2.080000e+02</td>
<td>0.000000e+00</td>
<td>5.920000e+00</td>
<td>0.9945617</td>
</tr>
<tr>
<td>Sample 3</td>
<td>0</td>
<td>6.408300e+04</td>
<td>2.030000e+02</td>
<td>2.080000e+02</td>
<td>0.000000e+00</td>
<td>5.920000e+00</td>
<td>0.9945617</td>
</tr>
<tr>
<td>Sample 4</td>
<td>0</td>
<td>1.900000e+02</td>
<td>0.000000e+00</td>
<td>5.627000e+04</td>
<td>7.680000e+02</td>
<td>5.000000e+00</td>
<td>0.9831740</td>
</tr>
<tr>
<td>Sample 5</td>
<td>0</td>
<td>8.000000e+00</td>
<td>0.000000e+00</td>
<td>1.385000e+03</td>
<td>1.272030e+05</td>
<td>0.000000e+00</td>
<td>0.9971448</td>
</tr>
<tr>
<td>Sample 6</td>
<td>0</td>
<td>8.200000e+01</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>1.382000e+00</td>
<td>0.9439891</td>
</tr>
</tbody>
</table>

User Acc: 1.9946462e-01 9.849015e-01 9.723686e-01 9.940024e-01 0.1663657 NA
## 2001 Error matrix

Table B. 4 Error matrix for 2001 ASTER image classification using SVM

<table>
<thead>
<tr>
<th>Sample</th>
<th>Predicted 1</th>
<th>Predicted 2</th>
<th>Predicted 3</th>
<th>Predicted 4</th>
<th>Predicted 5</th>
<th>Predicted 6</th>
<th>Producer Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample 1</td>
<td>4138.000000</td>
<td>1.800000e+01</td>
<td>0.00000000</td>
<td>2.000000e+00</td>
<td>0.000000e+00</td>
<td>0.00000000</td>
<td>0.99519000</td>
</tr>
<tr>
<td>Sample 2</td>
<td>0.00000000</td>
<td>6.444200e+04</td>
<td>198.00000000</td>
<td>1.720000e+02</td>
<td>0.000000e+00</td>
<td>54.00000000</td>
<td>0.99346340</td>
</tr>
<tr>
<td>Sample 3</td>
<td>0.00000000</td>
<td>5.900000e+00</td>
<td>3715.00000000</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0.00000000</td>
<td>0.98436670</td>
</tr>
<tr>
<td>Sample 4</td>
<td>6.000000e+00</td>
<td>1.690000e+02</td>
<td>0.00000000</td>
<td>2.521700e+04</td>
<td>1.640000e+02</td>
<td>40.00000000</td>
<td>0.98519300</td>
</tr>
<tr>
<td>Sample 5</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>1.260000e+02</td>
<td>2.001000e+04</td>
<td>0.00000000</td>
<td>0.99374320</td>
</tr>
<tr>
<td>Sample 6</td>
<td>0.00000000</td>
<td>2.358000e+03</td>
<td>0.00000000</td>
<td>1.510000e+02</td>
<td>0.000000e+00</td>
<td>614.00000000</td>
<td>0.19669580</td>
</tr>
</tbody>
</table>

User Acc: 0.9985521 9.61161e-01 0.9493994 9.824295e-01 9.918715e-01 0.8672316 NA

## 2018 Error matrix

Table B. 5. Error matrix for 2018 ASTER image classification using SVM

<table>
<thead>
<tr>
<th>Sample</th>
<th>Predicted 1</th>
<th>Predicted 2</th>
<th>Predicted 3</th>
<th>Predicted 4</th>
<th>Predicted 5</th>
<th>Predicted 6</th>
<th>Predicted 7</th>
<th>Producer Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample 1</td>
<td>6347.000000</td>
<td>2.700000e+01</td>
<td>0.000000e+00</td>
<td>6.400000e+01</td>
<td>0.000000e+00</td>
<td>3.00000000</td>
<td>0.000000e+00</td>
<td></td>
</tr>
<tr>
<td>Sample 2</td>
<td>5.00000000</td>
<td>7.978800e+04</td>
<td>1.590000e+02</td>
<td>3.720000e+02</td>
<td>0.000000e+00</td>
<td>74.00000000</td>
<td>1.780000e+02</td>
<td></td>
</tr>
<tr>
<td>Sample 3</td>
<td>0.00000000</td>
<td>2.100000e+02</td>
<td>1.184200e+04</td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
<td>0.00000000</td>
<td>0.000000e+00</td>
<td></td>
</tr>
<tr>
<td>Sample 4</td>
<td>6.000000e+00</td>
<td>1.185000e+03</td>
<td>0.000000e+00</td>
<td>6.010000e+04</td>
<td>2.235000e+03</td>
<td>65.00000000</td>
<td>1.291000e+03</td>
<td></td>
</tr>
<tr>
<td>Sample 5</td>
<td>0.00000000</td>
<td>1.000000e+00</td>
<td>0.000000e+00</td>
<td>1.859000e+03</td>
<td>6.307500e+04</td>
<td>0.00000000</td>
<td>2.370000e+02</td>
<td></td>
</tr>
<tr>
<td>Sample 6</td>
<td>0.00000000</td>
<td>9.340000e+02</td>
<td>0.000000e+00</td>
<td>1.094000e+03</td>
<td>0.000000e+00</td>
<td>785.00000000</td>
<td>6.000000e+01</td>
<td></td>
</tr>
<tr>
<td>Sample 7</td>
<td>0.00000000</td>
<td>5.500000e+02</td>
<td>0.000000e+00</td>
<td>2.280000e+03</td>
<td>4.120000e+02</td>
<td>1.00000000</td>
<td>2.100000e+04</td>
<td></td>
</tr>
</tbody>
</table>


Producer Acc

Sample 1 0.9854060
Sample 2 0.9902284
Sample 3 0.9819252
Sample 4 0.9263106
Sample 5 0.9678236
Sample 6 0.2876441
Sample 7 0.8656280
User Acc NA