### ASSESSMENT OF LIDAR SNOW DEPTH MEASUREMENTS AND THE SPATIO-TEMPORAL VARIABILITY OF THE SNOWPACK IN A FORESTED WATERSHED ON VANCOUVER ISLAND

by

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# Abstract

This study uses repeat airborne LiDAR surveys to assess snow distribution within complex forested terrain in Russell Creek, a 33 km<sup>2</sup> sub-basin of the Tsitika watershed, on northern Vancouver Island. LiDAR surveys used within this study were acquired in 2022 and 2023, with 4 - 5 flights per year timed with the intent to capture maximum snow depth, to the completion of the melt season. In addition, two separate bare earth models were used to assess error by acquisition date (2017 vs 2023). Over 2000 manual snow depth measurements were taken over the course of this study via a) cardinal plots within six different forest cover types and b) weather station snow courses conducted on gravel roads.

Mean difference (MD) of the averaged manual and LiDAR measurements were overall lowest for the weather station snow courses (-29 to 13 cm) and highest in the harvested (juvenile and regenerating) plots (-39 to 134 cm). Analysis of the LiDAR bare earth point returns showed that juvenile and regenerating plots both had a low percentage of pixels with ground returns – average of 24 and 35% respectively - a result of the tall (~ 2 meter) and complex ground vegetation. Error was reduced in the juvenile forest plots (-22 to 29 cm) when LiDAR snow depth was processed with an alternative bare earth model acquired in 2017, in which the average coverage of ground returns was much greater (96%). Total snow storage within Russell Creek was relatively similar (<5% difference) between the two bare earth models, and the higher elevations (>1000 m) of the snow. At high elevations (1400 – 1700 m) in the watershed, the snow volumes were much greater (28 – 44%) when processed with the 2023 bare earth model compared to the 2017.

An additional component to this study was a paired control-treatment approach to assess the impacts of forest harvest on a) the bare earth model and b) snow distribution. Evaluation of pre- (2020) and post-

harvest (2023) snow free models showed a slight (0.15 m) bias within treatment sites due to changes to the ground surface. After bias correction, the rate of increase in snow water equivalence between the pre-and post-harvest snow years in the treatment sites (1.4 - 4.2) doubled the control (0.7 - 1.7). Overall, these results highlighted the importance of the bare earth model to accurately measure snow, especially within complex forested and harvested watersheds.

# Table of Contents

Abstract
Table of Contents iv
List of Tables
List of Figures
Acknowledgement
Chapter 1 : Introduction
Chapter 2 : Background
2.1 Snow and Remote Sensing
2.1.1 LiDAR systems
2.1.2 Data processing
2.1.3 LiDAR validation
2.1.4 LiDAR Error and Uncertainty
2.2 Snow distribution in forests
2.3 Forest Disturbance and Hydrological Recovery14
2.4 Research Gaps and Objectives
Chapter 3 : Study Area and Data
3.1 Study Area
3.2 Weather Station Network
3.3 Land Cover Classification
3.4 LiDAR surveys
3.4.1 Snow Free acquisition
3.5 In-Situ Observations
3.5.1 Snow Sampling
3.5.2 Sampling error and mitigation
3.5.3 Vegetation surveys
Chapter 4 : Data Processing and Analyses
4.1 LiDAR processing
4.2 In-Situ Observations and Supplementary Data
4.2.1 Weather Stations
4.2.2 Game Cameras

4.3 Plot Analyses	
4.3.1 Test of Normality	
4.3.2 Snow Depth Variability	
4.3.3 Mean Snow Depth	
4.3.4 Timing error and mitigation	
4.4 Watershed Scale Analysis	
Chapter 5 : Results	
5.1 Snowpack and Weather	
5.2 Vegetation Surveys	
5.3 LiDAR Point Densities	
5.4 In-situ vs LiDAR Snow Depths	
5.4.1 Snow depths Validation	
5.4.2 Variability of Observed Snow Depths	
5.5 Bare Earth DEM	
5.6 Watershed Snow Storage	
5.6.1 Snow Volumes by Elevation	
5.6.2 Snow Volumes by Forest Cover	
Chapter 6 : Forest Harvest Experiment	
6.1 Introduction	
6.2 Methods	
6.2.1 Snow free surface assessment	
6.2.2 Snow distribution and volume change	
6.3 Results	
6.3.1 Weather Station Overview	
6.3.2 Ground surface change	
6.3.3 Snow Distribution and water storage	
6.4 Discussion and Recommendations	
Chapter 7 : Discussion and Recommendations	
7.1 LiDAR Accuracy within complex ground cover	
7.2 Impact of the Bare Earth Model	
7.3 Snow Distribution: Plot and Watershed Scale	
7.3.1 Plot scale distribution	
7.3.2 Watershed snow storage	

7.4 Study Limitations and Recommendations	
Chapter 8: Summary	
Data Availability Statement	
References	
Appendices	
Appendix A: ACO 2023 Bare Earth Model	
lasAppendix B: LiDAR Processing	
Appendix C: GNSS report	
Appendix D: Snow depth variability results tables	
Appendix E: Old Growth Forest: Canopy Snow Depth Variability	
Appendix F: Average snow depth results tables	
Appendix G: Bias corrections for meteorological variability	
Appendix H: Watershed Snow Volume	
Appendix I: Harvest Experiment Slash Pile Analysis	

# List of Tables

Table 3.1 Breakdown of the land cover categories within the Russell Creek watershed, which were used
to: a) determine plot locations and b) for watershed scale analyses
Table 3.2 LiDAR products and metadata for the Tsitika survey area from 2020 to 2023 used within this
research project
Table 3.3 Meta data for cardinal plots used within the in-situ sampling campaign. Precise plot locations
and GNSS accuracies for the 2022 and 2023 sampling campaigns can be found in Appendix C
Table 3.4 Game camera sites and metrics for the 2022 and 2023 LiDAR campaigns. Precise position of
the game camera stakes can be found in Appendix C
Table 5.1 Average daily air temperature across all weather stations. Highlighted values represent that the
temperature was higher between the two years, and a dash indicates there was no data for that month. 50
Table 5.2 Summary of 2022 and 2023 snow depth measurements at four weather stations, selected for
consistent snow depth data across 2022 and 2023. Metrics include: 1) peak snow depth and date, 2)
length of melt period in days (defined as sustained loss of 0.5 cm per day) and rate of snow melt, and 3)
snow free date
Table 5.3 Vegetation composition by cover type, summarized by the average height ( $\mu$ ) and the standard
deviation ( $\sigma$ ) of the shrubs and ferns, woody debris, and heather
Table 5.4 Median ground point density per meter squared for the snow surveys, as well as the average
proportion of valid pixels per each of the cover types
Table 5.5 Summary table of LiDAR and manual dates for 2022 and 2023 and how the snow depth
changed within that time frame. Snow depth change includes the SR50 data of all seven weather
stations in Russell Creek, provided the sensor was collecting data in that time frame

Table 5.6 Standard Deviation (SD) of the in-situ snow depth observations at each weather station snow course. Snow courses which were snow free are shaded blue. To assess whether the in-situ snow depth variability changed as snow melted, the Levene's test was conducted, where for each weather station and year, each groups (LiDAR survey) variance were compared to each other. Snow free and no data Table 5.7 Standard Deviation of the LiDAR collected snow depth at each weather station snow course. Snow courses which were snow free are shaded blue. To assess whether the LiDAR snow depth variability changed as snow melted, the Levene's test was conducted, where for each weather station and year, each groups (LiDAR survey) variance were compared to each other. Snow free and no data Table 5.8 Standard deviation for in-situ snow depth measurements for the cardinal plot sampled across 2022 and 2023. Cells highlighted blue indicate snow-free. To assess whether the in-situ snow depth variability changed as snow melted, the Levene's test was conducted, where for each plot and year, groups (LiDAR survey) variance were compared to each other. Snow free and no data surveys were not Table 5.9 Standard deviation for LiDAR cardinal plot snow depth measurements across both years. Cells highlighted blue indicate snow-free. To assess whether the LiDAR snow depth variability changed as snow melted, the Levene's test was conducted, where for each plot and year, groups (LiDAR surveys) variance were compared to each other. Snow free and no data surveys were not included as groups.....74 Table 5.10 Snow storage by elevation band, with percent of overall snow stored in the Russell Creek watershed shown in brackets, between the two different bare earth models (2017 vs 2023), for the 9th of March 2022 and 10th March 2023 acquisitions. Highlighted values indicated which model predicted the 

Table 5.11 Snow storage by cover type, with the percent of overall snow stored in the Russell Creek
watershed shown in brackets, between the two different bare earth models (2017 vs 2023), for the 9th of
March 2022 and 10 <sup>th</sup> March 2023 acquisitions. Highlighted shows which model predicted more snow
per cover type
Table 6.1 Topographic and canopy metrics for the control, treatment and road area which was used
within this study. Metrics for slope, canopy cover, and height represent the average value
Table 6.2 LiDAR surveys for 2022 and 2023 paired for comparing snow distribution change pre-harvest
(2022) and post-harvest (2023). Weather station snow depth data from Lower Cain (1260 m) included
for each survey
Table 6.3 Results from pre and post-harvest ground surface changes, in which the control, treatment, and
road plot types average and standard deviation elevation were calculated, and error metrics mean bias
error (MBE), mean absolute error (MAE) and root mean square error (RMSE) were calculated between
the 2022 (pre-harvest) and 2023 (post-harvest) bare earth models
Table 6.4 Snow water equivalence (mm) for both the pre-harvest (2022) and post-harvest years (2023),
+/- standard error, for the three snow on LiDAR surveys. Rate of change represents the increase or
decrease in SWE from 2022 to 2023, for the control and treatment blocks
Table 7.1 Error results from airborne LiDAR snow depth studie which evaluated LiDAR accuracy using
in-situ measurements and in forested terrain

# List of Figures

Figure 3.1 Overview map of the study site: Russell Creek (32 km <sup>2</sup> ) sub-basin of the Tsitika watershed
(397 km <sup>2</sup> ), located Northern Vancouver Island, British Columbia
Figure 3.2 Overview of Russell Creek watershed showing A) the landcover type, B) the landcover
broken down by elevation, C) the orthoimagery of the watershed, and D) aspect
Figure 3.3 Images of the forest cover types where plots were sampled within this research project:
Juvenile (A), Regenerating (B), Dense Old Growth (C), Old Growth (D) and Alpine (E)
Figure 3.4 LiDAR survey area within the Tsitika watershed, showing the ACO 2023 bare earth
boundary and snow surveys(red), the 2017 BCTS bare earth coverage of the AOI (orange), and the ACO
2020 acquisition which was targeted to fill the missing area over Mount Cain (blue). Note that the linear
boundary to the SE was used to cover the highway and provide generally snow free stable terrain 25
Figure 3.5 Location of the game camera sites (blue), weather stations (purple), and cardinal plots (red)
within the Russell Creek watershed
Figure 3.6 Cardinal plot snow sampling strategy of density (open circles) and snow depth (dash)
measurements. Distances (red) are in meters
Figure 3.7 GNSS set-up showing the base station (A) established on a permanent ground control point,
and the rover (B) set up at the plot centre of Juvenile site ST2CC2
Figure 3.8 Game camera snow stake set up – this imagery is of game camera site ST2GC1 as seen in
snow free and snow on conditions
Figure 4.1 Hillshade of snow-on surface for the Russell Creek watershed, showing the A) interpolated
(gap-filled) raster surface and B) the non-gap filled (pixels with zero ground returns removed, and
shown in red) for March 10 <sup>th</sup> 2023 LiDAR survey. For both years, the area of no ground point returns
increased through the snow melt season

Figure 4.2 Histograms of the snow-free pixel values of the stable terrain for each snow survey
acquisition in 2023. The ground point density has been classified by greater than five points per m <sup>2</sup>
(green), $2-5$ points per m <sup>2</sup> (yellow) and less than two points per m <sup>2</sup> (grey). Pixels with no ground
points were excluded from this analysis
Figure 4.3 Ortho-imagery and snow depth data for dense old growth forest plot, ST1OG6, from the
April 29th 2023 survey. The in-situ (A) and LiDAR (B) snow depths are averaged separately, and mean
difference calculated. Missing pixels in the LiDAR are a result of no valid snow surface returns for the
survey
Figure 5.1 Hourly air temperature (upper) and snow depth (lower) data recorded from Steph 2(1164m)
weather station, for water years 2022 and 2023
Figure 5.2 Snow depth records from 2016 - 2023 for Steph 6 (upper) and Steph 2 (lower) weather
station, with the years of this study highlighted with a blue (2022) and red (2023) dashed line
respectively. Of the 7 years of data shown for Steph 6 and Steph 2 weather stations. 2022 had the latest
date on record for snow free, whereas 2023 had the second earliest
Figure 5.3 Average vegetation height by cover type broken into the categories of shrub, woody debris,
and heather. Vegetation measured 5 cm or less, as well as trees, were not included in the results. Error
bars represent the 95% confidence interval
Figure 5.4 Percentage of the cardinal plots which had at least one LiDAR ground or snow surface point
return per m <sup>2</sup> , grouped by forest cover type, for each LiDAR acquisition in 2022 (upper) and 2023
(lower). Hatched bars denotes acquisitions that were snow-free for all plots within the cover type. Error
bars represent the 95% confidence interval
Figure 5.5 Imagery of the juvenile forest from the (A) May 25 <sup>th</sup> 2023 and (B) June 12 <sup>th</sup> 2023
acquisitions showing the green up of the vegetation

Figure 5.6 Steph 2 weather station showing the change in average daily snow depth which occurred between the manual sampling window and the LiDAR survey for the April 29th 2023 acquisition ...... 57 Figure 5.7 The mean difference for snow courses from the 2022 and 2023 snow season. A 10 day delay between the LiDAR acquisition and manual sampling -which coincided with a period of snow melt - is Figure 5.8 2022 and 2023 snow-on surveys mean difference grouped by whether LiDAR was flown pre or post manual sampling, and the snow depth change between acquisition and sampling. Snow depth Figure 5.9 Alpine cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Meteorological corrections from the weather station snow depth data is denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual measurements. Figure 5.10 Dense old growth cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Meteorological correction applied using the game camera data is denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual Figure 5.11 Game camera ST1GC1 showing the rapid snow melt which occurred, with a loss of approximately 10 cm between 10 am on the 28th of April to 3 pm on the 29th of April 2023. Snow Figure 5.12 Old growth cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Error corrected using the game camera imagery is denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual measurements. Hatched 

Figure 5.13 Regenerating cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Error corrected using the meteorological or game camera data is denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual Figure 5.14 Juvenile cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Error corrected using SR50 snow depth sensor denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual measurement. Hatched bars Figure 5.15 Boxplots of the mean difference for each plot by cover type, with "open" referring to the weather station snow courses. For each vegetation type, the left box represents 2022 data and the right box 2023. For 2022, phase 4 has been excluded due to the noted offset due to delay in LiDAR acquisition and manual sampling, and subsequent snow melt. The box shows the quartiles of the dataset, with whiskers extending to points within 1.5 x the inter-quartile range. Observations outside of this Figure 5.16 Scatterplot of the slope angle of the cardinal plots and the mean absolute bias error for the 2022 and 2023 LiDAR surveys. Each marker represents the mean absolute bias error of the cardinal plot, Figure 5.17 Snow distribution for Steph 1 weather station snow course for each LiDAR survey in 2022, showing the manual (red) and LiDAR (blue) snow depth distribution. None of the measurements were significantly different in snow depth variability. The offset between the LiDAR and the manual sampling in the June 24<sup>th</sup> acquisition is due to the snow melt which occurred between manual sampling  Figure 5.18 KDE plot for 2022 showing the variability of snow depth for old growth plot ST1OG7. None of the survey dates were significantly different in snow depth variability between the in-situ and Figure 5.19 KDE plot for the regenerating forest plot ST4RF1 for 2022. The snow depth distribution was significantly different across all phases between the in-situ and LiDAR. For the 24<sup>th</sup> of June survey, Figure 5.20 Boxplot comparing the mean difference of plot snow depth for the manual observations and LiDAR across both years, with open cover representing the weather station snow courses. Blue boxes represent results of the 2017 BCTS model, and the orange boxes are of the 2023 bare earth model. The box shows the quartiles of the dataset, with whiskers extending to points within 1.5 x the inter-quartile Figure 5.21 Bar graphs to show the comparison of the two bare earth models - 2017 BCTS (hatched) and 2023 ACO (non-hatched) showing the total ground points per plot, broken down by point density per meter squared (top) and the proportion of the plot which had valid ground returns (bottom). Bars represent the average of the cardinal plots by each cover type, and error bars represent standard error . 78 Figure 5.22 Comparison of the total snow storage in the Russell Creek watershed between the 2017 BCTS model, and the 2023 ACO model for each snow survey, broken down by forest cover type. Grey Figure 5.23 Snow volume by elevation band for the 2017 BCTS model (red) and the 2023 ACO model Figure 6.1 Site maps for the natural experiment with a) showing the AOI relative to the Tsitika watershed, northern Vancouver Island, and b) scaled to the AOI, showing the road, control, and treatment area used within the analysis and c) the extent of Cain creek catchment inclusive of the Lower 

Figure 6.2 Overview of the Lower Cain (1260 m) weather station air temperature (red) and snow depth Figure 6.3 Histogram of the residuals for the control, treatment, and road sites between the post-harvest (2023) and pre-harvest (2020) bare earth. A positive skew is indicative of the post-harvest elevation Figure 6.4 Snow depth distributions of the three snow free acquisitions, ie. no snow, comparing the control and the treatment site processed with the post-harvest (2023) bare earth model. The 24<sup>th</sup> of June 2022 (left) shows a negative offset when using the harvested ground model to measure snow in the treatment site which - as it is prior to harvesting – is forest covered. The 25<sup>th</sup> of May 2023 (middle) and 12<sup>th</sup> June 2023 (right) show good agreement between the post-harvest ground surface model and the Figure 6.5 Box plots of the snow depth (m) in the control and treatment sites for the pre and post-harvest conditions. The box shows the quartiles of the dataset, with whiskers extending to points within 1.5 x the Figure 6.6 Total water storage in cubic metres for the control (green) and treatment (orange) sites for the Figure 7.1 Images from the regenerating stand (A) and dense old growth (B), showing notable difference Figure 7.2 Mean difference of the cardinal plots from both 2022 and 2023, for only harvested plots (the regenerating and juvenile), using three different bare earth models: 2017 BCTS survey acquired in September 2017 (orange), 2023 ACO survey (blue), and the substitute bare earth model: the May 2023 snow survey which was snow-free in the juvenile and regenerating stands (green). Individual points represent each plot validation across 2022 and 2023......108

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# Chapter 1 : Introduction

Climate change directly affects coastal mountain snowpacks. Warm temperatures reduce snow water storage, shift snow melt earlier in spring, and decrease summer soil moisture, which can increase the magnitude of flood and drought events (Schnorbus et al. 2014; López-Moreno et al. 2021; Gillett et al. 2022; Hidalgo-Hidalgo et al. 2022). Further, numerous studies (eg. Swanson et al. 1986; Gelfan et al. 2004; Winkler et al. 2005) have shown that forest management can have an impact on snow at the plot scale, but scaling these results to the watershed is challenging due to landscape and forest complexity. Thus, basin wide estimates of snow water storage are critical to understand the impacts of climate change and forest management on watershed scale hydrology.

Advances in remote sensing technology have improved the ability to map snow depths for entire watersheds. A Light Detection and Ranging (LiDAR) sensor fixed to an airborne platform can acquire millions of high accuracy surface elevation points over several hundred square kilometres in a time span of just several hours (Hojatimalekshah et al. 2021). To derive a snow depth surface, a snow-free LiDAR digital elevation model (DEM) is subtracted from a snow-on LiDAR DEM. LiDAR performs best in open, relatively flat terrain where light pulses can easily penetrate to the ground (Hojatimalekshah et al. 2021). Uncertainty increases when using LiDAR to measure snow in forested environments, as trees and vegetation obstruct the ground and the snow surface, which reduces the number of surface returns (Hopkinson et al. 2004; Hopkinson et al. 2012; Zheng et al. 2016). Dense ground cover vegetation can also increase elevation uncertainty by being mis-classified as ground in the bare earth model (Hopkinson et al. 2005; Gould et al. 2001). Additionally, forest snow accumulation and melt patterns are much more variable than in open areas, due to complex relationships between the canopy and energetic inputs into

the snowpack (Pomeroy and Gray 1995; Varhola, Coops, Bater, et al. 2010). This holds particular significance to watershed management in regions where a significant proportion of the snowpack is stored within forests.

As winter temperatures increase due to climate change, lower elevation coastal mountains will see an increase in winter precipitation falling as rain (Evan and Eisenman 2021). Having accurate data for the snow water storage in the forest is essential for sustainable water resource consumption, in particular for managing watersheds with "at-risk" snow (Nolin and Daly 2006). Forest management and natural disturbance lead to a mix of forest structure from clear open areas to regenerating stands of mixed species, age and structure (Floyd 2012; Winkler et al. 2021). Furthermore, there is a need to assess how snow storage varies with forest regeneration to contribute to our understanding of how stands and watersheds hydrologically recover after disturbance, as well as advance models for large and complex watersheds.

This research project will focus on the use of airborne LiDAR to measure snow depth in Russell Creek Experimental watershed (established in 1991), a heavily forested watershed on Northern Vancouver Island (Hudson and Anderson 2006; Floyd 2010). Beginning in the late 1970s, forest harvest began in Russell Creek, resulting in a range of stand ages and forest stand composition. The objective of this research is to assess LiDAR uncertainty in forested watersheds typical of the coastal mountain region of British Columbia to improve our understanding of catchment scale snow water storage.

With repeat LiDAR acquisitions and plot scale sampling for depth, this research aims to answer the following questions:

1. How accurate is LiDAR at capturing the spatial variability of the snowpack under different forest stand structures?

- 2. How does the spatial variability of the snowpack vary among different forest stands, and how does this variability change through the snow melt season?
- 3. How does the bare earth model impact LiDAR snow depth accuracy under different forest stand structures?

This research project will contribute towards current literature on forest snow interactions in a region with at-risk snow due to climate change and a history of forest management going back to the 1970s. It will also contribute to development of hydrological recovery assessment methods in coastal British Columbia. This part of a larger study using LiDAR snow surveys in forested watersheds in British Columbia, which is the first of its kind in the province.

This thesis is organized as follows:

Chapter 2 provides a comprehensive review of literature related to LiDAR observations of snow depth in forested catchments and summarizes the current state of knowledge with respect to forest disturbance hydrology. Chapter 3 identifies the study area and data collection methods used in this research, while Chapter 4 summarizes the methods of analysis. In Chapter 5, the main results section addresses the research questions and objectives. Chapter 6 follows with a case study, in which harvesting activity that occurred over the course of this research is used to quantify the impacts of harvesting on the ground surface and subsequent DEM, and the change to snow storage. Chapter 7 discusses the key findings and implications of this research. Chapter 8 provides the overall conclusions and recommendations for future research.

# Chapter 2 : Background

Airborne LiDAR has drastically up scaled the speed, size, and quantity of snow depth acquisitions, from manually collected points or data from discrete weather stations, to millions of measurements at the catchment scale. Despite this, using LiDAR within heavily forested terrain is challenging both due to limitations of the LiDAR instrument, as well as the complexity of the snowpack under canopies. Section 2.1 will discuss how LiDAR is used to measure the snowpack, as well as sources of error and uncertainty. Section 2.2 will follow with an overview of the complex snow distribution within forests. Section 2.3 will focus on how forest disturbance changes snow distribution and can influence watershed scale hydrology.

## 2.1 Snow and Remote Sensing

In-situ methods to measure snow depth and density are generally limited to single point measurements, either through manual depths with snow probes or tubes, imagery from snow stakes or remote cameras, or automated instruments, like snow depth sensors and snow pillows associated with weather stations (Hopkinson et al 2001; Kinar and Pomeroy 2015). To quantify catchment wide snow water storage, these snow depth and density point measurements can be used to validate physically based hydrological models (e.g. Pomeroy et al. 2007), however the sparse sampling leads to high uncertainty in estimates. Snow depth measurements predominantly occur in relatively flat, un-forested and sheltered areas which a) are recommended for representative meteorological station locations that aim to measure incoming precipitation and snow storage that in unaffected by wind (World Meterological Organization 2008) and, b) avoid exposure to avalanches and other hazards endemic to complex terrain. Despite efforts to establish weather stations in more remote and under-represented regions within British Columbia (Foord et al. 2014), as well as the extensive Snow Telemetry Network (SNOTEL) network in the U.S. (U.S.

Department of Agriculture), point measurements are limited in their ability to describe catchment-wide snow depth variability, particularly within forested watersheds.

Major advantages to remote sensing methods are the ability to capture spatially continuous snow depth data, and coverage of areas too remote or complex to access with manual measurements. Snow covered area has been observed through satellite remote sensing since the 1960s, where the high reflectance in visible wavelengths, and low reflectance in the SWIR band clearly distinguishes snow from other surfaces (Hall et al. 2005), however these data provide no information about depth and are limited to cloud free days. Currently, satellites like Sentinel-1 synthetic aperture radar (SAR) data and ICESat-2 can collectively determine snowpack properties such as the depth, wetness, and water equivalence (Karbou et al. 2021), though coverage can be limited and both forests and wet snow surfaces complicate interpretation of data. While recent studies have shown that ultra-high-resolution satellite imagery can derive high resolution (1-4 m) and decimeter accuracy snow depth mapping (Marti et al. 2016; Deschamps-Berger et al. 2023), the majority focus on large scale snow measurements in alpine terrain due to limitations of spatial resolution and complications associated with forest cover (Lievens et al. 2019; Karbou et al. 2021). In contrast, Structure from Motion (SfM), in which a camera is attached to an unpiloted aircraft (UAV), is capable of centimeter resolution, but generally focused on relatively small study areas ( $<5 \text{ km}^2$ ) due to aircraft battery limitations and acquisition time (Harder et al. 2016). Studies have shown that UAV SfM can accurately map snow depths (RMSE: 8.0 - 13.0 cm) in open environments, but data are poor in areas of exposed vegetation and forests due to the obscuration of the snow surface (Harder et al. 2020; Dickinson 2022; Landry et al, 2021).

Airborne LiDAR has been used to measure snow since 2001 and is now a well-established technology to map snow depth across expansive alpine terrain (Hopkinson et al. 2001; Painter et al. 2017; Currier et al. 2019). Applications of LiDAR snow depth data cover a diverse range, inclusive of evaluation of hydrological models (Dickerson-Lange, Lutz, Gersonde, et al. 2015; Vionnet et al. 2020), improved knowledge of snow distribution patterns (Deems et al. 2006; Currier and Lundquist 2018; Pelto et al 2019), and quantification of derived snow water equivalence (Tedesco et al. 2014; Floyd et al. 2020; Geissler et al. 2023). Despite widespread application in alpine environments, there are limited examples in forested watersheds. This is especially important in the low elevation coastal mountains, where typically snowpack accumulation is high but alpine terrain limited, thus a considerable proportion of snow is stored in the forest.

#### 2.1.1 LiDAR systems

LiDAR is a remoting sensing technology which emits light pulses and measures the time of flight for a given photon to calculate distance from the sensor. A LiDAR system is composed of a laser scanner, a global navigation satellite system (GNSS), and dedicated inertial measurement unit (IMU). The laser scans perpendicular to the line of flight and measures the return time of the laser pulse to the unit to determine a three-dimensional elevation point. To calculate snow depth, LiDAR data are acquired in both snow-on and snow-free conditions, processed into a separate DEMs, co-registered and then differenced. The LiDAR scanner can be either terrestrial laser system (TLS) or airborne laser system (ALS); each hold advantages and disadvantages. TLS provides high density returns- in the order of thousands of returns per metre squared - therefore suited for producing accurate, high resolution datasets (< 10 cm mean bias error; Prokop et al. 2008; Hartzell et al. 2015; Maté-González et al. 2022). A TLS is well suited to describe fine scale forest-canopy snow relationships, as the ground-based system provides the ideal scan angle to capture vegetation structure, as well not be obscured by the canopy (Disney 2019; Hojatimalekshah et al. 2021). For example, Revuelto et al (2016) used TLS to quantify the forest management practice of pruning lower branches reduced canopy area by 36% and increased total snow depth by 14%. Handheld terrestrial LiDAR sensors have become more widely available, a recent study by King et al (2022) conducted with an iPhone 12 Pro LiDAR module produced very high accuracy

(RMSE ~ 6mm) snow depth measurements. Studies have found snow depth accuracy decreases with distance and high (>60 degrees) incidence angles, therefore TLS are best suited for short-to-medium range ( $<500 \text{ m}^2$ ) areas and recommended several scans per site (Prokop et al. 2008; Revuelto et al. 2014; Hartzell et al. 2015).

Airborne LiDAR configurations are commonly mounted to aircraft such as helicopters or fixed wing airplanes, or Uncrewed Aerial Vehicles (UAVs). Plane mounted systems are well suited for larger area (order of hundred kilometers) campaigns at the watershed scale (e.g. Floyd et al. 2020), and under ideal circumstances, accurate to the decimetre level at a 1 metre resolution (Deems et al. 2013). The drawback for a more extensive survey area is a generally a lower density of ground point returns (~ < 10pts/m<sup>2</sup>) than helicopter or UAV mount LiDAR, which can be a source of uncertainty in the measurements (Menounos et al. 2020). UAV-mounted LiDAR systems provide a compromise between the terrestrial and plane mounted LiDAR systems in terms of point density (~100 pts/m<sup>2</sup>) and area coverage, and are thus well-suited to stand level studies (Harder et al. 2020). LiDAR sensor capabilities continue to expand as technologies rapidly improve. For example, geiger mode LiDAR – a photon counting system – has become more prominent, and can capture high resolution datasets (on par with UAV LiDAR) with the coverage of plane mounted systems (Deems et al. 2013; Lin et al. 2022).

### 2.1.2 Data processing

Imagery - either ortho-imagery collected coincidentally with a LiDAR survey, or satellite - can be an important part of the processing workflow for identifying snow free and stable terrain in the survey area to help with co-registration and confirm snow cover when snowpacks are shallow (Deems et al. 2013; Floyd et al. 2020; Vionnet et al. 2020). Raw LiDAR data are represented as a point cloud, comprised of single x,y,(horizontal) and z (vertical) points, of which z may represent either a discrete return or the full waveform (Deems et al. 2013). Discrete returns are the more common approach, as full waveform

requires a complex processing methodology, higher computational power, and a greater cost (Anderson et al. 2016). Full waveform LiDAR is popular for forestry applications as it allows for much more detailed description of vegetation, including the canopy and ground vegetation characteristics, as discrete points only separate sufficiently spaced objects into separate returns (Lindberg et al. 2012). Anderson et al (2016) found bare earth was captured with greater accuracy in vegetated terrain by full waveform, and conversely in non-vegetated terrain (roads) by discrete returns. Thus, full waveform data shows great potential in the snow depth mapping application to better distinguish vegetation from ground, and thereby improve accuracy of the ground surface.

From the raw LiDAR point cloud, algorithms are used to a) filter and remove noise and outlier data points, and b) for classification to identify the ground surface and other attributes like vegetation and structures. A digital elevation model (DEM) is rendered from the ground point class to represent either the snow or snow-free surface. The highest resolution a DEM can support is usually a function of the ground point density, for example an average ground point density between 1 - 2 points per m<sup>2</sup> could support a 1 m<sup>2</sup> gridded surface (Guo et al. 2010).

### 2.1.3 LiDAR validation

Typically, LiDAR snow depth accuracy is assessed against in-situ measurements, which are georeferenced with a GNSS system to ensure high accuracy and precision. A common sampling strategy is by a linear transect with GNSS measurements at the start and end with manual measurements between, or a radius approach with transects at cardinal directions from a centre GNSS position (Hopkinson et al. 2012; Floyd et al. 2020; Proulx et al. 2022). Generally, studies compare a one-to-one manual-to- LiDAR snow depth measurement, which can be a source of geo-positional error, especially under the canopy where GNSS accuracy is reduced (Murgaš et al. 2018). To address this, Broxton et al (2019) used canopy height maps in the field combined with GNSS to ensure trees were correctly

identified for under canopy snow depth measurements. In-situ measurements are generally taken with graduated avalanche probe or an automated version known as a magnaprobe – or a Federal snow sampler, which also measures density. A review of the different manual sampling methods by Proulx et al (2022) showed a slight positive snow depth bias (average 1.7 cm) between the magnaprobe and the snow tube, attributed to penetration of soil by the probe, with a greater difference in the forest than open sites. As snow tube measurements are considerably slower and more strenuous than a snow probe, a hybrid approach (snow tube and probe) is recommended for in-situ measurements to obtain both depth and density at a selection of sampling points (Proulx et al. 2022).

#### 2.1.4 LiDAR Error and Uncertainty

Sources of error in airborne LiDAR system can be classified as either systematic, errors which can be reproduced and potentially can be removed, or random, which reflects the measurement uncertainty. Sensor based geo-positional errors are a result of poor accuracy within the GPS, INS, IMU systems, with generally horizontal error greater than vertical (Hodgson and Bresnahan 2004a; Deems et al. 2013). As well, an increase in laser scan angle, flight height, and laser beam incidence angle tends to correspond to an increase in LiDAR error (Goulden et al. 2016)

Terrain features that can affect the precision of LiDAR surveys include forest canopy cover, ground vegetation, and slope (Hopkinson et al. 2012; Zheng et al. 2016). Slope introduces error as a small horizontal geo-positional error will lead to a large error in the vertical position on steep terrain (Nuth and Kääb 2011). Several studies have found that the vertical error on slope angles greater than 30 degrees nearly doubles (Hodgson and Bresnahan 2004b; Tinkham et al. 2012).

Total LiDAR ground returns are reduced under the canopy as the trees interact with emitted photons, which results in data gaps in the ground point cloud. Areas with very high forest density are likely to have larger areas with no LiDAR ground returns, in which interpolation of pixel values is required.

Zheng et al (2016) found that under-sampling under mixed deciduous forest resulted in an overestimation of snow depth of an average of 10 cm under the canopy due to the interpolation of data with the adjacent open pixels, which had a higher snow depth than under canopy.

Dense ground vegetation has been shown to cause a systematic underestimation of snow depth as a result of both the inability of the laser to penetrate through to ground as well as misclassification of vegetation as ground from the bare earth acquisition (Hopkinson et al. 2005; Gould et al. 2013; Currier et al. 2019). Gould et al (2013) found that airborne LiDAR ground models in areas with *ceanothus*, a dense ground shrub species, had elevation errors (RMSE: 17 to 37 cm) that were attributed to the inability of LiDAR pulses to penetrate the shrub, and misclassified as ground. An accuracy assessment of LiDAR by vegetation types conducted by Hodgson and Bresnahan (2004a) showed the highest error in brush and low trees (RMSE 23.3 cm) and the lowest error in pavement and evergreen forests (RMSE of 14.9 cm and 12.9 cm). The low error within the evergreen forest is attributed to the minimal ground vegetation and generally uniform height of forest canopy, resulting in two distinct levels of which ground can be easily distinguished. The opposite effect is true for the brush and low trees: the multistory environment, and variable height of the low vegetation, increases the likelihood of misclassifying ground. Reutebuch et al (2003) found minor difference in mean ground surface error (16 - 31 cm)between four forest categories (cutblock, heavily thinned, lightly thinned, and uncut), attributed to the relatively lower flying height (200 m), which results in stronger return signals due to the shorter distance the laser travels. Thus, the LiDAR errors in snow depth mapping attributed to vegetation may be largely dependent on the accuracy of the ground surface representation.

Recent studies with UAV LiDAR systems generally show lower snow depth error in forest (RMSE: 9 – 16 cm) than compared to plane mounted systems (RMSE: 5 - 35 cm), likely due to their ability to fly lower to the ground surface, though generally errors were worse in forest compared to the open (Mazzotti et al. 2019; Harder et al. 2020; Jacobs et al. 2021; Geissler et al. 2023). Menounos et al (2020)

suggested the use of lower flight altitudes (to increase the density of the point cloud) and in-situ measurements (to correct detected bias) to improve LiDAR snow depth accuracy in forested terrain. Other studies have highlighted the importance of in-situ snow depth measurements which encompass forested terrain in addition to the open to better understand snow depth uncertainties (Painter et al. 2016).

## 2.2 Snow distribution in forests

Snow distribution is governed by energy inputs into the snowpack, as well the interactions of vegetation, topography and wind. The snow energy balance of the snowpack can be represented as

$$\Delta Q = R_{net} + H_S + H_L + H_G + H_R \tag{2.1}$$

where  $\Delta Q$  is change in snowpack energy, and the energetic fluxes are: net radiation ( $R_{net}$ ), sensible heat ( $H_S$ ), latent heat ( $H_L$ ), ground heat ( $H_G$ ), and advective heat transfer from precipitation ( $H_R$ ). The contributions of net radiation to the snow energy balance are five to ten times greater than all other components, though the relative inputs of the short and longwave radiation vary considerably (Marks and Dozier 1992). Net radiation is the sum of the incoming and outgoing radiant fluxes, and can be expressed as

$$R_{net} = (1 - \alpha)R_s + R_{li} + R_{lo}$$
[2.2]

Where  $\alpha$  is albedo, R<sub>s</sub> is direct and diffuse incoming radiation, R<sub>li</sub> is the incoming longwave, and R<sub>lo</sub> is the outgoing longwave radiation. Longwave radiation is emitted by the ground surface and objects, and by the atmosphere, and is generally higher: 1) under cloudy skies as opposed to clear, 2) in higher air temperatures and humidity, and 3) within a forest vs in a clearing (Dingman 2015). Shortwave radiation is emitted directly from the sun and is a function of the declination of the sun, latitude, and time of year (Dingman 2015). Albedo measures the proportion of short-wave radiation which is reflected; fresh snow with a small grain size has a higher albedo value (0.9) than older and wetter snow (0.5) (Jones et al. 2001). As ground and vegetation are exposed, albedo will decrease and longwave and conductive energy from the ground and vegetation will generally increase in snow melt rate (Pomeroy et al. 2003).

Snow distribution under forests differs from in the open due to the interactions with the canopy altering snow redistribution and components of the snow energy balance. Generally, snow will accumulate slower and reach shallower depths within forests, due to first, snow interception, and then a combination of sublimation, meltwater drip, evaporation and mass unloading from the canopy. Mechanics for snow loss to the canopy vary across climatic regions: in cold and dry climates, up to 30 to 45% of annual snowfall may be lost to canopy sublimation (Pomeroy and Gray 1995), versus in maritime climates where sublimation generally only account for approximately 10% of loss, with meltwater drip and mass unloading from the canopy are the dominant processes (Storck et al. 2002). Methods to assess how intercepted snow is removed from the canopy have included:

- Individual branch experiments: warmer branches will bend easier, therefore snow will unload more rapidly at warmer temperatures, or in maritime climates (Schmidt and Pomeroy 1990)
- Cut-Tree experiments: Storck et al (2002) found that the variability of snow interception was minimal between the species compared (douglas fir, white fir, and ponderosa pine) in a maritime environment, and interception variability was mostly a function of the snow event itself. A novel approach using TLS by Russell et al. (2020) shows potential, with initial results showing good agreement between the TLS and cut-tree measured snow mass.
- Time lapse photography: Floyd and Weiler (2008) captured mass release events from the canopy, and observed that snow release occurred over a broad area under the tree, and snow depth remained the same in areas which snow unloaded, but snow density increased.

Trees can either enhance or reduce ablation rates of the snowpack, but generally melt rates are slower under forests than in the open due to the sheltering effects of the trees from short-wave radiation

12

and turbulent energy fluxes associated with wind (Hedstrom and Pomeroy 1998; Varhola, Coops, Bater, et al. 2010). Recent studies conducted in maritime climates, which typically have deeper snowpacks, warmer temperatures, and larger trees, have shown that in many cases the pattern of snow melt under forest and in the open is reversed. In maritime climates, an increase in long-wave radiation from the trees can dominate the energy balance, which in turn accelerates the melt rate within the forest, and results in longer snowpack duration in adjacent open sites (Lundquist et al. 2013; Dickerson-Lange, Lutz, Martin, et al. 2015; Roth and Nolin 2016). This pattern is more pronounced below tree-line, in warm dense forest stands sheltered from the wind (Dickerson-Lange, Lutz, Martin, et al. 2015). In colder and more arid climates, trees alter the energy balance by reducing incoming shortwave radiation which reduces melt beneath forest canopies.

Wind also impacts snow distributions through a) transportation of snow from exposed to sheltered areas, b) turbulent fluxes of energy into the snowpack causing melt or c) sublimation of the snow into the atmosphere, though this tends to be a small component in coastal watersheds (Currier and Lundquist 2018). Blowing snow is more prevalent in cold climates due to a lower wind speed threshold required to transport cold and low density snow, than the warm, and higher density snow typical of the coastal climate (Li and Pomeroy 1997). A study by Currier and Lundquist (2018) showed significant differences to snow depth between the windward and leeward side of a forest in a high wind cold climate site in Colorado, and no significant different in a maritime location with equal or greater wind speeds. High wind speed sites (> 8 - 17 m/s) in a study in the Pacific Northwest showed accumulation rates were equal between forest and open due to the depositional differences from the wind transported snow (Dickerson-Lange et al. 2017).

Large rain-on-snow (ROS) events occur with greater frequency in temperate climates and can rapidly change the snowpack and its distribution (Marks et al. 1998; López-Moreno et al. 2021; Gillett et al. 2022). When the snowpack is near isothermal, there is a low energy requirement to begin snowmelt

during a ROS event, which can rapidly result in flood and landslide events (Harr 1981). Melt rates during ROS events have been found to be significantly higher in openings and clear cuts than in forests (Berris and Harr 1987; Marks et al. 1998). The major difference in the energy balance between forested and un-forested sites is the turbulent fluxes of sensible and latent heat, as the trees shelter the surface of the snow from wind. Slope and aspect also affect melt rates, as areas positioned towards the incoming wind will be subject to greater turbulent transfer and increased melt rate (Harr 1981). In areas where snowpacks are generally shallow, such as the transient snow zones, the snowpack can melt entirely during a single large rain-on snow event (Berris and Harr 1987). Musselman et al (2018) investigated the impacts of climate change to ROS events, and in a maritime environment frequency at lower elevations will reduce due to declining snowpack and increase at mid elevations, as well as the major ROS events shifting earlier in the season. While studies have shown these differences at the stand level during rain-on-snow, linking these stand level effects to watershed scale stream flows has been challenging due a sparsity of data.

## 2.3 Forest Disturbance and Hydrological Recovery

Forest disturbance can cause major shifts to the snow energy balance, by both a) changes to accumulation resulting from loss of canopy interception and b) changes to ablation from loss of canopy cover altering the long and shortwave radiation inputs and turbulent fluxes (Boon 2009; Marks et al. 1998; Varhola, Coops, Weiler, et al. 2010; Winkler et al. 2015). Numerous studies have been conducted to assess how forest and open site melt rates differ as it has clear implications for forest management practices (eg. Hubbart et al. 2006). Gelfan et al (2004) found melt rate in the open to be 3.2mm day<sup>-1</sup> faster than in the forest. Increased snow accumulation mostly occurs in the openings, but even with a higher antecedent snowpack, averaged snow melt duration were longer in the forest (30 days) than in the open (22 days) (Gelfan et al 2004).

The size and aspect of the harvested block affects the snow retention, which is an important consideration for water resource management. Swanson et al. (1986) found that cut blocks that were 1-2 tree height in width, and 60 - 80 meters in length, with the long side perpendicular to the prevailing wind, were ideal for snow retention. Clear cuts which are south facing and situated on level terrain have shown an increase in melt rate than north aspect (Murray and Buttle 2003; Pomeroy et al. 2012). Forest thinning also impact snowmelt timing; Ellis et al (2013) found that on southern aspects melt rate increased due to greater shortwave radiation, and on northern aspects decreased, due to loss of longwave radiation from the trees.

Stand level hydrological recovery describes to what extent a regenerating stand is behaving as an old growth or mature forest, and may be evaluated on the following metrics: rainfall interception, snow melt, snow accumulation and interception, ROS, and evapotranspiration (ET), although in coastal watersheds ET recovery is not deemed to be a major component (Hudson and Horel 2007). Generally in British Columbia, hydrological recovery focuses on snow accumulation and melt, and is estimated via canopy characteristics, such as height, density and species (Hudson and Horel 2007; Winkler and Boon 2017). Floyd (2012) investigated hydrological recovery through ROS events within the coastal Russell Creek watershed (the location of this study) and found recovery to be variable; low elevation (approximately 500 m) and sheltered forest plots with a canopy height of 13 m were 100% recovered in relation to energy inputs during ROS, but recovery of forests of a similar height at higher elevation was lower likely due to higher exposure to turbulent fluxes.

Since the 1990's, equivalent clear cut area (ECA) has been the primary metric within British Columbia to quantify the extent of disturbance, and is defined as the area that functions hydrologically as a clear cut in a disturbed area (Winkler and Boon 2017). To measure ECA, recovery curves as described above are used to assess each harvested area and its regenerating forests. For example, an area which is considered permanently disturbed, such as roads or powerlines, has an ECA of 100%, while a forest

15

15m in height may be considered 50% recovered. The next step is to calculate the area disturbed at the watershed level based on the ECA and use that resulting metric to assess the potential for current and additional harvest to negatively impact stream flow. A major shortcoming of the use of ECA is it is a highly simplified approach based on empirical relationships from a handful of studies, which fails to consider the impact of important watershed characteristics such as aspect, size, and elevation gradient (Winkler and Boon 2017). Despite these limitations, ECA along with a suite of other indicators is widely used to assess overall risk for harvesting to impacts peak flows and downstream values. There is a long history of using paired watershed studies to assess the impacts of forest harvest on stream flows (Richardson et al. 2023). Here, a control and treatment watershed which are of similar size and characteristics, are monitored pre and post forest harvesting to determine changes to stream flow, including water yield, low flows, and peak flows. The long-standing nature of many of the experimental paired watersheds (mean duration: 27 years), as well as their spatial distribution across North America (34 operational as of 2023) provides both a) a method to assess relative change due to disturbance which is not obscured by the effects of climate change, and b) comparison of watershed responses between different hydrological regimes and c) insights into the effects of forest regeneration on stream flow (Richardson et al. 2023). For example, Perry and Jones (2017) evaluated the impact of forest plantation on summer streamflow across 8 paired watersheds in the Pacific Northwest over six decades. They found that relatively young stands (25 - 45 years) of Douglas fir within the treatment watersheds resulted in summer stream flow deficits of 50% compared to the control basin, which was comprised of 150 - 500 year old forests. Coble et al (2020) found these effects can reverse at larger scales, when a broad range of regenerating forest are represented in the catchment. Despite widespread usage, criticisms and limitations of the paired catchment approach include:1) challenges to find representative paired watersheds, as well as basins which have pre-disturbance stream flow records, 2) the uncertainty of scaling for small basin to large, 3) problems with data quality and accessibility between watersheds,

and 4) the cost of maintaining long-term observations (Pike et al. 2010; Neary 2016; Richardson et al. 2023).

In theory, a greater area of disturbance results in greater potential for hydrologic change in terms of snow melt rate, peak SWE timing, and overall water yield. However, there is disagreement within the forest hydrology community on the effects of forest harvesting on the magnitude of the hydrological response, and whether disturbance impacts only average flows, or the frequency of peak flows (Alila et al. 2009; Bathurst et al. 2020; Pham and Alila 2024). Disagreement largely stems from a) differences in disturbance distributions within basins and hydro-climatic regimes, and b) the analysis methods which have been employed to assess change, specifically flood frequency vs chronological pairing (Alila et al. 2009). Some studies - both paired catchments and through other methods - have shown watersheds that are more than 30% logged have increased snow melt rates and peak flows, as well as peak flows that occur earlier in the season and low flows that occur later (Bosch and Hewlett 1982; Moore and Scott 2005; Winkler et al. 2015; Winkler et al. 2021). However, a recent study by Johnson and Alia (2023), which employed a flood frequency approach, found a lower threshold, in which 21% harvested watershed resulted in flood events of all magnitudes increasing in frequency, with 7, 20, 50, and 100 year flood events becoming 2, 4, 6 and 10 times more frequent respectively.

Much of the current understanding of forest disturbance has been gained through plot scale data, paired watersheds, or hydrological models which have utilized the paired watershed and plot data (Alila et al. 2009). Compounded with forest harvesting are the effects of climate change, which can result in snow melt occurring earlier, and can increase risk of early melt events, and summer droughts (Winkler et al. 2015). This highlights the need for robust snow water measurements at the catchment scale to improve our understanding of watershed processes and forest management practices.

17

## 2.4 Research Gaps and Objectives

Based on the background review presented above, there remain some key gaps in our understanding of the ability of LiDAR to evaluate snow distributions in forested catchments where logging has occurred. These gaps, and the research questions identified in Chapter 1, will be addressed in this thesis through the following objectives:

- Establish a manual sampling network to assess accuracy of snow depth derived from LiDAR samples and calculate error metrics at the plot scale (Chapter 4)
- Characterize forests and vegetation attributes at manual sampling network, and ground return point density in different forest cover types, to determine if these contribute to LiDAR error (Chapter 5)
- Compare the plot results using an alternative bare earth DEM with different ground sampling point densities and acquisition times (Chapter 5)
- Assess the spatial distribution of snow at the watershed scale, and the differences between the two bare earth models (Chapter 5)
- 5) Evaluate the impact of harvesting activities on bare earth models and snow depth distributions in a control-treatment forest harvest experiment (Chapter 6)

# Chapter 3 : Study Area and Data

# 3.1 Study Area

This study is situated within the Russell Creek Experimental Watershed, a sub-basin of the Tsitika River watershed (397 km<sup>2</sup>), located on Northern Vancouver Island (Figure 3.1), British Columbia, Canada. Access to the watershed is via a network of resource roads. The watershed encompasses an area of approximately 32 km<sup>2</sup>, with predominantly north to northwest aspects, and spans an elevation range from 220 to 1670 m. The area is 85% forested and with limited alpine terrain. Three biogeo-climatic zones are within the watershed: coastal mountain-heather alpine, coastal western hemlock, and mountain hemlock (Meidinger and Pojar 1991). The coastal mountain-heather alpine zone is characterized by most vegetation being low growing white and pink mountain-heathers, and treeline tree species are predominantly mountain hemlock (Tsuga mertensiana). It encompasses only 12% of the watershed and is generally above 1500 m. The mountain hemlock zone occurs at the approximately 900 to 1400 metre range, with extensive parkland from 1100 to 1400 depending on aspect, with Mountain Hemlock, amabilis fir (Abies amalabis) and yellow cedar (Chamaecyparis nootkatensis) being the dominant tree species. The largest zone is the coastal western hemlock, which is approximately 65% of the basin, situated in the low to mid elevation range and bordered by the mountain hemlock zone. Dominant tree species are western hemlock (*Tsuga heterophylla*), western red cedar (*Thuja plicata*), and large areas of regenerating stands of douglas fir (Pseudotsuga menziesii). The watershed is characterized by high precipitation (approx. 2300 mm per year), rain-on-snow events, and deep winter snowpacks from 3 to 5+ m in the alpine (Floyd 2010). Average temperatures are mild, with annual average temperatures of 7.1, 5.2 and 2.9 degrees Celsius at 400, 840, and 1500 m respectively (Floyd 2010). It is typical for seasonal snowpacks to develop above 700 m, with transient snowpacks below that elevation, but this can vary
from year to year. Rain-on-snow events are typical in this watershed and are associated with the highest peak flows on record.



Figure 3.1 Overview map of the study site: Russell Creek (32 km<sup>2</sup>) sub-basin of the Tsitika watershed (397 km<sup>2</sup>), located Northern Vancouver Island, British Columbia

Active logging has occurred in the Russell Creek Watershed since 1978, which presents the opportunity to study a spectrum of regenerating and old growth forest stands within the same hydrological zone. The regenerating forest at lower elevations is a mix of planted western hemlock, western red cedar and douglas fir (*Pseudotsuga menziesi*), while at higher elevation regenerating forests western hemlock and douglas fir are more common. As of 2023, approximately 40% of the watershed has been harvested, all of which occurs below 1300 metres.

### 3.2 Weather Station Network

Russell Creek Experimental Watershed was established in 1991, originally to address concerns that timber harvesting was causing ecological harm to a nearby rubbing beach for Orcas (Floyd 2010). Since

2009, ten weather stations have been operated by the Ministry of Forests Coast Area Research, though the construction and data acquisition of several of the stations precede this. The weather stations are located at an elevation gradient from 280 to 1516 meters and located to capture the elevation gradient of the watershed and in areas with different exposure to energy fluxes. Each station measures at a minimum rain via a tipping bucket, temperature and relative humidity, while most measure wind speed and direction, solar radiation and snow depth, with three stations located at 493, 820 and 1164 m measuring total precipitation in a standpipe. Data can be found at http://graph.viu-hydromet-wx.ca/. Meteorological data from these stations, specifically snow depth and air temperature, were used to describe the seasonal snowpack, as well as assess change when manual measurements and the LiDAR acquisition occurred.

### 3.3 Land Cover Classification

To assess whether forest cover had an impact on LiDAR error, broad land cover types based on age and height were created in Russell Creek watershed (Figure 3.2). Roads within the watershed, both the highway and resource roads, were digitized from the bare earth model, and alpine terrain was classified by a combination of the BC bio geo-climatic zones, and ortho-imagery. The remaining forested portion of the watershed was first categorized by whether the forest was previously harvested, or not (old growth). Of the harvested forest, age was a relatively good proxy to distinguish between the different stand characteristics, and was broken into four categories: mature regenerating, regenerating, juvenile, and new harvest (Table 3.1; Figure 3.2). Figure 3.3 provides images of the typical cover types in the watershed.

*Table 3.1 Breakdown of the land cover categories within the Russell Creek watershed, which were used to: a) determine plot locations and b) for watershed scale analyses.* 

	<b>Canopy Height</b>	<b>Canopy Density</b>		Area
Cover Type	(Median, m)	[%]	Harvest year	[% of watershed]
Alpine	1.1	35%		12
Old Growth	21.1	84%		45
Mature Regenerating	14.4	95%	1986 or before	16
Regenerating	7.9	74%	1987 - 2005	21.8
Juvenile	2.7	25%	2006 - 2017	5
New Harvest	0.4	0%	2018 - 2023	1.1
Roads	2.8	33%		0.7



Figure 3.2 Overview of Russell Creek watershed showing A) the landcover type, B) the landcover broken down by elevation, C) the orthoimagery of the watershed, and D) aspect



*Figure 3.3 Images of the forest cover types where plots were sampled within this research project: Juvenile (A), Regenerating (B), Dense Old Growth (C), Old Growth (D) and Alpine (E)* 

# 3.4 LiDAR surveys

Airborne LiDAR data used in this study was collected by the Airborne Coastal Observatory (ACO), a partnership between the Hakai Institute, the University of Northern British Columbia, and Kisik Aerial Survey. As part of a greater project to quantify seasonal snow water storage, LiDAR surveys were flown over portions of four key watersheds in southern coastal British Columbia: Tsitika, Cruickshank, Englishman and Seymour. Five flights were targeted between March and June to capture peak snow accumulation and the subsequent melt for each year between 2020 and 2023. The exact timing of the flights is subject to weather and equipment availability, as well as the snow conditions. The focus of this study is the 2022 and 2023 snow years within the Tsitika watershed; an approximately 80 km<sup>2</sup> LiDAR survey area (Figure 3.4). The Hakai geospatial team processed the raw LiDAR data and produced a cleaned point cloud, ortho-imagery, and derived raster products (Table 3.3).

### 3.4.1 Snow Free acquisition

The LiDAR bare earth DEM for the Tsitika watershed was acquired in 2023. The motivation for an updated DEM was to have one acquisition for the full watershed, acquired with the same LiDAR system used to create the snow surface DEMs. The prior bare earth DEM was a mosaic of two separate acquisitions: the majority of the area was a BC Timber Sales LiDAR acquisition from 2017, and a small area was flown by the ACO in 2020 to cover the southern Mount Cain region (Figure 3.4). This provided an opportunity to compare two different bare earth DEMs created from separate acquisitions and subsequent impacts on resulting calculated snow depths and volumes. The updated LiDAR bare earth survey was captured by the ACO in August 2023 (see Appendix A: ACO 2023 Bare Earth Model), and is the primary DEM used within this research project.



Figure 3.4 LiDAR survey area within the Tsitika watershed, showing the ACO 2023 bare earth boundary and snow surveys(red), the 2017 BCTS bare earth coverage of the AOI (orange), and the ACO 2020 acquisition which was targeted to fill the missing area over Mount Cain (blue). Note that the linear boundary to the SE was used to cover the highway and provide generally snow free stable terrain

LiDAR product	Format	Acquisition date	Source	Raster Resolution (m)	Average ground/snow surface point density (pt/m <sup>2</sup> )
Bare Earth: 2017 BCTS	raster (.tiff); point cloud (.laz)	September 3 2017	BC Timber Sales	1	n/a
Bare Earth: 2020 ACO (Mount Cain)	Raster(.tiff); Point cloud (.laz)	September 29 2020	ACO	1	n/a
Bare Earth: 2023 ACO	Raster(.tiff); Point cloud (.laz)	August 19 2023	ACO	1	1.19
Snow surveys: 2022	raster (.tiff); Point cloud (.laz)	Phase 1: March 9 Phase 2: April 11 Phase 3: May 21 Phase 4: June 24 Phase 5: cancelled	ACO	1	1.24 1.12 1.09 0.86
Snow Surveys: 2023	raster (.tiff); Point cloud (.laz)	Phase 1: March 10 Phase 2: April 4 Phase 3: April 29 Phase 4: May 25 Phase 5: June 12	ACO	1	2.88 n/a 1.08 1.01 0.97
Ortho Imagery	Georeferenced imagery(.tiff)	Produced for each snow survey acquisition	ACO	10 – 20 cm	-
Canopy Density	raster (.tiff)	Produced for each bare earth	ACO	1	-
Canopy Height	raster (.tiff)	Produced for each bare earth	ACO	1	-
Canopy Cover	raster (.tiff)	Produced for each bare earth	ACO	1	-
Ground returns	raster (.tiff)	Produced for each bare earth	ACO	1	-
All returns	raster (.tiff)	Produced for each snow survey acquisition	ACO	1	-

Table 3.2 LiDAR products and metadata for the Tsitika survey area from 2020 to 2023 used within this research project

# 3.5 In-Situ Observations



Field validation measurements occurred at cardinal plots and weather station snow courses within an approximately 4 km<sup>2</sup> area in the southern portion of the Russell Creek watershed (Figure 3.5)

Figure 3.5 Location of the game camera sites (blue), weather stations (purple), and cardinal plots (red) within the Russell Creek watershed

### 3.5.1 Snow Sampling

Thirteen cardinal plots were located at elevations ranging from 809 m to 1505 m. Sites were selected to incorporate the different forest cover types captured in the watershed (Figure 3.5), while also allowing for summer and winter access. Each plot had a GNSS-sampled plot centre, with cardinal and intercardinal arms extending 10 m (Figure 3.6). Every 2.5 m, a snow depth measurement was taken, with a total of 33 snow depth measurements per plot. A federal snow sampler was used to measure depth, snow water equivalent and density at the plots enter and at the 10 m of each cardinal arm (n=5).



Figure 3.6 Cardinal plot snow sampling strategy of density (open circles) and snow depth (dash) measurements. Distances (red) are in meters

Manual snow depth measurements were recorded using an iPad via the Device Magic field form application (Device Magic, 2022). For each probed snow depth, canopy cover was observed (open, edge or under canopy, tree well) as well as characteristics of the ground hit (wood, rock, or other notes). Plot naming conventions started with the prefix of the next highest weather station: for example, ST1 is located at an elevation below Steph 1 and above Steph 2 weather station. The suffix denotes the cover type of the plot (A: alpine, OG: old growth, CC: clearcut, RF: regenerating forest), and numbered from highest to lowest elevation. For the plot-scale study, old growth with denser canopy closure (>70% of plot) was further sub-categorized as dense old growth. Slope and aspect metrics were derived from the bare earth DEM.

*Table 3.3 Meta data for cardinal plots used within the in-situ sampling campaign. Precise plot locations and GNSS accuracies for the 2022 and 2023 sampling campaigns can be found in Appendix C* 

Cover (harvest year)	Plot ID	Average Canopy height (m)	Canopy Cover (%)	Average Slope (degrees)	Elevation (m, ellipsoid)	Aspect
	ST1A1	2	6	18	1505	Е
Alpine	ST1A2	2	27	10	1507	SW
	ST1OG3	8	30	33	1379	W
Old Crowth	ST10G7	15	40	20	1254	Ν
Growin	ST1OG8	18	41	25	1228	NE
Donso	ST10G4	18	84	30	1331	W
Old Crowth	ST10G5	15	81	26	1311	W
Growth	ST1OG6	15	72	18	1296	W
Regenerating	ST4RF1	6	76	30	832	NE
(1988)	ST4RF2	5	53	20	830	NE
(1988)	ST6GC1	7	88	18	809	W
Juvenile	ST2CC1	2	9	25	1007	Ν
(2008)	ST2CC2	2	2	12	1076	NE

Accurate geo-referencing of the snow validation site locations is essential to compare in-situ snow depth measurements to LiDAR depths. Two GNSS units were used to establish the plot position: one base head set up on a previously established and known point, and the second rover point at the plot centre (Figure 3.7). Precise position and accuracy of the GNSS plot centres is provided in Appendix C. The horizontal position of the plot location was of higher importance than the vertical, as purpose was to

geo-position the probed snow depths, rather than the elevation of the snow surface. Generally, plots were surveyed only the first validation trip of the season, as the plot centres remained in place to mark location for the future sampling campaigns.

Additional GNSS data points were collected in 2023 snow season as a means to improve the process of LiDAR survey alignment. This included elevation transects of the snow surface, as well as stable terrain points such as a cabin roof. High accuracy data points in the x,y, and z planes were required, therefore only FIXED solution points (corrections from the base received; 1 - 3 cm accuracy) were collected. Technicians also ensured best practices were followed, for example careful measurement of snow surface to rover, as well as rover was level and stable when data point collected.



Figure 3.7 GNSS set-up showing the base station (A) established on a permanent ground control point, and the rover (B) set up at the plot centre of Juvenile site ST2CC2

As part of long-term snow data collection in the watershed, manual snow survey measurements using a federal snow sampler were taken at seven weather stations (Steph 1 through Steph 8). For each of the stations, 10 measurements are taken at intervals of approximately 1 m, with GNSS positions for the start and end of the transect. With the exception of Steph 1, all weather station snow courses are conducted on relatively flat (less than 10 degree slope) gravel roads. Steph 1 weather station is in the alpine, where the ground is relatively flat and is either rock, moss or low-lying heather. The weather station sites provide a dataset free from steep slopes, canopy cover and ground vegetation, which are known to increase LiDAR uncertainty (see sec 2.1.3).

In addition to the manual snow depth plots, nine camera sites captured automated continuous data throughout the snow season. Each site was equipped with a wildlife camera, and five PVC snow stakes with associated GNSS position, either 2 or 3 m in length with increments of 20 cm (Figure 3.8). Cameras were programmed to take two images per day, which provided a continuous dataset for the snow accumulation and melt period, as well as the snow disappearance date. These data were used to measure change between surveys. *Table 3.4 Game camera sites and metrics for the 2022 and 2023 LiDAR campaigns. Precise position of the game camera stakes can be found in Appendix C* 

Cover (harvest year)	Plot ID	Average Canopy height (m)	Canopy Cover (%)	Average Slope (degrees)	Elevation (ellipsoid)	Aspect
	ST1_GC1	18	95	17	1290	W
	ST1_GC2	18	93	15	1268	W
	ST1_GC3	22	93	16	1211	Ν
Old Growth	ST2_GC1	25	97	21	1094	NW
	ST6_GC2	41	99	18	787	W
	ST6_GC3	36	98	24	771	NW
Regenerating (1988)	ST6_GC1	7	88	18	809	W
Mature Regenerating (1986)	ST7_GC1	22	100	19	606	NW
	ST7_GC2	15	100	23	584	NW



Figure 3.8 Game camera snow stake set up – this imagery is of game camera site ST2GC1 as seen in snow free and snow on conditions

### 3.5.2 Sampling error and mitigation

A known error in manual snow depth measurements can occur by over-probing into ground, with increased likelihood in unfrozen soils, complex terrain or areas with dense leaf litter. Though challenging to assess, other research has found probing error to be relatively small and infrequent, with an average error sub-10 cm, occurring in less than 10% of measurements (Hiemstra et al. 2020). Depth measurements when using a snow sampler will have less "over-probe" error as a soil plug would be in the tube and accounted for. For the probed measurements, technicians minimized this error by retaking a snow depth measurement if uncertain of ground strike (dirt on the probe end would be indicative of this).

Minor positional errors are likely to occur within the sampling plot, as a result of:

- Plot cord: Variation in the cord tension between each transects, bends in the cord when navigating through trees within the plot, as well as the slope of the plot can also contribute to positional errors.
- Compass: Though care is taken by technicians, compass error can result in slight offsets in direction. Even with correct use, situational choices, for example which side of tree to measure, are a factor in error.
- Movement of centre position marker: Snow creep can move or break the centre position post. Nearest trees were flagged with a bearing and distance to centre point to ensure plot center is returned to the same position if moved.

Since we compared the plot averages to the LiDAR averages over the same area i.e. not point to point, these errors were expected to be minor.

33

### 3.5.3 Vegetation surveys

Low lying vegetation can be a source of error when classifying bare earth by reducing the number of points that reach the ground, requiring interpolation over larger distances, and when especially dense, can be misclassified as ground which can result in a systematic bias. To account for this error the cardinal plots were surveyed in snow free conditions to evaluate the height and cover of ground vegetation in the different forest types. These data were used to evaluate whether a systematic bias in snow depth measurements was a result of ground vegetation.

A point sampling transect method was used to evaluate ground cover to mirror the cardinal snow plot methodology. At every 2.5 m interval on the cardinal and inter-cardinal directions, a 50 cm radius area was sampled. The following metrics were gathered: total number of species present, height of each species, and classification of species. Broad categories of species identification were used as the focus was to characterize the height of ground cover, not conduct a full species inventory. An avalanche snow probe was used to measure vegetation up to 3.2 m, exceeding that was noted as greater than 3.2 metres.

The vegetation categories were broken down into major groupings: Ground cover, heather, shrub, and woody debris. Ground cover was composed of mosses and lichens, which were less than 5 cm in height, and woody debris encompassed logs, stumps, and slash piles. The cardinal plots were grouped by cover type, and the average height and variability each vegetation category were calculated.

# Chapter 4 : Data Processing and Analyses

The following chapter describes the processing methods of each dataset, including LiDAR, manual observations, and weather station data. As this study is part of a larger study, some stages of the processing workflows were completed by other members of the team.

To assess snow depth variability and LiDAR accuracy within the different forest cover types, the following steps were completed and described in detail below:

- i) Analysis of weather and snowpack conditions for 2022 and 2023 snow years
- ii) Summary of vegetation height and broad species overview for each cardinal plot cover type
- iii) Calculation of LiDAR snow surface point density for each forest cover type and changes through the snow melt season
- iv) Comparison of the average and variability of snow depths between the manual and LiDAR observations
- v) Bare earth error analysis: Comparison of bias error when LiDAR snow depth is processed with alternate bare earth model (ACO 2023 vs BCTS 2017)

The final portion of analysis focused on watershed scale snow distribution using the LiDAR derived snow depth layer. Total snow storage in Russell Creek was calculated with both the 2017 and 2023 bare earth models, for each LiDAR acquisition, to assess how the bias and error analysis affected the final volumes.

## 4.1 LiDAR processing

The initial processing of the LiDAR data was completed by the Hakai Geospatial team. Processing steps closely follow the methodology described by Deems et al. (2013):

- I. Flight strip alignment
- II. Ground classification and filtering of noise
- III. Integration of GNSS ground control points
- IV. A manual co-registration using GCP's and pseudo-points within the LiDAR
- V. Generation of snow surface raster, and additional raster products

Ground classification of the point cloud is an important step in the processing, as the choice of algorithm can be a significant factor in the elevation accuracy (Tinkham et al. 2011). All ACO LiDAR snow-on acquisitions and the 2023 bare earth model were classified with LASground (Isenberg 2014), which is based on Axellson's (2000) progressive Triangulated Irregular Network (TIN) densification algorithm. First, a subset of low points are selected and used to form a coarse TIN surface. The algorithm then iterates through the points, and either adds to the TIN ground surface or filters as non-ground based on whether they fall within assigned threshold parameters. Specific LAStools processing parameters used are found for ground classification, noise filtering, and generation of the rasters are found in Appendix B: LiDAR Processing. The 2017 BCTS - which was merged with the 2020 ACO acquisition over Mount Cain - was re-classified by the Hakai geo-spatial team with the proprietary Terrasolid software product TerraScan, which also uses a TIN densification algorithm. All raster products were then aligned to the bare earth model using GDAL warp, to ensure consistency between the processing extents. LiDAR datasets were primarily processed in python, with some supplementary workflows completed with the GIS software ArcGIS Pro and QGIS.

#### 4.1.1 Non-gap Filled Rasters

The creation of LiDAR bare earth and snow surface rasters requires data interpolation between pixels when there are gaps in the ground returns. Where there are no ground or snow surface returns in a pixel, a value can be derived through a nearest neighbour algorithm (Deems et al. 2013).

To eliminate the smoothing effect from interpolation between pixels only the "true" LiDAR derived pixels in the plot-scale analyses were used in the comparisons between in-situ observations and LiDAR-derived snow depths. Non-gap filled (NGF; zero point return pixels removed) rasters were generated for each snow survey (Figure 4.1). The interpolated, or gap filled, snow surfaces were utilized in the watershed snow volume analyses, where the priority shifted to equal area (ie. number of pixels) between surveys, and a viable operational workflow.



Figure 4.1 Hillshade of snow-on surface for the Russell Creek watershed, showing the A) interpolated (gap-filled) raster surface and B) the non-gap filled (pixels with zero ground returns removed, and shown in red) for March 10<sup>th</sup> 2023 LiDAR survey. For both years, the area of no ground point returns increased through the snow melt season.

#### 4.1.2 Snow Depth Rasters

Co-registered snow depth rasters were produced by subtracting the bare earth DEM from the snow surface DEM, then converted to cm of snow (Eq. 1),

Snow Depth [cm] = (Z snow) - (Z bare) x 100 (1) where Z snow is the surface elevations with snow cover, and Z bare is the surface elevation without snow cover. This was repeated for the gap filled and non-gap filled snow surfaces, for both the primary 2023 ACO bare earth acquisition, and the 2017 BCTS.

#### 4.1.3 Bias Assessment

Snow-free and stable terrain within the LiDAR boundaries were isolated to assess each snow survey for systematic error. A section of the highway within the LiDAR survey boundary was ideal for this analysis, as it generally remained snow-free, had a high point return count, and was free of vegetation. Calculated snow depths on snow-free terrain should be zero, and can be used to assess bias. Orthoimagery collected contemporaneously with the LiDAR data was used to confirm the highway was snow-free, and a hillshade applied to the bare earth model guided the digitization of the highway. The non-gap-filled snow depth and point density rasters were then clipped to the extent of the highway.

Snow depth values were plotted in histograms, and categorized as high (greater than 5), medium (2-5) and low (less than two) ground point density (points/m<sup>2</sup>; Figure 4.2). Unbiased datasets will have peak in the snow depth values at or close to zero. Histograms that skew above or below zero indicate of a systematic error in the acquisition, and prompted a survey re-alignment to remove bias.





# 4.2 In-Situ Observations and Supplementary Data

Over 2000 manually probed snow depth data points were collected over the course of the LiDAR campaigns. A python script was developed to clean, summarize, and generate scatter plots from the data output by Device magic. The plot summaries and scatterplots were reviewed to identify and correct any errors within the dataset. In-situ snow depth data was then geo-positioned to the GNSS cardinal plot centre.

#### 4.2.1 Weather Stations

With the exception of Steph 3 which transmits via an Iridium Satellite Modem, weather station data were manually downloaded through the season. The meteorological data then underwent a QA/QC process to remove noise and outlier data points. With the cleaned datasets, analyses completed were:

- i) Seasonal review: Overview of the snow seasons in 2022 and 2023 in terms of air temperature and snow depth
- ii) Short-term change: An assessment of air temperature and snow depth data in the period between the manual sampling and LiDAR acquisition to determine if depth had changed
- iii) Historical averages: comparison of how 2022 and 2023 snow melt seasons and average monthly air temperature compare to previous years weather station data, going back to 2016

#### 4.2.2 Game Cameras

To assess the relative change in snow depth between the LiDAR acquisition and manual observations, game cameras captured daily images of five snow stakes within the forest at nine locations. Imagery for 2022 and 2023 was processed using the image manipulation software GIMP to create a workflow to measure pixels of snow, using the snow stakes increment of 20 cm to calibrate a pixel to snow ratio. A snow depth measurement per snow stake was acquired on the date of the LiDAR survey, as well as 10 days before and after each survey, to calculate the relative change in snow depth. Game camera observations were removed from this analysis if the snow stake had shifted or was not straight, and changes in snow depth were averaged between the five stakes.

## 4.3 Plot Analyses

To compare the manual and LiDAR snow depths at the plot scale, the mean snow depth per plot, rather than a point-to-point comparison, was employed. The use of mean snow depth reduces errors that may be introduced due to minor (less than 1 meter) offsets in position, the accuracy (<1m) of GNSS plot centres, as well as field sampling practices (see 3.5.2 Sampling error and mitigation).

LiDAR snow depth data was extracted for each plot using a 10 meter radius buffer from the GNSS plot centre for the cardinals, and a 5 m width line from the start and end GNSS points for the weather station snow courses. The total number of pixels captured in the LiDAR were variable due to a) the number of full and partial pixels contained within the plot buffer and b) the number of valid data points within the plot buffer for the non-gap filled rasters (Figure 4.3). The maximum number of LiDAR data points were 312 for the cardinal plots and 33 for the weather station snow courses. Manual snow depth measurements were generally 33 per cardinal plot, and 10 per a weather station snow course. Cardinal plot results were analysed individually, as well as aggregated by their respective cover type: juvenile, regenerating, old growth, or alpine (see sec 3.5.1)



Figure 4.3 Ortho-imagery and snow depth data for dense old growth forest plot, ST1OG6, from the April 29th 2023 survey. The in-situ (A) and LiDAR (B) snow depths are averaged separately, and mean difference calculated. Missing pixels in the LiDAR are a result of no valid snow surface returns for the survey.

Additional raster datasets used in the plot analysis include LiDAR-derived aspect, slope, and ground point density, and the canopy metrics of height and density. Canopy coverage and slope are both known topographical components which impact both LiDAR error and snow distribution (see sec 2.1 and 2.2). The ground point density is indicative of LiDAR error, as poor ground point coverage results in more

interpolated data points. The ground point density rasters were used to determine the total ground points, the proportion of pixels with no data (data gaps), and average point density per each plot. The point density analysis was completed for all snow-on surveys, as well as both (2017 BCTS and 2023 ACO) bare earth models.

#### 4.3.1 Test of Normality

Snow depth distributions for each plot were assessed for normality, as this dictated which statistical tests were valid for testing equality of variability and central tendency. Three metrics which were used to determine whether the plot snow depths followed a normal distribution were 1) a q-q plot, 2) a histogram, and 3) the sample Kolmogorov-Smirnov (KS) Goodness-of-Fit Test. The KS test is used to test the null hypothesis that a sample is distributed according to a normal distribution. Using a confidence level of 95%, the null hypothesis is rejected if the p-value is less than 0.05, and was calculated using the built in KS function within the SciPy stats package.

#### 4.3.2 Snow Depth Variability

Snow depth variability is known to be influenced by factors such as canopy cover and wind exposure. A highly variable snowpack poses more of a challenge to LiDAR, as the conventional gridded format will naturally smooth a dataset. A variability analysis was conducted for each of the different forest covers to assess a) how the variability of the snowpack changes through the snow melt season and b) whether LiDAR captures the same variability as the manual measurements.

For each plot, the standard deviation of snow depth was calculated independently for the manual observations and LiDAR. The coefficient of variation was not used due to misleading results as snow depths approach zero. Standard deviation was first compared separately for manual and LiDAR separately for each cover type, to establish whether the snow depth variability changes as snow melts.

Then, to assess whether LiDAR captures the same variability as the manual observations, the standard deviations were compared between the manual and LiDAR measurements.

The Levene's test was selected to assess for homogeneity of variance, as it does not require normality of data or equal sample sizes. The Levene's test was conducted for two different null hypotheses for each plot:

- Snow depths (LiDAR and manual observations separately) are equal in variance through the snow melt period, with number of groups (n) ranging between 2 and 5, dependant on number of surveys and/or manual observations per snow season
- ii) LiDAR and manual measurements captured equal variance (n=2)

Assumptions for the Levene's tests were that observations are independent, and the test variable is quantitative (not nominal or ordinal). Levene's test results were calculated with the SciPy python package, where a p-value of less than 0.05 at 95% confidence level rejects the null hypothesis for homogeneity of variance.

#### 4.3.3 Mean Snow Depth

To assess the accuracy of LiDAR within the different forest cover types, the average snow depth from manual sampling and LiDAR were compared for each plot. Mean difference (MD) was then calculated using the in-situ observations as the true measure of snow depth (Eq. 2). A positive value for MD indicates LiDAR over-estimation of snow depths and vice versa.

$$MD = \mu_{SD \ LiDAR} - \mu_{SD \ manual} \tag{2}$$

The Mann Whitney U test, a non-parametric statistical test, was selected to compare whether the LiDAR and manual measurements are equal in median. Again, this was selected for the less stringent assumptions, including:

- i) Two independent, non-paired samples
- ii) A minimum of 10 samples per group
- iii) Independence of observations

As with the previous statistical test, the manual and LiDAR snow depth measurements were not required to be normally distributed, or of equal sample size. The Mann Whitney test uses the rank sum of the snow depths, and the test statistic is calculated as the smaller of  $U_{manual}$  (Eq. 3) and  $U_{LiDAR}$  (Eq. 4)

$$U_{manual} = n_m n_L + \frac{n_m (n_m + 1)}{2} - R_m \tag{3}$$

$$U_{LiDAR} = n_L n_m + \frac{n_L (n_L + 1)}{2} - R_L$$
(4)

where *n* is the number of samples and *R* is the sum of the ranks, respective for the manual (m) and LiDAR (L) snow depth measurements. The test statistic was then compared to the critical value at the 5% significance level, and null hypothesis rejected if the test statistic exceeds the critical value.

A consistent MD within a particular cover type, ie. if LiDAR over- or under-estimates snow depth, may be the result of a systematic bias within the bare earth model. To establish the role of the bare earth model on LiDAR snow depth accuracy, the workflow described above was repeated with the 2017 BCTS bare earth model.

#### 4.3.4 Timing error and mitigation

A delay between LiDAR acquisition and manual sampling can be a source of error, as changes to the snowpack may occur between the two observations. A longer period of time between LiDAR and

manual sampling will generally increase the likelihood of snowpack change between the two observations, especially when in the snow ablation period. However, Geissler et al. (2023) noted a systematic bias due to snowpack settling in as short as a four-hour delay between manual sampling and LiDAR collection. To address this source of error, the weather station snow depth sensors and snow depth derived from the game camera stations were used to detect snow depth changes between the LiDAR and manual measurements. Plots which were forested (regenerating and old growth) used the nearest game camera imagery, and the more open plots (juvenile, alpine, and weather station snow courses) used the nearest weather station snow depth data. Relative change to the snowpack was calculated by subtracting snow depth observed on the date of the manual sampling, from the snow depth on the date of the LiDAR acquisition. The snow depth change value is referred to in the results as a meteorological bias correction.

A second timing-based error may incur when plots are manually sampled prior to the LiDAR acquisition. Here, there is potential for snow compaction from the survey team activities, which may result in an under prediction of the snowpack by LiDAR. Snow compaction is difficult to account for, as compaction may be non-existent when the snowpack is firm, or substantial in softer conditions. Ideally, approximate snow compaction was documented in field notes, however this was not a consistent protocol for each plot. Plots which were sampled prior to the LiDAR acquisition are noted in the results, but no error correction applied.

45

### 4.4 Watershed Scale Analysis

The final portion of the analysis describes total snow storage within the Russell Creek watershed. Here, the objectives were to assess:

- i) Snow distribution in the watershed, in terms of the forest cover types and elevation bands
- ii) How the snow distribution changes through the snow melt season
- iii) Whether biases observed at the plot scale were present when scaled to the watershed
- iv) The impact of the bare earth model to the proportion of snow stored by cover type and elevation band, as well as the total snow storage in the watershed

The interpolated (gap-filled) snow depth grids were used for the watershed scale analysis. The Russell Creek watershed was delineated from a 30 m SRTM DEM using ArcGIS Pro hydro tools, and the gapfilled snow depth grids were masked to the watershed extent. As the pixel size of the raster was 1 meter, snow volume for each pixel was calculated as:

Snow Volume 
$$[m^3] = (Snow Depth [m]) \times (1m^2)$$
 (5)

This process was completed using the snow depth grids generated with both the 2023 ACO and the 2017 BCTS bare earth model. For each snow survey, snow volume was aggregated by 200 meter elevation bands, as well as the cover type classifications.

# Chapter 5 : Results

This chapter summarizes meteorological and snowpack observations collected in 2022 and 2023, vegetation characteristics of the snow survey plots, and the plot scale mean and variability in snow depths from (a) ground surveys, (b) LiDAR measurements made with the 2023 ACO bare earth model, and (c) LiDAR measurements made with the 2017 BCTS bare earth model. The final portion of this chapter examines watershed-scale snow storage, the impacts of bare earth model selection, and the variability of snow storage across stand types.

### 5.1 Snowpack and Weather

Observations of air temperature from a selection of weather stations located in the Russell Creek watershed (Figure 3.5) were used to compare the 2022 and 2023 accumulation and melt seasons, and identify changes in snow depth (snow accumulation or melt) that occurred in the days between LiDAR acquisitions and in-situ snow depth sampling. Automated observations of snow depth were available at four weather stations.

Visual inspection of 2022 and 2023 snow depth and temperature records (Figure 5.1) show distinct differences in the snow accumulation and melt periods between seasons. Snow accumulation was slightly greater in 2022, and the timing of maximum snow depth was approximately 1 week earlier in the alpine in 2022 than in 2023. The snowpack melted rapidly in 2023, with a short period (26 - 42 days) between melt onset and snow-free conditions. In 2022, the snowpack persisted approximately one month later.

47



Figure 5.1 Hourly air temperature (upper) and snow depth (lower) data recorded from Steph 2(1164m) weather station, for water years 2022 and 2023

The 2022 snow season was the longest since 2017 at both the Steph 6 (827 m) and Steph 2 (1164 m) weather stations (Figure 5.2). The 2022 snowpack development started slow, but by the time of the first ACO flight was completed, snow depth was near average for the rest of the season and the second latest seasonal peak snow, before a rapid melt at Steph 2 and 6.



Figure 5.2 Snow depth records from 2016 - 2023 for Steph 6 (upper) and Steph 2 (lower) weather station, with the years of this study highlighted with a blue (2022) and red (2023) dashed line respectively. Of the 7 years of data shown for Steph 6 and Steph 2 weather stations. 2022 had the latest date on record for snow free, whereas 2023 had the second earliest

Air temperatures in March 2022 were warmer than March 2023, with average temperatures ranging from 0.4 to 2 °C across all stations (Table 5.1; Table 5.2). For April, May, and June the temperatures were warmer in 2023 than 2022. Notably, May 2023 had the greatest divergence in average monthly air

#### temperatures. When compared to the previous 7 years of weather station data, average monthly air

temperatures in the alpine were -3.3 °C cooler in 2022, versus 3.8 °C warmer in 2023.

		Average Air Temperature								
		March		April		May		June		
station	elevation	2022	2023	2022	2023	2022	2023	2022	2023	
Steph 8	576	2.6	1.4	2.3	3.5	6.0	11.2	11.0	12.1	
Steph 7	707	1.4	1.0	-	2.9	6.2	10.6	10.6	11.4	
Steph 6	813	1.1	0.1	0.6	2.3	3.8	5.6	9.4	-	
Steph 4	935	1.4	1.0	-	2.9	6.2	10.6	10.6	11.4	
Steph 3	1004	0.9	-0.4	0.1	0.9	3.3	8.6	9.2	9.7	
Steph 2	1158	-0.3	-1.8	-1.3	0.2	2.0	8.9	7.6	10.3	
Steph 1	1508	-2.3	-4.3	-3.8	-2.0	0.5	7.6	5.4	8.4	

Table 5.1 Average daily air temperature across all weather stations. Highlighted values represent that the temperature was higher between the two years, and a dash indicates there was no data for that month.

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Peak snow depths in 2022 were greater than 2023 at all weather stations, ranging from 8-26 % deeper (Table 5.2). With the exception of Steph 3, peak snow depth occurred 3 – 16 days later in 2022. The cooler temperatures in May 2022 resulted in the snowpack persisting 41 days longer at the alpine stations in 2022 than in 2023. Generally, snow melt periods were longer in 2022 than 2023 weather due to the greater antecedent snowpack.

Table 5.2 Summary of 2022 and 2023 snow depth measurements at four weather stations, selected for consistent snow depth data across 2022 and 2023. Metrics include: 1) peak snow depth and date, 2) length of melt period in days (defined as sustained loss of 0.5 cm per day) and rate of snow melt, and 3) snow free date

		peak snow depth (cm, date)		snow [cm/day, (d	loss rate lays of melt)]	Snow-free date	
station	elevation	2022	2023	2022	2023	2022	2023
Steph 6	813	125.8 (5-Apr)	91.9 (21-Apr)	4.3 (42)	4.3 (36)	28-May	6-May
Steph 3	1004	106.1 (5-Apr)	97 (3-Mar)	6.1 (8)	5.7 (13)	26-May	3-May
Steph 2	1158	212.2 (5-Apr)	170.3 (21-Apr)	5.1 (35)	6.1 (26)	23-Jun	18-May
Steph 1	1508	334.5 (13-Apr)	246.8 (16-Apr)	6.1 (47)	4.7 (42)	7-Jul	27-May

### 5.2 Vegetation Surveys

To evaluate the role of ground vegetation in LiDAR ground return point density, characteristics of the vegetation at each cardinal plot were collected in October, 2022. The height of ground vegetation is used here as a proxy for the vigour and density of ground vegetation that might affect LiDAR point densities.

Between 70 to 232 individual plant height measurements were collected at each cardinal plot (Figure 5.3; Table 5.3). Though a thorough species inventory was not collected, the most numerous species within the forested sites belonged to the genus *Vaccinium* (blueberries and huckleberries) and *Asplenium* (ferns), and *Phyllodoce* (mountain heathers) in the alpine. Vegetation measuring less than 5 cm in height and trees were not included in the results. Species were broadly categorized by whether they were a) woody debris, for example logs and stumps b) heather, or c) shrubs and ferns.

Vegetation	Shrubs and Ferns			V	Voody De	ebris	Heather		
Cover Type	μ [cm]	σ [cm]	% of total	μ [cm]	σ [cm]	% of total	μ [cm]	σ [cm]	% of total
Juvenile	116.3	44.9	84.7	71.2	66.6	15.3	n/a	n/a	n/a
Regenerating	78.8	87.8	88.1	72.8	55.1	11.9	n/a	n/a	n/a
Dense Old Growth	36.7	29.8	70.3	28.0	38.1	12.9	10.0	8.0	16.8
Old Growth	52.4	37.0	71.9	35.7	15.8	1.3	32.3	15.2	26.8
Alpine	26.5	26.3	57.1	n/a	n/a	n/a	19.5	10.0	42.9

*Table 5.3 Vegetation composition by cover type, summarized by the average height* ( $\mu$ ) *and the standard deviation* ( $\sigma$ ) *of the shrubs and ferns, woody debris, and heather.* 

i.

The average shrub height was greatest in the cardinal plots located in the juvenile and regeneratingforests, at 116 and 78 cm, respectively. The regenerating and juvenile forests had a high proportion of woody debris – stumps, logs, and slash piles – that are bi-products of the forest harvest, and they also had the greatest variability in shrub height of the cover types. Large canopy gaps and relatively small trees (less than 5 m) in juvenile forest stands allow for the ground vegetation to grow to greater heights. The tree and shrub layer were the least distinct within the juvenile forest, and in some cases the shrubs exceeded the tree heights.



Figure 5.3 Average vegetation height by cover type broken into the categories of shrub, woody debris, and heather. Vegetation measured 5 cm or less, as well as trees, were not included in the results. Error bars represent the 95% confidence interval.

The old growth forest was predominantly comprised of a single shrub layer, which was highest in the stands with large canopy gaps. As the canopy density increased in the cardinal plots, the average height of the shrub layer decreased. Alpine vegetation was predominantly low-lying mountain heather, with clusters of stunted trees and sparsely spaced shrubs. The alpine shrub layer was the lowest average height and the lowest variability of all the cover types.

Though ground vegetation layers were present at all cardinal plots, the harvested (juvenile and regenerating) cardinal plots were considerably more complex in terms of the height, density and

variability of the vegetation. As a result, the LiDAR ground earth model is likely to be less accurate in the harvested forests due to the a) potential misclassification of vegetation as ground, and b) reduced ground points due to the lasers inability to penetrate through the vegetation to the ground.

## 5.3 LiDAR Point Densities

The LiDAR snow surface point density returns varied by both the forest cover type, and the date of acquisition (Figure 5.4). Overall, as the snowmelt season progressed, the average point density decreased and the number of data gaps (pixels with zero ground returns) also increased (Figure 5.4). No changes were made to the planned snow survey density between the acquisitions.



Figure 5.4 Percentage of the cardinal plots which had at least one LiDAR ground or snow surface point return per  $m^2$ , grouped by forest cover type, for each LiDAR acquisition in 2022 (upper) and 2023 (lower). Hatched bars denotes acquisitions that were snow-free for all plots within the cover type. Error bars represent the 95% confidence interval.

With the exception of the regenerating forest, all plots in 2022 were snow-covered for each acquisition due to the late snow melt. As a result, 2022 had higher average point density per m<sup>2</sup>, as well as proportion of snow surface returns per plot than 2023. In contrast, the earlier snowpack meltout in 2023 led to reduced ground point densities in the snow-free acquisitions. This is interpreted as being the result of ground vegetation leaf-out, particularly in the juvenile and regenerating forests and between the May 25<sup>th</sup> and June 12<sup>th</sup> acquisition (Figure 5.5). An anomaly to this pattern occurs in April 2023 acquisition in the dense old growth forest, as the average proportion of ground point returns drops from 92% in the March 10<sup>th</sup> acquisition to 18% in the April 4<sup>th</sup>, despite snow conditions being stable. A less pronounced decrease in point density is also observed within the old growth in April 2023, but the overall decrease in returns through the melt season is consistent between the two acquisitions. Changes to the snow surface, i.e. reduced reflectivity of snow with vegetation emerging or forest debris, may also contribute to variability in the snow surface point density.

LiDAR A	Acquisition Date	Median GPD/m <sup>2</sup> (Mean proportion of ground returns per plot [%])						
Cover		juvenile	regenerating	dense old growth	old growth	alpine		
	Mar-9	5 (99.0%)	2 (66.6%)	2 (83.3%)	2 (91.6%)	3 (97.6%)		
22	Apr-11	5 (99.4%)	3 (71.5%)	2 (85.8%)	3 (93.6%)	3 (99.6%)		
20	May-21	5 (97.4%)	2 (58.6%)	1 (69.1%)	2 (89.4%)	3 (98.2%)		
	Jun-24	3 (84.0%)	1 (37.5%)	1 (69.2%)	2 (85.0%)	2 (85.8%)		
	Mar-10	5 (98.5%)	2 (62.9%)	2 (92.2%)	3 (94.0%)	4 (97.8%)		
	Apr-4	3 (95.4%)	1 (50.5%)	1 (18.7%)	1 (57.4%)	3 (98.6%)		
2023	Apr-29	3 (96.6%)	2 (49.6%)	2 (75.8%)	2 (87.1%)	3 (98.3%)		
	May-25	1 (53.6%)	1 (32.9%)	1 (57.4%)	1 (71.5%)	2 (64.2%)		
	Jun-12	1 (14.2%)	1 (12.4%)	1 (57.4%)	1 (65.1%)	2 (66.8%)		

Table 5.4 Median ground point density per meter squared for the snow surveys, as well as the average proportion of valid pixels per each of the cover types

Despite highest canopy cover occurring in the dense old growth forest, the overall lowest proportion of snow surface and ground returns per plot was found in the regenerating forest, ranging from an average

high of 71.5% in high snow accumulation conditions, to a low of 12.4% when snow free. The alpine had the fewest gaps in ground returns, and median point returns of 3 - 4 points  $m^{-2}$  in high snow accumulation conditions, and 2 point  $m^{-2}$  in intermittent to snow-free conditions.

The greatest variability in the point density occurred in the juvenile forest. In snow-on conditions, minimal canopy cover resulted in high point density and less than 10% of data points missing per plot. As the snowpack thinned and melted, and vegetation exposed, the median point density dropped to 1 point per m<sup>2</sup>, and only 14.2% of ground points per plot.



Figure 5.5 Imagery of the juvenile forest from the (A) May 25<sup>th</sup> 2023 and (B) June 12<sup>th</sup> 2023 acquisitions showing the green up of the vegetation

# 5.4 In-situ vs LiDAR Snow Depths

LiDAR-derived snow depths, were compared with in-situ observations made at the weather stations and cardinal plots. Weather station data was used to establish to what extent the snowpack conditions changed between the time of the LiDAR survey and in-situ measurements. The mean difference (MD) and standard deviation (SD) was compared between the different forest cover types.
# 5.4.1 Snow depths Validation

In-situ snow depth sampling was targeted to overlap with the LiDAR acquisitions, however this was not always possible due to weather conditions and other logistics. In general, the manual observations took place within 3 days pre- or post-LiDAR (Table 5.5). An exception to this was the June  $24^{\text{th}}$  2022 acquisition, which occurred 6-10 days after the manual measurements. As this survey occurred during the snowpack ablation period, automated snow depth observations indicate that a large loss of snow (35 – 55 cm) occurred between manual sampling and the LiDAR acquisition (Table 5.5).

Table 5.5 Summary table of LiDAR and manual dates for 2022 and 2023 and how the snow depth changed within that time frame. Snow
depth change includes the SR50 data of all seven weather stations in Russell Creek, provided the sensor was collecting data in that time
frame

Year	LiDAR acquisition date	Manual sampling	SR50 snow depth change
	March 9th	March 8 <sup>th</sup> - March 10th	-1 cm to 2 cm change from manual sampling to LiDAR acquisition
2022	April 11th	April 5 <sup>th</sup> - April 10th	18 – 25 cm increase from the start of the manual sampling to LiDAR acquisition
	May 21st	May 21 <sup>st</sup> - May 25th	16 – 24 cm loss from LiDAR acquisition to end of manual sampling
	June 24th	June 14 <sup>th</sup> - June 18th	35 – 55 cm loss from start of manual sampling to LiDAR acquisition
	March 10th	March 9 <sup>th</sup> - March 13th	-2 to 2 cm change from manual sampling period to LiDAR acquisition
2022	April 4th	April 5 <sup>th</sup> - April 7 <sup>th</sup>	-1 to 1 cm change from LiDAR acquisition to manual sampling
2025	April 29th	April 26 <sup>th</sup> - April 27th	13 – 22 cm of loss from the manual sampling period to LiDAR acquisition
	May 25th	May 23 <sup>rd</sup> - May 25th	7 cm loss at Steph 1 recorded from start of manual sampling period to LiDAR acquisition
	June 12th	n/a	Snow free at plots and weather stations

LiDAR surveys in 2023 were generally aligned closer to the manual sampling windows than in 2022. Manual sampling occurred in the days immediately prior to the April 29<sup>th</sup> LiDAR survey, yet a rapid rise in temperature resulted in an average of 17 cm snow loss between start of sampling and the LiDAR survey (Figure 5.6).



Figure 5.6 Steph 2 weather station showing the change in average daily snow depth which occurred between the manual sampling window and the LiDAR survey for the April 29<sup>th</sup> 2023 acquisition

### 5.4.1.1 Weather Station Snow Courses

The weather station snow courses (with the exception of Steph 1) are conducted on gravel resource roads, and are therefore free from bias introduced by ground vegetation. Across the 2022 snow year, the 3<sup>rd</sup> of March survey had the lowest bias error between the LiDAR and manual sampling, with mean difference (MD) ranging from – 6 to 8 cm (Figure 5.7). This snow course represents the 'ideal' comparison between manual and LiDAR-derived snow depths, as it was conducted shortly after the March 9<sup>th</sup> LiDAR acquisition, with no disturbance to the snow surface from manual sampling, and the weather was stable with no accumulation or melt (Table 5.5). The greatest MD occurred in the June 24<sup>th</sup> acquisition, in which snow depth was underestimated by 37 to 56 cm due to melt between the snow course and LiDAR acquisition. A comparison of the snow-on and snow-free plots from the June survey

show a much reduced, though positive bias for the snow free plots, confirming the large negative bias is a result of the changes to the snowpack (Figure 5.7).



Figure 5.7 The mean difference for snow courses from the 2022 and 2023 snow season. A 10 day delay between the LiDAR acquisition and manual sampling -which coincided with a period of snow melt - is attributed to the large negative bias for June 24<sup>th</sup> 2022

In 2023, the greatest deviation between the manual and LiDAR snow depths occurred in April, where the April 29<sup>th</sup> LiDAR acquisition underestimated snow depth by 14 to 24 cm. This again coincided with a melt period between the manual sampling and LiDAR acquisition (Figure 5.6). The snow courses which were snow-free, Steph 7 and Steph 8, had a MD of -2 and 6 cm respectively, which indicates that snowpack changes between manual and LiDAR surveys were responsible for the observed bias.

In general, the systematic error was greater in plots in which LiDAR was acquired after the manual sampling occurred as opposed to before, as well as if it had snowed or melted in between the manual surveys and LiDAR acquisition (Figure 5.8). This suggests that both meteorological variability as well as potential snowpack interference from manual sampling can explain some of the systematic error for specific surveys.



Figure 5.8 2022 and 2023 snow-on surveys mean difference grouped by whether LiDAR was flown pre or post manual sampling, and the snow depth change between acquisition and sampling. Snow depth readings are compiled from the weather stations in Russell Creek, Steph 1-8.

### 5.4.1.2 Cardinal Plots

The cardinal plots were situated in more complex terrain than the weather station snow courses, with varying degrees of canopy cover and ground vegetation (see Table 3.3 and Figure 3.3). Over each of the 314 m<sup>2</sup> plot, the average snow depth of 33 in-situ measurements was compared to a maximum of 312 LiDAR measurements, dependent of pixels with at least one ground return point within the plot. Overall, systematic differences between LiDAR and manual snow depth observations at the cardinal plots were found to be related to the forest cover type.

As identified previously, changes to the snowpack that occur between LiDAR acquisition and manual sampling will affect the mean difference. To account for sources of accumulation or melt error, weather station snow depth sensors at nearby meteorological stations were used to estimate the snowpack change in the alpine and juvenile sites between manual and LiDAR surveys, while game camera images of snow stakes were used to evaluate snow depth changes in the forested sites. When the LiDAR was flown after

the manual measurements, compaction of the snow surface during manual snow sampling may introduce additional errors, depending on snow conditions. Plots in which the LiDAR was captured after manual sampling occurred are marked with a star, but no offset applied.

Despite a significant melt period between manual sampling and the June 24<sup>th</sup> 2022 LiDAR acquisition (Table 5.5), these data will still be used within the validation of snow depths, as the meteorological bias correction applied should counteract the melt. However, data from this survey will be omitted from the aggregated results.

### 5.4.1.2.1 Alpine

Differences in manual and LiDAR derived snow depths were inconsistent between acquisitions (Figure 5.9), however not all plots were sampled every time due to elevated avalanche hazard. In 2022, alpine plots were sampled for three of the four LiDAR surveys. The lowest mean difference (-7 cm) was observed during the first acquisition. While the May 21<sup>st</sup> LiDAR survey showed average snow depths 40 and 50 cm greater than the manual survey, this was reduced by a correction of 10 cm to account for snow melt that occurred between the LiDAR and manual measurements. In contrast, the negative bias for the June 24<sup>th</sup> survey is consistent with the snow melt which occurred between LiDAR flight and manual sampling (see Table 5.5).

For 2023, all five of the acquisitions were sampled, but the final acquisition were all verified snow free. Overall, MD was lower in 2023 for the alpine plots, ranging from -20 to +11 cm across all surveys with snowpack conditions that were stable between LiDAR and manual surveys. In snow-free conditions, MD was reduced to -4 and -2 cm, showing good agreement between the bare earth surfaces within the plots.



Figure 5.9 Alpine cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Meteorological corrections from the weather station snow depth data is denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual measurements. Hatched bars indicate plot was snow free.

### 5.4.1.2.2 Old Growth

Bias was similar across acquisitions and plots for the dense old growth forest (bias across all

acquisitions and plots. For both years, LiDAR snow depths were 3 to 33 cm lower than manual

observations (Figure 5.10). After the snow melt correction was applied to the June 24th 2022 acquisition,

the LiDAR snow depths were slightly higher than manual observations.



Figure 5.10 Dense old growth cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Meteorological correction applied using the game camera data is denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual measurements. Hatched bars indicate plot was snow free.

The highest MD (29 to 33 cm) for 2023 occurred on the April 29<sup>th</sup> survey, which may be attributed to the manual measurements occurring prior to LiDAR acquisition. Field notes documented approximately 10 cm compaction - as well as rapid warming and melt (see Table 5.5). In the one day between manual sampling and the LiDAR survey on April 29th, the forest game camera situated in nearby forest stand (ST1GC1) show an average 10 cm of melt (Figure 5.11). When conditions were snow-free, the bias remained negative, suggesting a consistent bias to the ground surface model in the dense canopy forest.



Figure 5.11 Game camera STIGC1 showing the rapid snow melt which occurred, with a loss of approximately 10 cm between 10 am on the 28th of April to 3 pm on the 29th of April 2023. Snow stakes are marked by 20 cm increments.

Manual and LiDAR-derived snow depths in the old growth plots were characterized by higher snow depths and variability (Figure 5.12). The median of the mean difference in snow depth was -17 cm. No significant differences in snow depths were observed for the March 9<sup>th</sup> 2022 LiDAR survey. For the May 21<sup>st</sup> 2022 survey, the LiDAR overestimated the snow-pack by an average of 82 cm for plot ST10G3, which was reduced to 74 cm after a correction for melt was applied. Notably, a) ST10G3 is situated in a steeper terrain, and is the highest of the old growth sites, and b) the May 21<sup>st</sup> survey also saw an over-estimation of snow depth in the two alpine plots. The greatest bias for old growth plots OG7 and OG8 – which are spatially closest together – occurred on the April 4<sup>th</sup> 2023, where LiDAR underestimated the snowpack by average of 57 and 103 cm respectively. The snow conditions were stable, sampling occurred post-LiDAR surveys, and manual measurements have been checked for error. However, this is consistent with the reduced proportion of snow surface returns shown in Figure 5.4.



Figure 5.12 Old growth cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Error corrected using the game camera imagery is denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual measurements. Hatched bars indicate plot was snow free.

### 5.4.1.2.3 Regenerating

In the regenerating forest plots LiDAR consistently over-estimated snow depths by 25 to 106 cm (Figure 5.13). Biases in snow depth during three snow-free acquisitions (i.e. snow depth should be zero) ranged from +160 to -30 cm, which indicates poor agreement between the snow-free elevations and the ground surface model. Plot ST6GC1 generally had the lowest MD (29 to 56 cm) in snow-on conditions, and is a denser forest canopy than both ST4RF1 and ST4RF2.



Figure 5.13 Regenerating cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Error corrected using the meteorological or game camera data is denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual measurement. Hatched bars indicate plot was snow free.

### 5.4.1.2.4 Juvenile

LiDAR over predicted snow depth in the juvenile forest cover in both snow years, though at much different magnitudes between the two plots (Figure 5.14). Of all the cover types, the juvenile plots showed the greatest error variability in snow-on conditions (32 to 127 cm), despite being similar in topography. Plot ST2CC2 had a MD which was consistently in a range three times greater than that of ST2CC1. Notably, as the vegetation greened up, the snow free error changed from positive on the May 25<sup>th</sup> survey (31 and 127 cm) to negative on the June 12<sup>th</sup> (-9 and -27 cm).



Figure 5.14 Juvenile cardinal plots mean difference between LiDAR and in-situ snow depth measurements for the 2022 and 2023 surveys. Error corrected using SR50 snow depth sensor denoted with the darker bars, and asterisk mark if LiDAR was acquired after manual measurement. Hatched bars indicate plot was snow free.

### 5.4.1.3 Summary

Overall, differences between the LIDAR and manual snow depth measurements were greater in the cardinal plots (characterized by complex terrain and a range of ground and canopy covers) than the weather station snow courses (characterized by graded surfaces with no ground vegetation or canopy cover; Figure 5.15). Though the meteorological corrections proved beneficial to some plot biases, the results were mixed, and in some cases bias increased. Therefore, MD ranges will be reported for the non-meteorological corrected version, with the June 24<sup>th</sup> 2022 survey excluded due to the significant melt which occurred (Table 5.5).

The Median MD for the weather station snow courses were -4 and -6 cm for 2022 and 2023 respectively. The greatest MD occurred in the regenerating (median MD: 55 cm) and juvenile (median MD: 76 cm) stands, with LiDAR generally over-predicting snow depth in the harvested stands. Ground vegetation in the regenerating and juvenile stands was notably much higher and more complex than the other cover types. Snow depths in regenerating plots were consistently overestimated by LiDAR across all three of the plots, with MD between +12 to +106 cm (Figure 5.14). The two juvenile plots were similar in topography, canopy cover, and ground vegetation, however they had two distinctly different ranges in MD (2 to 41 cm and 121 to 150 cm). Old growth forest plots had a general negative bias, with, a smaller range of MD observed in the denser canopy sites (-25 to -6 cm) than the more open sites (-58 to 4 cm; excluding ST1OG3, complex, sub-alpine plot). Alpine plots were inconsistent between snow years, with a mostly positive, and wider MD range in 2022 (-6 to 50 cm), and a negative range in 2023 (-18 to -4 cm). However, only three pairs of LiDAR and manual measurements are included for 2022. As observed with the weather station snow courses, the snow depth bias observed at the cardinal plots was generally reduced when sampling took place shortly after the LiDAR acquisition, when minimal changes to the snowpack had occurred.



Figure 5.15 Boxplots of the mean difference for each plot by cover type, with "open" referring to the weather station snow courses. For each vegetation type, the left box represents 2022 data and the right box 2023. For 2022, phase 4 has been excluded due to the noted offset due to delay in LiDAR acquisition and manual sampling, and subsequent snow melt. The box shows the quartiles of the dataset, with whiskers extending to points within 1.5 x the inter-quartile range. Observations outside of this range are displayed as points.

In addition to the forest cover and ground vegetation, slope is a topographic parameter which will impact LiDAR accuracy (see sec 2.1.3). The sampling strategy of this thesis focused on forest composition, and did not target slope angle to assess LiDAR accuracy due to both the well-established relationship between slope angle and LiDAR error (eg. Painter et al. 2017), as well as challenges of manual sampling in steep terrain. Therefore the average slope angle of the plots did not exceed 35 degrees, and, as a result, there was no clear relationship between the gradient of the plot, and the mean absolute bias (Figure 5.16).



Figure 5.16 Scatterplot of the slope angle of the cardinal plots and the mean absolute bias error for the 2022 and 2023 LiDAR surveys. Each marker represents the mean absolute bias error of the cardinal plot, color coded by cover type, and the vertical bars represent +/- sigma.

### 5.4.2 Variability of Observed Snow Depths

The spatial variability of snow depth is an important parameter (Lopez-Moreno et al., 2011) that may vary through the accumulation and melt seasons (Grunewald et al., 2010). However, there are few comparisons between LiDAR-derived and manual snow depth that specifically investigate the snow depth variability at the plot scale. This section summarizes the variability of snow depths measured (a) manually and (b) with airborne LiDAR scans at the snow courses and cardinal plots throughout the snow melt season.

### 5.4.1 Weather Station Snow Courses

Snow depth variability from both manual (Table 5.6) and LiDAR-derived (Table 5.7) snow depth observations were greatest at Steph 1, where standard deviation ranged from 16 to 31 cm across all three acquisitions. Steph 1 is an alpine site with reduced canopy and high wind exposure which results in greater wind transport of snow. As well, the ground surface of the Steph 1 snow course is much more variable than the rest of the weather station snow courses.

The lowest snow depth variabilities for both manual and LiDAR observations occurred in the low elevation and sheltered snow courses (Steph 8 and Steph 7), which do not receive much direct sun or wind. Manual observations yielded standard deviations between 3.0 and 5.2 cm at these sites, while LiDAR observations gave standard deviations between 7.4 and 12.1 cm. Overall, the snow depth variability did not change through the snow melt period for the manual nor LiDAR, though Steph 2 showed statistically different variance between sampling periods in 2022.

For the weather station snow courses, the manual sampling and LiDAR observations captured similar snow depth variability across both melt seasons (Figure 5.17). Of the 46 instances of manual and LiDAR comparison measurements, only 6 were statistically different in variability (full results in Appendix D).

These six occurred at lower elevations and were spread over all acquisitions. Both manual and LiDAR snow depth measurements identified the same sites as having the greatest snow depth variability (Steph

1 and Steph 3).

Table 5.6 Standard Deviation (SD) of the in-situ snow depth observations at each weather station snow course. Snow courses which were snow free are shaded blue. To assess whether the in-situ snow depth variability changed as snow melted, the Levene's test was conducted, where for each weather station and year, each groups (LiDAR survey) variance were compared to each other. Snow free and no data surveys were not included as groups.

In-situ Observations - Snow Depth Standard Deviation (cm)								
Weat	her Station	Steph 1	Steph 2	Steph 3	Steph 4	Steph 6	Steph 7	Steph 8
	9-Mar	33.0	4.5*	5.3	7.5	4.7	5.2	4.1
22	11-Apr	-	4.5*	14.9	8.4	3.3	4.8	3.0
20	21-May	29.9	10.7*	8.6	10.5	4.4	0.0	0.0
	24-Jun	30.3	4.6*	0.0	0.0	0.0	0.0	0.0
	10-Mar	16.9	3.9	5.4	5.0	3.1	2.3	1.7
ŝ	4-Apr	29.5	4.2	6.3	5.2	5.5	1.8	1.6
2023	29-Apr	-	7.3	7.7	5.9	4.4	0.0	0.0
	25-May	22.9	0.0	0.0	0.0	0.0	0.0	0.0
	12-Jun	0.0	0.0	0.0	0.0	0.0	0.0	0.0

\* Statistically significant at a p-value of 0.05.

Table 5.7 Standard Deviation of the LiDAR collected snow depth at each weather station snow course. Snow courses which were snow free are shaded blue. To assess whether the LiDAR snow depth variability changed as snow melted, the Levene's test was conducted, where for each weather station and year, each groups (LiDAR survey) variance were compared to each other. Snow free and no data surveys were not included as groups.

LiDAR - Snow Depth Standard Deviation (cm)								
Weat	her Station	Steph 1	Steph 2	Steph 3	Steph 4	Steph 6	Steph 7	Steph 8
	9-Mar	25.0	7.1*	9.1*	4.1	6.9*	9.3	7.4*
22	11-Apr	27.5	5.9*	15.5*	6.7	5.8*	12.1	8.7*
20	21-May	33.5	6*	13.7*	7.5	9.1*	8.3	6.0
	24-Jun	35.7	8.2*	5.1	4.5	6.5	8.3	8.5
	10-Mar	16.8	6.5	10.8*	3.8	5.4	7.5	4.9
ŝ	4-Apr	25.5	6.3	10.5*	4.1	7.0	8.3	4.1
2023	29-Apr	22.3	6	9.6*	7.8	8.6	6.3	4.2
	25-May	21.1	5.1	1.6	4.8	5.4	7.5	4.4
	12-Jun	2.7	3.5	2.8	3.3	9.3	8.6	5.1

\* Statistically significant at a p-value of 0.05



Figure 5.17 Snow distribution for Steph 1 weather station snow course for each LiDAR survey in 2022, showing the manual (red) and LiDAR (blue) snow depth distribution. None of the measurements were significantly different in snow depth variability. The offset between the LiDAR and the manual sampling in the June 24<sup>th</sup> acquisition is due to the snow melt which occurred between manual sampling and LiDAR survey. No in-situ measurements were taken at Steph 1 on April 11, 2022.

### 5.4.2 Cardinal plots

Snow depth variability was greater at the cardinal plots than at the weather stations for both the manual and LiDAR observation (Table 5.8; Table 5.9). While alpine sites were inconsistently sampled due to varying avalanche conditions, snow depth variability calculated using both manual and LiDAR observations was relatively stable through the 2022 and 2023 snow melt seasons.

Table 5.8 Standard deviation for in-situ snow depth measurements for the cardinal plot sampled across 2022 and 2023. Cells highlighted blue indicate snow-free. To assess whether the in-situ snow depth variability changed as snow melted, the Levene's test was conducted, where for each plot and year, groups (LiDAR survey) variance were compared to each other. Snow free and no data surveys were not included as groups.

In-Situ measur SI	ements D (cm)	9-Mar	11-Apr 50	21-May	24-Jun	10-Mar	4-Apr	2023-Apr 229-Apr	25-May	, 12-Jun
oine	ST1A1	25.5	-	34.6	27.8	30.0	37.3	-	28.2	0
Alı	ST2A2	-	-	44.5	46.9	30.8	38	-	34.9	0
vth	ST1OG3	-	-	57.8	44.1	39.2	42.3	-	26.2	0
Gro	ST1OG7	34.7	46.9	41.7	36.8	26.0*	37.1*	40.2*	21.1*	0
0	ST1OG8	44.8	46.4	44.3	39.9	33.2*	51.4*	43.4*	16.3*	0
wth	ST10G4	-	30*	17.3*	13.6*	21.3*	15.8*	21.3*	0	0
Gro	ST1OG5	24.6	29.1	28.0	19.8	21.3*	29.4*	25.9*	5.1*	0
DO	ST1OG6	21.3	28.7	25.5	20.1	22.4*	19.1*	18.2*	5.8*	0
g.	ST4RF1	54.2*	40.7*	30.1*	0	24*	30.9*	33.2*	0	0
lege	ST4RF2	37.6	40.3	46.7	0	27.5	27.2	34.3	0	0
<b>K</b> .	ST6GC1	33.2*	55.3*	29*	0	29.7*	35.5*	27.9*	0	0
enile	ST2CC1	-	51.2*	46.4*	5.4*	25.4	34.3	40.8	0	0
Juve	ST2CC2	-	30.2*	46.5*	17.6*	23*	26*	34.6*	0	0

\* Statistically significant at a p-value of 0.05

Open canopy old growth forest plots had the greatest snow depth variability among the manual observations (SD = 16.3 to 57.8) but not in the LiDAR (SD = 21.1 to 61.5 cm) observations, and the highest snow depth variability coincided with the timing of the greatest average snow depth in both years (April acquisitions). With both snow depth observation types, plot ST1OG3 stands out with higher variability in snow depths due to its location in the sub-alpine and greater exposure to wind. At all old growth sites and in both datasets and seasons, snow depth variability decreases from the maximum snow depth through to the end of the melt season.

Dense old growth forest overall had less variable snow depths than open canopy sites in both manual (SD = 5.1 to 30.0 cm) and LiDAR (SD = 7.1 to 26.1 cm) observations, and was the least variable

snowpack across all the forest cover types. Similar to the old growth, snow depth variability was consistent across all acquisitions and observation types for 2022, and more variable in 2023 as the plots were largely snow free by the May 25<sup>th</sup> acquisitions.

Regenerating and juvenile plots showed no change in snow depth variability as the melt seasons progressed, and had the highest variability observed with the LiDAR observations (SD = 46 to 93 cm). This variability is likely due to ground features endemic to harvested terrain, such as the stumps, slash piles and compressed shrubs. Leaf-out in the spring would also affect the variability observed through the LiDAR observations (but not the manual probing).

Table 5.9 Standard deviation for LiDAR cardinal plot snow depth measurements across both years. Cells highlighted blue indicate snowfree. To assess whether the LiDAR snow depth variability changed as snow melted, the Levene's test was conducted, where for each plot and year, groups (LiDAR surveys) variance were compared to each other. Snow free and no data surveys were not included as groups.

Standa I	rd Deviation (cm) .iDAR	9-Mar	11-Apr 205	21-May	24-Jun	10-Mar	4-Apr	2023 - 2023	25-May	12-Jun
oine	ST1A1	32.1	36.2	36.0	34.4	32.1*	32.9*	33.5*	17.2*	10.8
Alı	ST2A2	35.2	34.2	28.5	32.5	28.8	30.5	32.8	26.9	22.9
wth	ST1OG3	51.8*	61.5*	52.3*	41*	34.7*	27.2*	33.5*	25.5*	10.8
Gro	ST10G7	33.5*	44.3*	39.7*	36.7*	26.4*	28.4*	29.3*	23.3*	10.9
Old	ST1OG8	34.7*	41.3*	36.4*	32.6*	26.3*	31*	25.6*	21.1*	19.5
plc h	ST10G4	20.5*	23.7*	23.7*	18.5*	13.5*	7.1*	13.9*	10.8	9.8
nse ( rowt	ST10G5	23.6*	26.1*	26*	16.8*	17.9*	12.3*	20.1*	10.2*	10.2
Der	ST1OG6	18.2*	22.7*	20.7*	16.4*	14.0*	12.8*	16.4*	11.4*	9.1
u.	ST4RF1	80.0	85.2	78.4	93.1	83.3	76.1	72.2	72.2	32.5
nile Rege	ST4RF2	66.0	62.6	67.7	88.1	61.1	62.3	63.6	65.0	59.7
	ST6GC1	75.6	75.8	70.0	81.7	71.4	69.9	74.2	67.7	41.2
	ST2CC1	58.2	62.3	61.0	60.4	58.1	57.7	59.4	55.0	80.5
* Juve	ST2CC2	53.5	50.9	51.1	63.6	57.4	54.4	52.6	58.0	46.0

\* Statistically significant at a p-value of 0.05

Only two of the cardinal plots were equal in variance between the manual and LiDAR measurements for every acquisition: the alpine plot ST1A1, and old growth plot ST1OG7 (Figure 5.18). Of the cover types, the old growth forest had the most cases of equal variance between the manual and LiDAR, with only 13% significantly different in variance through the snow melt period (full results table in appendix D).



Figure 5.18 KDE plot for 2022 showing the variability of snow depth for old growth plot ST1OG7. None of the survey dates were significantly different in snow depth variability between the in-situ and LiDAR

The majority of the regenerating and juvenile sites were significantly different in variability between the manual and LiDAR measurements (89% and 84% of all plots respectively). In each case, the LiDAR snow depth variability was greater than the manual observations (Figure 5.19).



Figure 5.19 KDE plot for the regenerating forest plot ST4RF1 for 2022. The snow depth distribution was significantly different across all phases between the in-situ and LiDAR. For the  $24^{th}$  of June survey, the 33 in-situ measurements not visible on the graph recorded zero snow.

# 5.5 Bare Earth DEM

To assess bias which may be inherent to the bare earth acquisition, the snow depth analysis was re-run with an alternative bare earth model for Russell Creek, a BCTS acquisition flown in 2017. Here, the manual to LiDAR snow depth validation results are compared between both models to assess whether the errors differ by cover type. Additionally, the LiDAR ground point coverage and density per each plot is compared between the bare earth models.

Validation results for the weather station snow courses, conducted on stable ground with no canopy cover (open), are relatively uniform using either the 2017 or 2023 bare earth DEMs (Figure 5.20). However, distinctly different errors were produced within the juvenile, regenerating and dense old growth forest when processed with the 2017 bare earth model.



Figure 5.20 Boxplot comparing the mean difference of plot snow depth for the manual observations and LiDAR across both years, with open cover representing the weather station snow courses. Blue boxes represent results of the 2017 BCTS model, and the orange boxes are of the 2023 bare earth model. The box shows the quartiles of the dataset, with whiskers extending to points within 1.5 x the inter-quartile range. Observations outside of this range are displayed as points.

The juvenile plots had the greatest MD range between plots with the 2023 BCTS model (-27 to 134 cm), whereas with the 2017 BCTS model, it had the lowest MD ranges across the cardinal cover types (-13 to 29 cm). The juvenile forest low MBE was consistent for both of the plots for the 2017 model, versus the inconsistent results with the 2023 model. Within the regenerating forest plots, bias shifted from generally positive with the 2023 bare earth model (median MD = 45 cm), to predominantly negative (median MD = -30 cm) with the 2017 model, though both had a wide range in error (>80 cm). Error increased in the dense old growth forest with the 2017 bare earth model, with LiDAR over-estimating the snow depth in the range of 25 - 86 cm across all acquisitions. However, the old growth

with larger canopy gaps did not over-estimate snow, and the MD was the most consistent between

models of all the cardinal cover types.

Overall, the percentage of the plots with valid ground return points is greater in the 2017 model than the 2023, but to varying degrees across the different cover types (Figure 5.21). The greatest discrepancy occurs in the juvenile forest plots, with ground point returns is on average 95% coverage with the 2017 model – akin to the alpine - and drops to 35% with the 2023 model. The standard error for the juvenile is also much greater, due to the inconsistency between the two plots. The regenerating forest plots are the lowest proportion (24 - 25%) and most consistent result between both models.



Figure 5.21 Bar graphs to show the comparison of the two bare earth models - 2017 BCTS (hatched) and 2023 ACO (non-hatched) showing the total ground points per plot, broken down by point density per meter squared (top) and the proportion of the plot which had valid ground returns (bottom). Bars represent the average of the cardinal plots by each cover type, and error bars represent standard error

With the exception of the juvenile forest, the 2023 bare earth model had more total ground points per plot than the 2017 model. Despite a greater proportion of data gaps, the point density was higher in the 2023 model, resulting in overall a higher number of ground returns per plot. Notably, the dense old growth forest, which over-predicts snow depth in the 2017 model, is almost entirely comprised of single

point returns in the 2017 model. The juvenile forest is the exception; total ground point returns for the juvenile forest plots are approximately double within the 2017 model versus the 2023.

# 5.6 Watershed Snow Storage

Total snow volumes were calculated for the Russell Creek watershed with both the 2017 BCTS and 2023 ACO bare earth models using interpolated (gap-filled) rasters (Figure 5.22). Using the 2023 bare earth model resulted in greater snow volumes (3-6%) across all LiDAR acquisitions.

Consistent with the meteorological observations (Sec. 5.1), peak snow storage in 2022 was captured in the April 4<sup>th</sup> acquisition, and substantial snow volumes persisted in the watershed until the last survey on June 24<sup>th</sup>. In 2023, peak snow storage was captured on the March 3<sup>rd</sup> survey, with significant melt (76 – 82% of snow volume) occurring between the April 4<sup>th</sup> and May 25<sup>th</sup> acquisitions. The watershed was largely snow free, with intermittent snow in the alpine, for the final acquisition on June 12<sup>th</sup> 2023. Overall, peak snow storage captured in 2022 was 28% greater than in 2023. For the 2023 snow surveys,



Figure 5.22 Comparison of the total snow storage in the Russell Creek watershed between the 2017 BCTS model, and the 2023 ACO model for each snow survey, broken down by forest cover type. Grey bars for the 12<sup>th</sup> June 2023 represent that the snow volumes were negative overall.

# 5.6.1 Snow Volumes by Elevation

Across all acquisitions, peak snow volumes were observed between 1200 and 1400 meters (Figure 5.23).

In 2022, more snow was stored below 800 meters, (20 - 33%) and stayed through until the June

acquisition. Contrasted with 2023, from the April 4th survey onwards, less than 9% of total snow is

stored in the lower 800 meters. The choice of bare earth model had negligible impacts on the distribution

of snow volume by elevation, with the exception of the 1400 - 1700 m range.



Figure 5.23 Snow volume by elevation band for the 2017 BCTS model (red) and the 2023 ACO model (blue), showing the 2022 (top) and 2023 (bottom) LiDAR surveys

The pattern was consistent between all acquisitions as to which bare earth model predicted more snow per elevation band. With the exception of two elevation bands, the 2017 bare earth model predicted more snow than the 2023 model across all acquisitions, but not by a substantial volume overall. However, as the 2023 bare earth model predicted a much greater (28 - 44%) volume of snow in a sub-alpine and alpine elevation band (1400 - 1700 m), overall the 2023 total snow storage was consistently higher.

Table 5.10 Snow storage by elevation band, with percent of overall snow stored in the Russell Creek watershed shown in brackets,
between the two different bare earth models (2017 vs 2023), for the 9th of March 2022 and 10th March 2023 acquisitions. Highlighted
values indicated which model predicted the greater snow volume per elevation band.

Date Flown	3/9/	2022	3/10/2023		
Bare Earth	2017, BCTS	2023, ACO	2017, BCTS	2023, ACO	
	m <sup>3</sup> (percent of to	tal snow volume)	m <sup>3</sup> (percent of to	tal snow volume)	
200 - 400	432,489(1.3%)	438,489(1.3%)	103,995(0.3%)	120,090(0.3%)	
400 - 600	3,327,715(10.2%)	2,879,070(8.4%)	2,417,108(7.2%)	1,829,453(5.3%)	
600 - 800	3,425,212(10.4%)	3,314,036(9.7%)	3,254,608(9.8%)	2,925,779(8.5%)	
800 - 1000	4,706,684(14.3%)	5,126,971(15.0%)	5,490,746(16.4%)	5,883,739(17.1%)	
1000 - 1200	5,641,676(17.2%)	5,231,501(15.3%)	7,120,985(21.3%)	6,715,517(19.5%)	
1200 - 1400	9,030,259(27.5%)	8,791,304(25.7%)	10,044,987(30.1%)	9,755,978(28.3%)	
1400 - 1700	6,237,263(19.0%)	8,404,252(24.6%)	4,952,145(14.8%)	7,211,324(20.9%)	
Total	32,801,298	34,185,623	33,384,574	34,441,880	

# 5.6.2 Snow Volumes by Forest Cover

The majority of snow in Russell Creek is stored in the alpine and old growth forest (Figure 5.22). The alpine makes up only 6.8% of the watershed by area, but contains 32 - 58% of the total snow storage, regardless of the bare earth model used (Figure 5.22). Though total snow volume decreases, the proportion of snow stored in the alpine increases steadily by acquisition date, as the lower elevation portions of the watershed loses snow. Old growth forest is the dominant forest type at higher elevation where a deeper snowpack develops (see Figure 3.3), so it contains a higher relative proportion of the total snow volume.

Table 5.11 Snow storage by cover type, with the percent of overall snow stored in the Russell Creek watershed shown in brackets, between the two different bare earth models (2017 vs 2023), for the 9th of March 2022 and 10<sup>th</sup> March 2023 acquisitions. Highlighted shows which model predicted more snow per cover type

Date Flown	3/9/2	2022	3/10	/2023
Bare Earth	2017, BCTS	2023, ACO	2017, BCTS	2023, ACO
	m <sup>3</sup> (percent of tot	tal snow volume)	m <sup>3</sup> (percent of to	otal snow volume)
Alpine	11,814,549(36.0%)	13,712,941(40.1%)	11,053,398(33.1%)	12,968,040(37.6%)
Old Growth	13,007,977(39.7%)	11,230,885(32.9%)	14,129,254(42.3%)	12,200,555(35.4%)
Mature Regen.	1,299,083(4.0%)	1,070,746(3.1%)	1,131,221(3.4%)	763,779(2.2%)
Regenerating	4,823,783(14.7%)	5,947,794(17.4%)	4,816,056(14.4%)	5,934,958(17.2%)
Juvenile	1,572,433(4.8%)	2,059,789(6.0%)	1,883,514(5.6%)	2,358,069(6.8%)
New Harvest	195,834(0.6%)	73,387(0.2%)	269,670(0.8%)	116,560(0.3%)
FSR	87,639(0.3%)	90,081(0.3%)	101,461(0.3%)	99,919(0.3%)
Total	32,801,298	34,185,623	33,384,574	34,441,880

Differences in snow cover volumes and percentages of total snow volume are consistent between all acquisitions in terms of which bare earth model is used (Table 5.11). The biases observed at the plot scale (Sec 5.4.1) were present when scaled to the watershed. In juvenile forest plots, the use of the ACO 2023 bare earth model results in overestimated snow depths, whereas with the BCTS 2017 model there is good agreement between manual and LiDAR-derived observations of snow depth. When scaled to the watershed, juvenile forests appear to contain 33% more snow (e.g.  $1.5 \times 10^6 \text{ m}^3 \text{ vs } 2.0 \times 10^6 \text{ m}^3$  in March 9 2022 survey) using the 2023 ACO bare earth model, though the overall impact on total snow volume is ~1%.

In contrast, snow depths in old growth forest are likely overestimated when using the 2017 BCTS bare earth model versus the 2023 ACO bare earth model, which had a much lower MBE (Sec 5.6). At the watershed scale, the use of the less accurate 2017 bare earth DEM in old growth forests results in substantially greater relative contributions to overall snow volumes (39.8 vs 33.1% in 2022). The choice of bare earth DEM, and their respective accuracies in different forest types, thus plays an important role in determining the relative importance of different forest cover types for total snow storage.

In other regions of the Tsitika watershed outside of Russell Creek, forest harvesting has recently occurred at higher elevations, where snow accumulates to greater volumes. The following chapter will use this recent forest harvesting as an experiment to assess the changes which occurred to both the ground surface model and snow distribution pre- and post-harvest.

# Chapter 6 : Forest Harvest Experiment 6.1 Introduction

Forest harvesting can change snow accumulation and melt due to removal of the canopy which alters the energy balance, generally increases wind and eliminates interception of snow (Boon 2009; Varhola, Coops, Weiler, et al. 2010; Winkler et al. 2015). Current forest practices also change the ground characteristics, with slash piles, woody debris and roads potentially changing the elevation. Further, after harvest low lying shrubs can become a dominant ground cover as the stand regenerates. Though numerous studies have investigated the impact of forest harvesting on snow storage (e.g. Swanson et al. 1986, Winkler et al. 2015), most focus on the post-harvest condition, rather than the change which occurs before and after disturbance. As well, studies which have looked and pre- and post-disturbance changes to the snowpack and hydrological response pre-dominantly are based in cold climate watersheds which develop shallower snowpacks than coastal British Columbia (Richardson et al. 2023). Forest harvesting in coastal British Columbia is occurring at higher elevations, of which the impacts to snow accumulation and melt are poorly understood.

Active forest harvesting within the Tsitika watershed which occurred during the span of the LiDAR campaign presents a unique opportunity to assess how snow distribution changed pre-and post-harvesting, and through the accumulation season. As described in section 2.3, paired catchment studies which compare water yield pre and post disturbance through control and treatment watersheds, have been the longstanding method to assess impacts of forest disturbance (Richardson et al. 2023). Here, a similar control-experiment before-after approach was taken, in which cut blocks harvested in 2022 were designated "treatment" sites, and adjacent forest stands, not harvested, were assigned "control". Then, the change in snow storage and water equivalence between 2022 and 2023 for both the control and treatment areas were compared to evaluate the impact of forest harvesting.

As demonstrated within the previous chapter, an accurate snow-free surface model is critical to quantify snow depth variability and snow storage (see sec 5.5 Bare Earth DEM). An advantage to recently harvested areas is vegetation is yet to regrow and trees have been removed and therefore provide relatively good conditions for LiDAR. However, the debris which remains after forest harvesting may pose challenges. This study area has ACO acquired bare earth models pre- and post-harvest, which provides the opportunity to assess whether the bare earth model changes from canopy covered to harvested conditions. The first objective of this analysis was to assess whether the LiDAR snow-free ground surface model changed after harvesting. The results of the ground surface analysis were then integrated into the second objective: quantification of snow distribution change that occurred after forest harvesting. This section focused on snow volume and water storage changes at the plot scale, and used LiDAR derived snow depths to quantify the change. This also provided an opportunity to assess how these changes impact overall snow storage at the watershed scale.

# 6.2 Methods

In June to August 2022, forest harvesting (16 hectares) occurred in the southern portion of the Tsitika watershed adjacent to the Mount Cain ski hill, within the Cain Creek catchment (634 hectares). LiDAR snow surveys acquired in 2022 therefore reflect the pre-harvest conditions, and surveys acquired in 2023 reflect post-harvest conditions. Additionally, the ACO acquired bare earth models for this region in 2020 (pre-harvest), and in 2023 (post-harvest). Meteorological data were collected at the Lower Cain (50.225 ° N, -126.356 ° W, 1260 m) and Cain Ridge Run (50.227 ° N, -126.352 ° W, 1330 m) weather stations, situated approximately 1.2 km south and 100 - 200 meters higher in elevation (Figure 6.1).







Figure 6.1 Site maps for the natural experiment with a) showing the AOI relative to the Tsitika watershed, northern Vancouver Island, and b) scaled to the AOI, showing the road, control, and treatment area used within the analysis and c) the extent of Cain creek catchment inclusive of the Lower Cain (1260 m) and Ridge Run (1330 m) weather stations

A relatively homogenous 30ha area of interest (AOI) where harvesting occurred between the 2022 and 2023 snow survey was delineated (Figure 6.1b). Harvested areas within the AOI were identified through ortho-imagery collected by the ACO, and were designated as the treatment sites. Only areas which were harvested after June 24<sup>th</sup> 2022 - the last LiDAR acquisition of the season - were included. Unharvested areas were the control sites. A minimum 10 meter buffer was applied to the boundaries of the control and treatment to each other, as well as the road (Figure 6.1c). The buffer distance was based on current literature on forest edge effects as well as canopy height on snow distribution (Currier and Lundquist 2018). Treatment and control areas were summarised by the metrics of slope, elevation, aspect, forest canopy density and stand area (Table 6.1). One section of road was built prior to the pre-harvest bare earth collection in 2020, and was used to assess any change to stable terrain between the two bare earth surfaces.

Plot	Elevation range	Slope	<b>Canopy Cover</b>	Canopy Height	Area	Aspect
	[ <b>m</b> ]	[degrees]	[%]	[ <b>m</b> ]	[ha]	Ispect
Control	1039 - 1361	27	88	18	14	South
Treatment	1080 - 1353	28	91	25	16	South
road	1077 - 1124	4	0	0	0.54	South

Table 6.1 Topographic and canopy metrics for the control, treatment and road area which was used within this study. Metrics for slope, canopy cover, and height represent the average value.

# 6.2.1 Snow free surface assessment

A primary goal of the snow free surface assessment was to identify whether the LiDAR ground models changed after harvesting. Post-harvest surfaces are a complex mix of slash piles, stumps, and debris which may influence the ground surface model if the LiDAR pulse cannot penetrate to the ground. This will have direct implications as to a) whether a bare earth LiDAR model captured prior to harvesting is a viable product to measure snow once harvesting has occurred or vice versa and b) whether the bare earth model post-harvest is capturing the ground, or surface debris.

The road constructed prior to the 2020 bare earth acquisition was used to first establish whether the two bare earth models had good agreement on the stable terrain. If there was no significant change between the elevation values between the two bare earth models, this would be indicative of no systematic error between the models due to timing of acquisition and potential instrument bias. Average and standard deviation of the road surface elevation values were calculated for both the 2020 (pre-harvest) and 2023 (post-harvest) models. As this portion of the analysis employs a point to point approach to compare LiDAR pixels, different error metrics were able to be calculated which were not possible with the unequal sample sizes of the plot-scale analyses. Error metrics were mean bias error (Eq. 6.1), mean absolute error (6.2), and root mean squared error (6.3), where z is the elevation raster value.

$$MBE = \frac{1}{n} \sum_{i=1}^{n} (z_{2023} - z_{2022})$$
(6.1)

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |z_{2023} - z_{2022}|$$
(6.2)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (z_{2023} - z_{2022})^2}$$
(6.3)

Then, the same process was applied to the control and treatment sites. As the ground surface distributions were not normally distributed, the Levene's and Mann-Whitney U test were selected for testing whether the variability and mean of the surfaces were significantly different.

Additionally, the snow depth rasters in which the AOI was snow-free were used to confirm the existence or absence of changes in ground surface elevations pre- and post-harvest within the treatment and control areas. Ortho-imagery captured coincidently with the LiDAR was used to verify whether there was snow in the AOI. Then the "snow depth" i.e. no snow pixel values were extracted for the control and treatment sites. If the treatment site snow depth distributions were centered at zero in the pre- and post-harvest snow free surveys, this would indicate the LiDAR bare earth DEM is unchanged by forest harvesting. If the treatment site elevations differ after the treatment, indicates a change to the ground surface due to harvesting.

### 6.2.2 Snow distribution and volume change

Pre-harvest snow depth distributions were compared between control and treatment plots to confirm snow depths were similar before harvesting. Snow depths were then converted to snow water equivalent (SWE mm) by multiplying the snow depth pixels by a modelled snow density pixel value. Snow densities were modelled using a random forest regression with the key factors being snow depth, elevation, and meteorological variability, which is a proxy using hourly weather station data (Bisset et al, 2024 (in prep)). A relative change assessment was conducted by comparing the snow-on acquisitions from 2022 and 2023. This analysis is based on the control area remaining stable, despite the date of the LiDAR acquisitions and the snowpack changing between the two years. Three surveys in both 2022 and 2023 were acquired when the average snow depth exceeded 1 m at the weather stations and snow visible in the ortho-images. These three surveys were defined as phases, identified to compare change between the two years (Table 6.2). A ratio was calculated for the control and treatment sites, to reflect the relative increase or decrease in SWE from 2022 to 2023.

Table 6.2 LiDAR surveys for 2022 and 2023 paired for comparing snow distribution change pre-harvest (2022) and post-harvest (2023). Weather station snow depth data from Lower Cain (1260 m) included for each survey

	LiDAR Acqui	sition Date	Lower Cain: snow depth [m]		
Phase	2022	2023	2022	2023	
1	9 <sup>th</sup> March	10 <sup>th</sup> March	1.69	1.74	
2	11 <sup>th</sup> April	4 <sup>th</sup> April	2.21	1.94	
3	21 <sup>st</sup> May	29 <sup>th</sup> April	2.27	1.76	

# 6.3 Results

#### 6.3.1 Weather Station Overview

The two weather stations located on Mount Cain - Lower Cain (1260 m) and Ridge Run (1330 m) provide important context to the snow distribution results and the differences in the 2022 and 2023 snow seasons. In 2022, peak snow depth occurred on the 12<sup>th</sup> of April, 266 cm at Lower Cain and 303 cm at Ridge Run (Figure 6.2). The start of snow melt was defined as the date at which an average loss of .5 cm of snow depth occurred for a minimum of 14 day period. Sustained snow melt started on the 19<sup>th</sup> of May for both stations lasting 42 -45 days, with an average 6 cm snow loss per day. Both weather stations snow depth sensors were recording no snow as of July 3<sup>rd</sup>. Relative to the LiDAR acquisitions, peak snow occurred 2 days after the 10<sup>th</sup> of April acquisition. Based on the orthoimagery from the June 24<sup>th</sup> 2022 LiDAR acquisition, the snowpack within the area of interest was intermittent and mostly snow free, with snow patches still present in natural openings within forested areas.


Figure 6.2 Overview of the Lower Cain (1260 m) weather station air temperature (red) and snow depth (blue) measurements for the 2022 and 2023 peak snow and snow melt season.

The 2023 snow season was characterized by an earlier melt, with both stations being snow free by May 27<sup>th</sup>, over a month earlier than 2022. The weather stations recorded a shorter sustained snowmelt period and lower peak snow depths, 34 and 47 cm less at Lower Cain and Ridge Run stations respectively. By the May 25<sup>th</sup> LiDAR survey, the natural experiment AOI was snow-free. Peak snow occurred approximately halfway between two LiDAR acquisitions, on April 18<sup>th</sup> 2023.

The first three LiDAR acquisitions of both the pre-harvest 2022 acquisitions, and the post-harvest 2023 acquisitions had a measurable snowpack, so will be referred to in this analysis as the snow-on surveys. There were three surveys near or completely snow-free within the experiment AOI: the 24<sup>th</sup> of June 2022 and the last two surveys in 2023 (25<sup>th</sup> May and 12<sup>th</sup> June). All of the LiDAR surveys will be included in the snow distribution assessment, and only the snow-on surveys will be incorporated into the water storage analysis.

#### 6.3.2 Ground surface change

The road within the harvested block showed good agreement in elevation between the 2022 and 2023 bare earth models, with an RMSE value of 0.02 m (Table 6.3). A histogram of the residuals showed the peak close to zero, indicating minimal change between the two bare earth surfaces (Figure 6.3). Thus, the stable terrain within the AOI was consistent between both surface models.

Table 6.3 Results from pre and post-harvest ground surface changes, in which the control, treatment, and road plot types average and standard deviation elevation were calculated, and error metrics mean bias error (MBE), mean absolute error (MAE) and root mean square error (RMSE) were calculated between the 2022 (pre-harvest) and 2023 (post-harvest) bare earth models.

Plot type	Average [m]		Standard D	Deviation [m]	MBE	MAE	RMSE
	2022	2023	2022	2023	[m]	[m]	[m]
control	1171.93	1172.08	97.38	97.43	0.15	0.37	0.48
treatment	1179.03	1179.33	69.38	69.25	0.3	0.4	0.49
road	1107.31	1107.32	13.04	12.95	0.01	0.12	0.2

\* Statistically significant at a p-value of 0.05

The variability of the ground surface showed good agreement for both the control and treatment sites. The average elevation for the control and treatment area showed an increase from 2022 to 2023, with a mean bias error of 15 and 30 cm, respectively. The RMSE was marginally higher for the treatment (0.49 m) versus the control (0.48m), though both were quite high overall (Table 6.3). The histogram of the residuals shows a slight positive skew for the treatment. Neither the Levene's test for equal variance nor Mann-Whitney U test produced significant results for the control, treatment or road groups (Figure 6.3).



Figure 6.3 Histogram of the residuals for the control, treatment, and road sites between the post-harvest (2023) and pre-harvest (2020) bare earth. A positive skew is indicative of the post-harvest elevation greater than the pre-harvest.

The second component to the ground surface analysis compared the calculated snow depth distributions for the snow free acquisitions, which, if unbiased, should be centred around zero (Figure 6.4). The distributions of "no snow" snow depth for the snow free acquisitions exhibit a negative bias for the pre-harvest treatment areas, suggesting that the process of forest clearing introduced a significant change to the ground surface. For the 2023 post-harvest surveys, the control and treatment average snow depth were within .05 m of zero.

Surface elevation differencing for two snow-free and post-harvest acquisitions (25<sup>th</sup> May 2023 and 12<sup>th</sup> June 2023) with the average depth ranging from -0.05 to 0.03 m. The standard deviation for the forested control sites was greater for both surveys than the harvested treatment.



Figure 6.4 Snow depth distributions of the three snow free acquisitions, ie. no snow, comparing the control and the treatment site processed with the post-harvest (2023) bare earth model. The 24<sup>th</sup> of June 2022 (left) shows a negative offset when using the harvested ground model to measure snow in the treatment site which - as it is prior to harvesting – is forest covered. The 25<sup>th</sup> of May 2023 (middle) and 12<sup>th</sup> June 2023 (right) show good agreement between the post-harvest ground surface model and the harvested treatment and forested control sites

As the treatment sites were already harvested in the bare earth model, the 2022 treatment distribution was a harvested ground model used to measure snow within forest. This resulted in a negative offset (-0.21 m) in comparison to the control (-0.05 m).

When using the post-harvest 2023 bare earth model, snow depth was underestimated in the pre-harvest treatment sites. This was consistent with the results of the snow-free bias assessment, which showed a positive bias to the 2023 ground surface model. To accurately quantify snow storage change from harvesting, a bias correction must be applied to the pre-harvest treatment snow depths. The difference between the mean bias error for the control (0.30m) and treatment (0.15m) was differenced, and a 0.15 m increase was applied to the treatment sites snow depth measurements for 2022.

#### 6.3.3 Snow Distribution and water storage

Prior to harvesting, the average snow depth for the control and treatment were closely aligned, with 0.04 m or less difference across all the acquisitions (Figure 6.5). The average snow depths ranged from 0.31 to 0.92 cm for both control and treatment. The snow depths increased for the first three acquisitions, with the average snow depth peaking on the  $21^{st}$  May 2022 (0.91 – 0.92 cm).



Figure 6.5 Box plots of the snow depth (m) in the control and treatment sites for the pre and post-harvest conditions. The boxes (green control and orange treatment) shows the quartiles of the dataset, with whiskers extending to points within 1.5 x the inter-quartile range. Observations outside of this range are not shown on the graph

After harvest, the average snow depth was consistently higher for the treatment versus control sites. The largest discrepancy in average snow depth occurred in the March 10<sup>th</sup>, 2024 survey, where the average snow depth was 0.75 m greater in the treatment than the control. Between the April 29<sup>th</sup> and May 25<sup>th</sup> 2023 surveys, all the snow in both groups melted. Sentinel data were examined for dates between April 9<sup>th</sup> and May 25<sup>th</sup>, and while the approximate date for snow free status identified in the treatment area, it was too difficult to see the snow cover in the forested treatment areas, thus it was not possible to compare the bulk ablation rates. However, as the average snow depth for the 29<sup>th</sup> April survey was 76% greater in the treatment than control sites, a greater quantity of snow was available to melt than prior to harvest. Despite the observed similarities in distribution of the control and treatment sites pre-harvest,

and differences post-harvest, statistical testing produced significant differences in both the before and after harvest scenarios.

After forest harvest, there was a notable shift in both the distribution and the total water storage between the control and treatment groups (Figure 6.6). Isolating the control group, peak water storage across both snow years surveys occurred on 21<sup>st</sup> May 2022. For the treatment sites, all of the post-harvest surveys exceeded the water storage of the pre-harvest surveys. Therefore, despite the 2022 exceeding water storage within the forest, the overall water storage was greater for the April 29<sup>th</sup> survey due to the harvested areas.



Figure 6.6 Total water storage in cubic metres for the control (green) and treatment (orange) sites for the pre- and post-harvest years.

When comparing 2022 to 2023 snow years, the change in SWE was positive and greater for the treatment group than control across all phases (Table 6.4). Phase 1 (March 9, 2022 and March 10, 2023) had the greatest increase in SWE for both groups, though the treatment increased by over double that of the control. The third surveys of each year resulted in the largest difference between the control and treatment, as well as a direction change: whereas the control group decreased in SWE, the treatment sites still increased compared to 2022.

Table 6.4 Snow water equivalence (mm) for both the pre-harvest (2022) and post-harvest years (2023), +/- standard error, for the three snow on LiDAR surveys. Rate of change represents the increase or decrease in SWE from 2022 to 2023, for the control and treatment blocks

SWE [mm]	Phase 1		Phase 2		Phase 3	
	(Mar 9 2022 : Mar 10 2023)		(Apr 11 2022 : Apr 4 2023)		(May 21 2022: April 29 2023)	
Snow year	control	treatment	control	treatment	control	treatment
2022	125 +/- 0.44	95 +/- 0.32	192 +/- 0.45	187 +/- 0.38	340 +/- 0.52	317 +/- 0.54
2023	216 +/- 0.31	398 +/- 0.34	224 +/- 0.36	375 +/- 0.36	244 +/- 0.43	428 +/- 0.52
Rate of change (percent)	1.7 (72%)	4.2 (318%)	1.2 (15%)	2.0 (100%)	0.7 (-28%)	1.4 (35%)

#### 6.4 Discussion and Recommendations

Through a comparative experiment approach, this case study used LiDAR to quantify snow depth and snow water volume change that occurred after forest harvesting. An important finding from this study is the shift to the bare earth model after harvesting. The increase to the surface elevation in the cut block suggests the debris from the harvesting caused the ground surface to overall register higher. A potential source of this bias is the slash piles or logs are being classified as ground, causing an overall increase to the ground elevation distribution. However, an analysis of the logs and slash compared to ground within the treatment site showed the bias was consistent, and not caused specifically by log piles (appendix I), suggesting that forest harvest caused a general increase to the ground surface, which is being reflected with the bare earth LiDAR model. It is critical to address this change, as the underestimation of the preharvest treatment snow depth which occurred due to the use of the harvested ground surface model would cause the relative change to snow depth after harvesting to be amplified. For example, without the bias correction applied, snow depth change within the treatment sites would have been overestimated by 12 - 33%. This highlights the importance of using a ground surface model which reflects the current state of the land surface to accurately measure snow. Any additional changes to the ground surface which may occur (removal of slash for example) or on a greater temporal scale, the regeneration of forest, may introduce error to measuring snow with LiDAR. Furthermore, this supports and adds to results from the previous chapter, in which the regrowth of vegetation post-harvest reduced the accuracy of the bare earth model, and subsequently the snow depth measurements. In this case, the removal of vegetation reduced the accuracy of retrospective snow depth measurements by the introduction of a positive (.15m) bias, with the post-harvest open ground surface being higher than the pre-harvest forested surface. With the change to the ground surface addressed, the overall confidence in the LiDAR snow depth measurements was high. First, both bare earth models were flown by the ACO within 4 years of each other, using the same LiDAR sensor and systems, with similar ground classification algorithms employed (see sec 4.1). As discussed in the previous chapters, LiDAR snow depth measurements in the open and old growth plots were the two most accurate cover types, with median MBE of -0.9 m and -0.16 m respectively, as well as captured the variability. Despite no in-situ snow depth data, the snow-free validation provided confidence that the snow on and bare earth surfaces were in good agreement pre- and post-harvest.

Results of the snow distribution analysis follows the most prevalent finding from numerous studies of this nature: snow will accumulate to greater snowpacks in the clear cuts than in the adjacent forest (Berris and Harr 1987; Hudson 2000). Exceptions to this can occur include larger clear cuts under high winds, due to evaporative losses in the opening and snow may be blown in to and stored within the forest (Troendle and King 1985; Swanson et al. 1986). Studies have found maximum snow accumulation occurs when the width of the cutblock is 2 to 5 times the height of the trees (Swanson and Stevenson 1971; Troendle and King 1985), though these results were found in cold climate conditions. In this case study, cut blocks fell within this threshold, and were on average between 4 times in width (77 m) than surrounding tree height (18m).

Hydrological effects of forest harvesting are a combination of the harvested area and recovery, the spatial distribution of the cut blocks, as well as the specific topographic characteristics of the watershed (Ellis et al. 2013; Winkler et al. 2015; Johnson and Alila 2023). The 2022 harvested sites encompassed 2.5% of the Cain Creek catchment, though with prior harvesting which occurred, mostly within the last

10 years, 9% of the catchment was harvested overall. Snow water storage between the plots increased at a higher rate in the treatment sites than control between 2022 and 2023, with increased rates respective for control and treatment were 72% vs 318% for phase 1, 15% vs 100% for phase 2, and -28% to 35% for phase 3. To infer the impact of the harvested sites on snow storage at the watershed scale, the relative difference which occurred between the plots was scaled to the Cain Creek watershed, for example, for the phase 1 (Mar 9 2022 – Mar 10 2023), the treatment SWE increased 40% more than the control. This only resulted in a 1.6, 1.02, and 1.36 % overall increase in water storage for the march 10<sup>th</sup>, April 4<sup>th</sup>, and April 29<sup>th</sup> LiDAR surveys within the Cain Creek watershed as a result of the forest removal. This suggests that snow at this elevation makes up a proportionately smaller amount of snow at the watershed scale. The relatively high elevation of the study area was beneficial to quantifying snow depth change. At a lower elevation, we could expect less snow to accumulate both within the open and the dense canopy, as warmer temperatures increase the amount of precipitation falling as rain rather than snow.

One limitation of this case study is the inability to describe and compare the snow melt rates with LiDAR, as for both 2022 and 2023, the snowpack within the AOI melted out in entirety between the third and fourth LiDAR surveys. Based on the available sentinel imagery, weather station data, and understanding of the snow energy balance, we can infer some of the likely impacts on melt rate. As the entire AOI is southerly facing, it would receive greater net shortwave from the solar incident angle and increased longwave inputs from the heating of tree trunks, therefore likely a higher melt rate than a comparable site on a northerly aspect (Seyednasrollah and Kumar 2019). As captured with sentinel imagery, snow melt rate in 2023 appeared to be quite rapid in the treatment sites, with full snow coverage May 10<sup>th</sup>, intermittent snow coverage May 13<sup>th</sup>, close to snow free as of May 18<sup>th</sup>, and no snow as of the LiDAR acquisition on May 25<sup>th</sup>. Notably, a 2021 cut block (3 hectares) on the northern aspect at a similar (1054 – 1117 m) elevation, was still fully snow covered as of May 18<sup>th</sup>. Higher

100

antecedent snowpack was captured on the northern cut block vs southern aspect treatment, with a 1.45 m and 1.2 m average snow depth respectively as of the April 29<sup>th</sup> 2023 LiDAR survey. Based on recent studies in a maritime environment, the melt rate in the forest may have exceeded that in the open, as this site was relatively warm, sheltered, and below treeline. Notably though, the average snow depth was 44% less under the canopy, therefore less snow was available to melt. The accelerated melt on south aspect forest harvesting may increase the synchronicity of snowmelt within the watershed, ie. the higher and lower elevation areas melting at the same time, which Pomeroy et al (2012) found contributed to higher peak flows.

One recommendation is to increase the temporal scope of this analysis to include additional years of LiDAR survey data, where harvesting occurred over a broader area within the watershed. As LiDAR surveys in the Tsitika span back to 2020, an inclusion of the 2021 harvested areas may strengthen these findings, as well as provide greater understanding of how the size, aspect, and spatial distribution of forest harvesting impacts snow storage within a coastal watershed. An additional recommendation is to introduce more frequent LiDAR surveys to capture melt rate, and compare these rates between the forested and open sites. This case study demonstrated the utility of airborne LiDAR to provide robust figures for the change in snow storage which occurs after forest harvesting.

## Chapter 7 : Discussion and Recommendations

This study focused on snow distributions and potential sources of LiDAR error at the plot and watershed scale, through analysis of vegetation, ground point returns, and the bare earth model. This discussion is centred on several key themes:

- The vegetation and surface characteristics of the juvenile and regenerating plots, which lead to greater observed errors in LiDAR-derived snow depths in the complex surface and canopy of harvested forest;
- The choice of bare earth model is important: two independent bare earth models are similar in stable terrain but show differences between forest cover types;
- Confidence in overall snow volumes is high, despite the differences in the bare earth models, but there are differences and compensating errors.

### 7.1 LiDAR Accuracy within complex ground cover

This study assessed LiDAR accuracy by comparing plot averages of LiDAR and manual snow depth measurements - as opposed to point-to-point which is prevalent across most studies - in order to not introduce known geo-positional error associated with a) imprecise position of manual measurement and b) accuracy of the GNSS in the forest (Murgaš et al. 2018; Broxton et al. 2019). Mazzotti et al (2020) precisely referenced their snow probes in the forest with specific trees which were identified on ortho-imagery, but this approach would have been impractical within this study due to the density of canopy. A drawback of the average snow depth approach used in this study is the inability to calculate and compare error metrics reported across other literature, commonly root mean square error (RMSE), mean absolute error (MAE), and mean absolute difference (MAD)(Table 7.1). Median of the mean differences for this study were lowest for the open sites, the weather station snow courses and alpine plots (-9 cm for

both), followed by the old growth (-16 cm) and dense old growth (-15 cm) plots, and highest for the juvenile (76 cm) and regenerating (55 cm) plots. Generally, error values from this study were similar or slightly greater in magnitude in the open and old growth forest sites to other LiDAR studies, and substantially greater in the harvested. However, it is important to note that no published studies have endeavored to measure snow with airborne LiDAR in the complexity of forest stands which were done so in this study.

Table 7.1 Error results from airborne LiDAR snow depth studies which evaluated LiDAR accuracy using in-situ measurements and in

Study	Airborne LiDAR type	Error Evaluation	
Currier et al, 2019	Airplane	Forest error metrics: - Mean difference: 6 cm - RMSD: 8 cm - MAD: 7 cm	
Geissler et al., 2023	UAV	Equal error for open and forested terrain: - RMSE: 2 cm, and MAE:1 cm	
Jacobs et al, 2021	UAV	Greater error values in forest than open. Field (open): MAD: 0.96 cm, RMSE: 1.22 cm Forest: MAD: 9.6 cm, RMSE:10.5 cm	
Hopkinson et al., 2012	Airplane	<ul> <li>Higher mean difference in forest than open.</li> <li>Mean differences were: <ul> <li>Open area, high elevation: 7 cm</li> <li>Open area, alpine: -4 cm</li> <li>Forest: 13 cm</li> </ul> </li> </ul>	
Mazzotti et al, 2019	Airplane	Forest metrics: RMSE: 6 cm mean, 3cm standard deviation	

forested terrain.

When compared with ground observations, LiDAR estimates of snow depth were most accurate in stable terrain with no ground vegetation or canopy cover, demonstrated by the consistent low MD attributed to the weather station snow courses. However, in terms of the snow storage, roads are an inconsequential area of Russell Creek (<1%) and contributed less than half a percent of snow volume. The weather station snow course validations confirmed that bias found at the cardinal plots was likely due to vegetation misclassified as ground in the bare earth model.

Uncertainty increased in complex ground cover and vegetation, with notably the harvested plots (regenerating and juvenile) responsible for the greatest mean differences. Ground point coverage within the regenerating plots was low within both of the bare earth models. Even in snow-on conditions, ground point density within the regenerating forest plots was lower than the other cardinal cover types, with 29 -50 % of plot with no ground point returns, and less coverage later in the season. This was not necessarily a function of the canopy coverage, as the dense old growth forest plots had the highest canopy coverage of all the cardinal plots (90%), yet the snow-on point coverage of the plots were considerably higher (69 - 97%). A notable difference between the two cover types were the tree characteristics: tall ( $\sim 20$  m) trees, with a small ratio of branches to tree height, and no branches close to ground in the dense old growth, versus the smaller ( $\sim 8 \text{ m}$ ) trees with a comparatively dense crown and low to ground branches in the regenerating plots (Figure 7.1). Similar results were found in a study by Mazzoti et al (2019), in which dense spruce tree stands had more data gaps in the LiDAR snow surface and ground returns in comparison to less dense stands. Hopkinson et al. (2004) suggested a speciesspecific bias correction, but within the Russell Creek watershed, which encompasses a range of harvested and old growth forest, a stand age component may render more accurate results.



Figure 7.1 Images from the regenerating stand (A) and dense old growth (B), showing notable difference in tree branch height in relation to the ground.

In addition, complex ground vegetation increased LiDAR error at the plot scale by obscuration of the ground surface, which resulted in both less and low quality LiDAR ground point returns. In the harvested plots, the ground vegetation was tall (avg: 116 cm) and variable (std: 45 cm), and as the average tree height was ~ 3 meters, there was not a clear distinction between the two. Again, this resulted in fewer ground point densities than in the over cover types. The ground vegetation present in the old growth forest appeared to pose less of a problem to LiDAR penetration to ground, based on the relatively high ground point density and coverage, despite the vegetation being not inconsequential in the larger canopy gaps (approx. 50 cm). This may be a factor of both a) the vegetation being relatively uniform in height, and b) the large difference in height between the canopy and the ground vegetation in the old growth forest plots.

The ambiguity of ground in the harvested forests introduced uncertainty in both the LiDAR and in situ measurements. Large air pockets from vegetation, as well as slash piles and stumps were sources of error within the in situ measurements. Air pockets could be identified when using the snow tube, as the core of snow may be substantially less than the depth measured, and measurements were retaken. The LiDAR interpretation of ground is also important to consider, as it may not capture how snow accumulates in the landscape. For example, if the LiDAR model classifies a slash pile as vegetation, this will result in a substantial over-estimation of snow. Geissler et al (2020) observed fallen logs classified as vegetation in the snow-off point cloud resulted in a large systematic error in snow depth data. Though in this study the over-estimation of snow in the juvenile forests was not limited to areas of stumps and slash piles, this may be a contributing factor to the error observed.

Overall, this study found that a good proxy for LiDAR snow depth accuracy was the ground point density of the snow-free surface. Plots with both a) good ground point coverage and b) higher density (>1) of returns generally had a lower mean difference. An exception to this is the alpine plots in 2022, which despite being free from complex vegetation and canopy coverage, had greater range in mean

difference than anticipated (Figure 5.9). However, this may be an artefact of the less frequent validation of the plots and the more variable snowpack when compared to the other cardinal plots. A similar result was found in Tinkham et al (2014), with the highest error attributed where the snowpack was highly variable, which in their case was the edge of the canopy.

#### 7.2 Impact of the Bare Earth Model

The bare earth DEM and how it classifies ground and vegetation appears to be a significant source of error. This is demonstrated when comparing the 2023 ACO bare earth to the 2017 BCTS acquisition. Both bare earth models were accurate on stable terrain, demonstrated by the weather station snow courses low mean difference, but biases in the cardinal plots differ (Figure 5.20). The juvenile forest plots had the greatest difference: the highest MD when processed with the ACO 2023 model, and the lowest MD with BCTS 2017 model.

As discussed in the previous section, the juvenile plots were characterized by tall and complex ground vegetation, and small trees. This resulted in low ground point density and, most importantly, large data gaps in the 2023 bare earth model, though not in the 2017 BCTS model. In snow-on conditions, juvenile plots were consistent between both bare earth models as very high snow surface point density, due to snow coverage of all vegetation and debris.

Several possible theories as to why the 2023 model was substantially lower in bare earth ground point returns in the juvenile plots than the 2017 model are: 1) more vegetation has grown in the 6 years between the bare earth acquisitions, and 2) vegetation was greened up at the time of the 2023 acquisition, thus more challenging for the laser pulse to penetrate thorough to ground. However, this is not a product of the top of vegetation being misclassified as ground as observed in other literature (Kucharczyk et al. 2018), as in this scenario, the overestimation of the snow-free surface elevation would result in LiDAR under-estimation of snow depth in the juvenile forest plots. It is not clear why

the juvenile plots under-estimated surface elevation in the 2023 model, and this result has not been produced in other studies.

Support for the vegetation green up theory is provided with an additional snow-free surface experiment: the May 23rd, 2023 LiDAR acquisition. At the time of the May 2023 survey, the juvenile and regenerating plots were snow free, and the vegetation was free of foliage (Figure 5.5). To test whether vegetation green-up is a factor in error, the May 2023 survey was used in the place of a bare earth model to validate only the harvested plots. With the experimental May bare earth, MD was much reduced for both the juvenile and regenerating plots, and was in fact the lowest of the bare earth models tested (Figure 7.2). For the Juvenile, range of MBE with the experimental May 2023 bare earth model (-16cm to +18 cm) was consistent with the lower bias error value from the 2017 BCTS model. The regenerating plots also were the lowest bias error recorded with the May 2023 snow-free surface. This suggests that for areas of high and dense ground vegetation, such as regenerating and juvenile forests, timing the bare earth acquisition with leaf off conditions will significantly reduce error. It also points to the challenge of using a static bare earth model when vegetation not only changes seasonally, but also annually. One possible solution to this problem would be creating a mosaic bare earth using multiple surveys and selecting areas with a minimum number of returns. This would not reduce the problems associated with misclassification of vegetation as ground, but would limit errors associated with interpolation over large distances in complex terrain.

107



Figure 7.2 Mean difference of the cardinal plots from both 2022 and 2023, for only harvested plots (the regenerating and juvenile), using three different bare earth models: 2017 BCTS survey acquired in September 2017 (orange), 2023 ACO survey (blue), and the substitute bare earth model: the May 2023 snow survey which was snow-free in the juvenile and regenerating stands (green). Individual points represent each plot validation across 2022 and 2023.

The algorithm used to classify LiDAR ground returns can introduce error due to misclassification, especially within more complex terrain and vegetation (Tinkham et al. 2011). Both bare earth models used an iterative TIN densification approach to classify ground, but the specific algorithms used did differ between the two (see sec 3.4). A study by Moudry et al. (2018) found the LASground algorithm to perform well overall, but in complex areas, was more likely to omit a ground point rather than falsely classify vegetation, which resulted in low ground point density. Within this study, the omission of points through ground classification may be the cause of the low ground point returns in the 2023 ACO model harvested forests, although it is not clear whether the LiDAR pulse was able to penetrate the vegetation. Tinkham et al. (2011) found between a comparison of two open source algorithms (MCC and BCAL) the greatest deviation (40 cm) in the ceanothus, (with the BCAL being the more accurate),

and suggested a multiple algorithm approach by cover types may produce the most accurate ground surface.

#### 7.3 Snow Distribution: Plot and Watershed Scale

#### 7.3.1 Plot scale distribution

LiDAR and ground-based observations of snow depth distributions are similar for all forest cover types with the exception of harvested forests. LiDAR snow depths are more variable in open and wind exposed sites (e.g. alpine) than the sheltered sites (e.g. dense old growth). In the old growth forests with larger canopy gaps, both manual and LiDAR snow depth observations show deeper snow in the openings, and shallower snow under and at the edge of canopy (see Appendix E: Old Growth Forest: Canopy Snow Depth Variability).

Snow depth variability did not appear to change through the melt season, for manual or LiDAR measurements. Notably, neither the 2022 nor 2023 LiDAR campaigns were well suited to answer questions pertinent to snow melt rates: in 2022 the snowpack sustained until the last survey with minimal melt, and 2023 had fairly consistent snowpack through the first three surveys, and rapid melt between the third and fourth acquisition. Despite being an important metric, there are limited studies which evaluate LiDAR ability to capture snow depth variability.

#### 7.3.2 Watershed snow storage

In Russell Creek, the majority of the snow was stored above 1000 m (58 - 82%), with 14 - 28% of the total volume of snow found in the 1400 – 1700 m elevation range. On Vancouver Island, the low to mid elevation zones typically develop a shallow, intermittent snowpack due to the mild winter temperatures and higher frequency of rain-on-snow events. Therefore, it is critical to understand not only LiDAR

snow depth accuracy at higher elevations, which in the case of Russell Creek, were the old growth forest and the alpine, but the mid-range elevations too.

The comparison of watershed snow storage between both bare earth models produced relatively similar results overall, with less than 5% difference in the total snow volume estimates. This is likely an effect of the two bare earth models countering biases (over and under predictions of snow depth) by different cover types which, to a degree, cancelled at the watershed scale. The pattern of which bare earth model predicted more snow within each cover type was a) consistent with each survey acquisition and b) generally reflective of the comparative biases seen at the plot scale. This gives some confidence to which bare earth model may be more accurate within the different cover types, but still difficult to assert which model represents the "true" snow water storage.

In terms of the cover types which store the most snow - the old growth and alpine - there is evidence within both the plot error comparison and snow free watershed storage to suggest the ACO 2023 model may be the more accurate representation within the old growth, but likely the "true" snow volume is between the 2017 and 2023 models for the alpine. For the dense old growth, the reverse pattern was observed in the snow free acquisition in 2023: median MBE of +62 cm for BCTS 2017 bare earth model, vs -13 cm for the ACO 2023 bare earth model. The inconsistencies in biases between the bare earth models may be attributed to differences in: 1) the acquisitions and how well the LiDAR pulses were able to penetrate to ground, 2) the alignment of the model, and 3) the LiDAR processing and classification. As detailed in the following section (re: study limitations), caution should be applied for upscaling the errors observed at the plots to the watershed. However, due to the consistent relationship between the two bare earth models - which also were consistent with the plot scale bias errors - it is probable that the BCTS model under-predicted snow in the alpine, and over-predicted snow in the old growth forest.

Within the alpine plots, the BCTS model had a MBE of -50 and -5 cm error in the snow free acquisition which may be a result of a positive elevation bias in the bare earth model ground surface. In support of this, the watershed snow storage was entirely negative for the alpine on the 12<sup>th</sup> of June 2023 survey for the 2017 BCTS model (see Appendix H: Watershed Snow Volume), despite visible snow in the orthoimagery. The 2023 ACO model generally showed good agreement on the snow free ground surface within the plots (MBE -3 and -4 cm), but there are several substantial data gaps (450 to 13,900 m<sup>2</sup>) isolated to steep (average slope: 51 degrees) rocky peaks, which resulted in extremely high (average: 20 m) and clearly not representative snow depth values due to the interpolated data. Though these areas make up a relatively small proportion (4%) of the alpine, the snow volume accounted between 22 – 32% of the total snow in the alpine. In the same areas of missing data in the ACO 2023 version, the 2017 BCTS model under-estimated snow depth, notably in 2023(average: -8 m), and snow volumes were negative, which may be indicative of an alignment issue. This demonstrates both a) LiDAR inaccuracies on steep slopes, which are well documented within other studies (Hodgson and Bresnahan 2004a; Tinkham et al. 2012), and b) a limitation of the plots to assess accuracy at the watershed scale.

The over estimation in the harvested forests observed at the plot-scale with the ACO 2023 model did not have a significant impact (<5%) on total snow volume within the watershed, due to the proportion and elevation of the regenerating and juvenile stands within Russell Creek. The juvenile and regenerating forest stands had the greatest uncertainties at the plot scale, therefore if represented a larger portion of the watershed, or higher elevation areas which accumulate a deeper snowpack, could have more of an impact on estimates of basin wide snow storage.

For the  $12^{th}$  of June survey 2023, in which all plots surveyed were snow-free, both bare earth models measured negative snow depths. Though clearly erroneous, this result is consistent with the mean difference observed at the plot scale within that survey, in which for all cover types the bias was negative, ranging from on average a slight negative on the road (-4 +/- 3 cm) and alpine (-3 +/- 1 cm),

to more negative in the dense old growth (-12 +/- 3 cm), old growth (-17 +/- 4 cm), juvenile (-18 +/- 12 cm) and regenerating stands (-31 +/-7 cm). As Russell Creek appeared to only hold snow in the higher alpine portions of the watershed outside of the sampling extent, the accumulation of the negative snow depths would result in a negative snow volume overall. For the old growth, the negative bias was consistent with the biases observed with the snow on, versus for the regenerating and juvenile, this was the opposite, as all other surveys –including other snow free surveys – the bias was positive, with LiDAR over-predicting snow. As vegetation was greened up in the regenerating and juvenile stands by June 12<sup>th</sup> survey, the poor ground point coverage of the snow-on surface combined with the poor ground point coverage of the snow-on surface combined with the poor ground point coverage of the snow-on surface combined with the poor ground point coverage of the uncertainty overall.

The watershed scale component of the analysis utilized the interpolated rasters, in order to be a viable operational workflow with equal pixel count between surveys. At the watershed scale, the proportion of missing data was substantial (42 – 68%), particularly in the lower elevation portions of the watershed and regenerating stands (Figure 7.3). As the snowpack thinned and melted, the number of no data pixels increased across all cover types. The most significant data gaps occur in the mature regenerating stands, where the range of missing data was consistently high (76 to 83%) across Russell Creek regardless of whether snow on or snow free conditions. As observed within the alpine, small, isolated areas of extreme snow depth errors (>15 m snow depth at 600 m elevation) coincide with areas in which there are no ground returns. Compounded with the proportion of data missing in the bare earth model (76%), and absence of manual observations, additional analysis outside the scope of this study is required to assess overall confidence in the mature regenerating forest. For example, the game camera sites ST7GC1 and ST7GC2 could be used to determine approximate snow depth within the regenerating forest for each LiDAR survey.



Figure 7.3 Imagery of the ground point density (GPD) within the Russell Creek watershed showing the March 10<sup>th</sup> acquisition (A1, A2), where snowpack is covering much of the watershed and high snow accumulation survey, and low snow accumulation May 25<sup>th</sup> 2023 (B1, B2). As snow melts in the watershed, the number of no data pixel increases, and the ground point density decreases.

## 7.4 Study Limitations and Recommendations

This study highlights the importance of in-situ measurements which are spatially distributed over the different cover types represented in a watershed to validate LiDAR snow depth. Through the sampling strategy employed in this study, biases inherent to specific stand types at the plot scale were detected. If the manual measurement campaign were more constrained - for example only the weather station snow courses - error would been misconstrued as a much narrower range than when inclusive of the cardinal plots in complex terrain (Figure 7.4).



Figure 7.4 Distribution of the cardinal (blue) and weather station snow course (orange) mean difference for 2022 (left) and 2023 (right) processed with the 2023 ACO bare earth model.

Although the manual snow depth measurements encompassed a range of cover types, the location was limited to a fairly small (~4 km<sup>2</sup>) portion of the Russell Creek watershed (33 km<sup>2</sup>). Additionally, plots of the same cover type generally were close together. The watershed cover types were fairly broad, as well not all cover types classified were able to be sampled (new harvest and the mature regenerating, see sec 3.4). In addition to the spatial distribution of the plots, the timing of in-situ measurements and LiDAR acquisitions represents another limitation. In general, when in-situ measurements were timed shortly after LiDAR acquisition, systematic error was reduced. The meteorological correction (based on the change to snow depth observed at either the game camera snow stake plots or weather station snow depth sensors) did seem effective at correcting error in some cases (e.g. dense old growth: April 29<sup>th</sup> 2023 survey), but not in others (e.g. dense old growth: June 24<sup>th</sup> 2022 survey; Figure 5.10). This may be due to a thin and intermittent snowpack which results in over-compensation in the bias correction.

An accurate snow free model is crucial to measure snow in complex forested terrain. LiDAR bare earth collection timed as soon after snow melt as possible to capture leaf-off and potentially still compressed vegetation is one approach to reduce error. However, this may be impractical for a plane based LiDAR system, due to the variability of snow free conditions in a watershed, and the high cost of repeat acquisitions. For example, in 2023 there was a 46 day difference between the first (ST7GC1 at 540 m)

and last (ST1GC3 at 1210 m) snow-free game camera plots within Russell Creek. UAV LiDAR has potential for improving the ground surface model, due to the flexibility of repeat acquisitions, ability to fly low to the ground, and higher ground point density. Thus, a mosaic approach to a bare earth model, in which particular elevations or forest stands are flown as per their optimal condition, ie. before leaf-on, may improve LiDAR error.

The processing methods for the raw LiDAR data were outside the scope of this study. Suggested steps to consider within the processing of LiDAR data which may improve the bare earth model include:

- A comparison of classification algorithms used to distinguish ground and vegetation, which may "save" more points in the harvested forests
- ii) Investigation of full waveform data, particularly in areas of complex vegetation
- iii) Comparison of interpolation algorithms by different cover types

This study presented several key findings and novel results for measuring snow in predominantly forestcovered and heavily harvested watersheds. The bare earth model proved to be a crucial component in the ability to measure snow depth accurately, in particular for forests with complex canopy and vegetation structures such as the harvested stands. In the case of Russell Creek, forest harvesting has occurred below 1300 meters, which coincides with the approximate elevation threshold where snow accumulates to a lesser degree. Therefore, the overall impact of the LiDAR accuracy in harvested terrain is dictated by the spatial distribution within the watershed.

## Chapter 8: Summary

This study evaluated airborne LiDAR as a method to measure snow in a densely forested watershed, with great variability and complexity to the stands as a result of over 40 years of forest harvesting. Though the methodology to evaluate accuracy with LiDAR with manual snow depth measurements is well established, there were several components to this study which were novel: 1) the complexity of forest stands in which manual observations were collected, 2) the comparison of LiDAR accuracy in two bare earth models, and 3) LiDAR snow depth observations for pre- and post- forest harvest. Through both the manual plots and forest harvest experiment components of this study, it is shown that airborne LiDAR can quantify snow storage, even in dense forest, provided a high accuracy ground surface model is used. Important considerations for the bare earth model which may impact snow depth accuracy are: the characteristics of the trees, the height and complexity of the ground vegetation, the seasonality, and changes to forest cover. The need for timely and accurate snow depth data at the watershed scale has never been greater, as forest harvesting occurs at increasingly higher elevations as well as the compounded effects of climate in coastal watersheds is poorly understood (Bathurst et al. 2020; Gillett et al. 2022; Johnson and Alila 2023). Results from this study support the validity of LiDAR as a tool to increase our understanding of hydrological recovery in coastal watersheds, however there remains high uncertainty in some regenerating stands making it difficult to quantify differences.

# Data Availability Statement

Data and code used in this thesis are not currently available in public repositories. Please contact Dr. Bill

Floyd (Bill.Floyd@viu.ca) for data access.

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# Appendices Appendix A: ACO 2023 Bare Earth Model

In order to have the full AOI an ACO acquisition (previously BC Timber Sales), a new bare earth was initially flown on July 14th 2023. Due to high errors concentrated within the harvested areas of the watershed, a reacquisition occurred on August 19<sup>th</sup> 2023. Although overall an improved acquisition, the August flight has a critical data gap (~860 m2) in the old growth forest, partially within the Russell Creek watershed AOI. Though it makes up a small portion of the watershed, six of the cardinal plots - ST10G7, ST10G6, ST10G5, ST10G4, ST10G3 and half of ST1A2 – are situated within this data gap.



Figure A 1 Hillshade of the August LiDAR acquisition, showing the data gap in red, and the Russell creek watershed in blue
An analysis of similar and adjacent old growth forest stands showed good agreement in the ground surface between the July and August acquisitions. A histogram of the difference in pixel values between the two bare earth models showed no bias within the old growth forest adjacent to the data (Figure A- 1). Based on this result, I filled the data gap has with the pixels from the July 14<sup>th</sup> acquisition bare earth model.



Figure A-1 A histogram (A) of the difference in pixel values between July and August bare earth models from the Old Growth AOI boundary (B), which is similar forest stand to the data gap in the August acquisition

# Appendix B: LiDAR Processing

LAStools	Command
1 - lastile	lastile -cpu64 -i "(input).laz" -o "tile.laz" -tile_size 225 -buffer 25 -flag_as_withheld -
	faf -cores 12 -odir "(output)\1 Tiles" –olaz
2 - lassort	-i tiles_raw\*.las ^ -odir tiles_sorted -olaz ^-cores 7
3 - lasnoise	lasnoise -cpu64 -i " tile.laz" -step_xy 1 -step_z 0.1 -isolated 100 -remove_noise -odir
	"3 Noise" -o "noise5.laz"
4 – lasground	lasground -i LAS\tiles_isolated\*.laz ^ -city -ultra_fine -ignore_class 0 7 ^
(temporary)	-odir LAS\tiles_temp_ground -olaz ^ -cores 7
5 – lasheight	lasheight -cpu64 –lof *.txt -classify_below -2 7 -classify_between 0.3 20 3 -olaz
6 – las2las	-cpu64 -i "noise5.laz" -keep_classification 2 -odir "las2las de-noise" -olaz
7 - lasthin	lasthin -cpu64 -i "*.laz" -step 0.25 -adaptive 0.1 -odir " \7 Thin" -olaz
8 – lasground	lasground_new -cpu64 -i " \noise5.laz" -city -hyper_fine
(final)	-odir " \8 Final Ground" -olaz

Table B 1 LAS tools processing commands used to take the raw LAS files to a gridded raster product

# Appendix C: GNSS report

C- 1 GNSS data results for plot centres for 2022 and 2023, with metrics for horizontal root mean square (HRMS), vertical root mean square (VRMS), number of satellietes (SATS),DOP stands for Dilution of Precision, and PDOP is Position of DOP, HDOP is Horizontal of DOP, VDOP is vertical of DOP, TDP is time DOP, and GDOP is geometric DOP, all measured im meters

(m)	2.757	2.047	2.414	1.563	3.381	3.674	3.674	3.674	n/a	2.225	2.083	2.06	2.3	2.3	2.1	1.8	2.8	3.5	4.4	4.4	4.4	4.4	2.1	2
TDOP (m)	1.483	1.026	1.284	0.74	1.823	0.724	2.07	1.941	n/a	1.19	1.103	1.084	1.2	1.1	1.1	0.9	1	2	2.7	2.8	2.8	2.9	1.1	1.1
VDOP (m)	1.952	1.468	1.734	1.113	2.487	2.788	2.788	2.788	n/a	1.517	1.468	1.443	1.8	1.8	1.5	1.3	1.9	2.5	3.2	3.2	3.2	3.2	1.5	1.5
HDOP (m)	1.261	0.991	1.084	0.81	1.386	2.5	1.2	1.4	n/a	1.111	0.982	0.992	0.8	1	0.9	0.9	1.8	1.4	1.5	1.2	1.2	0.9	0.9	0.9
PDOP (m)	2.324	1.771	2.045	1.377	2.847	3.744	3.035	3.119	n/a	1.88	1.766	1.752	2	2.1	1.8	1.6	2.6	2.9	3.5	3.4	3.4	3.3	1.7	1.7
SATS	11	10	13	13	9	5	6	6	n/a	12	13	13	15	12	15	13	10	6	8	6	8	15	12	12
STATUS	FIXED	AUTONOMOUS	FIXED	FIXED	FLOAT	FLOAT	FLOAT	FLOAT	FLOAT	AUTONOMOUS	FIXED	FIXED	FIXED	FIXED	FIXED	FIXED	FLOAT	FLOAT	FLOAT	FLOAT	FLOAT	FIXED	FIXED	FIXED
VRMS (m)	0.016	2.935	0.005	0.008	0.111	0.114	0.114	0.114	n/a	3.034	0.006	0.009	0.043	0.043	0.006	0.005	0.011	0.035	0.464	0.464	0.464	0.464	0.007	0.007
HRMS (m)	0.012	1.982	0.004	0.006	0.041	0.046	0.046	0.046	n/a	2.222	0.004	0.007	0.019	0.018	0.004	0.004	0.009	0.024	0.234	0.234	0.234	0.234	0.004	0.004
Ellipsoid Height (m)	832.584	831.905	1077.448	1009.134	1230.75	1265.579	1301.229	1313.128	1351.823	1380.392141	1507.3	1509.596	830.827	832.733	1077.448	1009.134	1232.814	1258.292	1301.808	1311.976	1336.213	1382.505	1506.961	1509.788
Northing (m)	5577507.661	5577398.062	687952.609	687829.778	5576461.385	5576400.245	5576273.928	5576230.94	5576192.942	5576154.788	5575967.973	5575971.527	5577397.82	5577506.572	5577217.991	5577335.367	5576464.042	5576397.792	5576273.717	5576230.787	5576193.032	5576153.66	5575967.128	5575975.985
Easting (m)	688270.471	688444.08	5577217.991	5577335.367	687704.431	687700.971	687764.006	687795.912	687843.532	687932.934	688249.878	688200.887	688443.783	688271.451	687952.609	687829.778	687709.303	687698.028	687765.507	687801.632	687840.936	687934.342	688249.46	688197.309
Date	9-Mar	9-Mar	6-Apr	6-Apr	6-Mar	6-Mar	6-Mar	6-Mar	6-Mar	23-May	23-May	23-May	9-Mar	9-Mar	9-Mar	9-Mar	11-Mar	11-Mar	11-Mar	11-Mar	11-Mar	11-Mar	9-Mar	9-Mar
Plot	ST4RF1	ST4RF2	ST2CC1	ST2CC2	ST10G8	ST10G7	ST10G6	ST10G5	ST10G4	ST10G3	ST1A1	ST1A2	ST4RF1	ST4RF2	ST2CC1	ST2CC2	ST10G8	ST10G7	ST10G6	ST10G5	ST10G4	ST10G3	ST1A1	ST1A2
Year										5023						I								

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3.202	3.020	3.315	3.315	3.315	3.315	3.315	2.480	3.263	2.620	2.986	3.222
1.824	1.700	2.020	1.967	2.066	2.020	2.020	1.322	1.838	1.341	1.622	1.807
2.248	2.204	2.432	2.432	2.432	2.432	2.432	1.680	2.375	1.873	2.185	2.353
1.369	1.171	1.000	1.100	0.900	1.000	1.000	1.257	1.277	1.247	1.230	1.257
2.632	2.495	2.629	2.669	2.593	2.629	2.629	2.098	2.696	2.250	2.507	2.667
8	6	11	5	12	11	10	12	11	11	11	10
FLOAT	DGPS	DGPS	DGPS	DGPS	DGPS						
3.339	8.683	13.398	13.398	13.398	13.398	13.398	12.679	12.895	13.041	13.195	13.363
2.034	4.615	6.332	6.332	6.332	6.332	6.332	6.141	6.196	6.235	6.278	6.328
775.4	772.787	618.892	607.447	599.308	602.312	600.519	586.577	577.589	584.985	590.954	582.918
5577912.534	5577911.828	5578850.857	5578851.073	5578849.846	5578850.379	5578849.166	5578932.5	5578931.256	5578930.363	5578931.798	5578931.243
688467.947	688471.034	687504.747	687503.797	687503.883	687504.467	687503.659	687489.534	687491.202	687488.521	687486.949	687488.39
10-13-2020	10-13-2020	10-15-2020	10-15-2020	10-15-2020	10-15-2020	10-15-2020	10-15-2020	10-15-2020	10-15-2020	10-15-2020	10-15-2020
4	5	1	2	3	4	5	1	2	3	4	5
						ST7GC1					ST7GC2

Appendix D: Sno	w depth varia	bility results tables
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STD. DEV. (cm) 2022	9-Mar	11-Apr <sub>H</sub>	21-May	24-Jun	9-Mar	LiDA TiDA	ar and a second	24-Jun
Steph 1	33.0	-	29.9	30.3	25.0	27.5	33.5	35.7
Ridge Run	-	12.6	15.2	20.5	18.6	17.3	15.9	17.8
Lower Cain	-	33.3	11.5	10.0	13	13.7	8.8	16.5
Steph 2	4.5	4.5	10.7*	4.6*	7.1	5.9	6.0*	8.2*
Steph 3	5.3	14.9	8.6		9.1	15.5	13.7	5.1
Steph 4	7.5*	8.4	10.5		4.1*	6.7	7.5	4.5
Steph 6	4.7	3.3	4.4*		7.0	5.8	9.1*	6.5
Steph 7	5.22	4.8*			9.3	12.1*	8.4	8.3
Steph 8	4.1	3.0			7.4	8.7	6.0	8.5

Table D 1 snow depth variability in cm from the weather station snow courses for 2022

Table D 2 Snow depth variability in cm from the weather station snow courses for 2023

STD DEV (cm) 2023	10-Mar	4-Apr	29-Apr D	25-May	12-Jun	10-Mar	4-Apr	iDAR 56-4pr	25-May	12-Jun
Steph1	16.9	29.5	-	22.9		16.8	25.5	22.3	21.1	2.7
ridge run	-	-	-	12.4		18.9	15.8	16.5	19.8	5.7
lower cain	-	-	-	6.9		7.7	7.7	8.5	11.4	7.6
steph2	3.9	4.2	7.3			6.5	6.3	6	5.1	3.5
Steph3	5.4	6.3	7.7			10.8	10.5	9.6	1.6	2.8
steph4	5	5.2	5.9			3.8	4.1	7.8	4.8	3.3
steph6	3.1	5.5	4.4			5.4	7	8.6	5.4	9.3
steph7	2.3*	1.8*				7.5*	8.3*	6.3	7.5	8.6
steph8	1.7*	1.6				4.9*	4.1	4.2	4.4	5.1

STD. DI 20	EV. (cm) 022	9-Mar	11-April 11-April	21-May	24-Jun	9-Mar	11-Apr TiDA	a Nay	24-Jun
	ST1A1	25.5	-	34.6	27.8	32.1	36.2	36	34.4
	ST2A2	-	-	44.5*	46.9*	35.2	34.2	28.5*	32.5*
Alpine	RRA1	-	-	-	68	43.3	44.2	58.1	66.7
	ST1OG3	-	-	57.8	44.1	51.8	61.5	52.3	41
	ST1OG7	34.7	46.9	41.7	36.8	33.5	44.3	39.7	36.7
Old	ST1OG8	44.8*	46.4	44.3	39.9	34.7*	41.3	36.4	32.6
Olu	RROG3	-	-	-	56.4	42	44.2	40.6	49
Growth	RROG4	-	-	_	31.7	30.7	31.9	34.7	34.8
	ST10G4		30	17.3*	13.6	20.5	23.7	23.7*	18.5
D. Old	ST1OG5	24.6	29.1	28	19.8*	23.6	26.1	26	16.8*
Growth	ST1OG6	21.3	28.7	25.5	20.1	18.2	22.7	20.7	16.4
	ST4RF1	54.2*	40.7*	30.1*		80*	85.2*	78.4*	93.1
	ST4RF2	37.6*	40.3*	46.7*		66*	62.6*	67.7*	88.1
Regen.	ST6GC1	33.2*	55.3	29*		75.6*	75.8	70*	81.7
	ST2CC1	-	51.2	46.4*	*5.4	58.2	62.3	61*	60.4*
<b>Juvenile</b> Table D 4	ST2CC2	-	30.2*	46.5	17.6*	53.5	50.9*	51.1	63.6*

Table D 3 Snow depth variability in cm from cardinal plots for 2022

Table D 5 Snow depth variability in cm from cardinal plots for 2023

STD. DI	EV. (cm)		I	Field			LiDAR						
2023		10-Mar	4-Apr	29-Apr	25-May	12-Jun	10-Mar	4-Apr	29-Apr	25-May	12-Jun		
	ST1A1	30	37.3	-	28.2		32.1	32.9	33.5	17.2	10.8		
	ST2A2	30.8	38	-	34.9*		28.8	30.5	32.8	26.9*	22.9		
Alpine	RRA1	-	-	-	64.9		45	43.8	56.9	54.7	38.3		
	ST1OG3	39.2	42.3*		26.2		34.7	27.2*	33.5	25.5	10.8		
Old	ST1OG7	26	37.1	40.2	21.1		26.4	28.4	29.3	23.3	10.9		
Growth	ST1OG8	33.2	51.4*	43.4*	16.3		26.3	31*	25.6*	21.1	19.5		

	ST10G4	21.3*	15.8	21.3*		13.5*	7.1	13.9*	10.8	9.8
D. Old	ST1OG5	21.3	29.4*	25.9	5.1*	17.9	12.3*	20.1	10.2*	10.2
Growth	ST1OG6	22.4*	19.1*	18.2	5.8*	14*	12.8*	16.4	11.4*	9.1
	ST4RF1	24*	30.9*	33.2*		83.3*	76.1*	72.2*	72.2	32.5
	ST4RF2	27.5*	27.2*	34.3*		61.1*	62.3*	63.6*	65	59.7
Regen.	ST6GC1	29.7*	35.5	27.9*		71.4*	69.9	74.2*	67.7	41.2
	ST2CC1	25.4*	34.3*	40.8*		58.1*	57.7*	59.4*	55	80.5
Juvenile	ST2CC2	23*	26*	34.6*		57.4*	54.4*	52.6*	58	46

### Appendix E: Old Growth Forest: Canopy Snow Depth Variability

Generally, canopy gaps in forests will accumulate more snow than under the trees, due to the tree intercepting snow and subsequent sublimation. For plots such as old growth forests with large canopy gaps, this was captured in both the field and LiDAR measurements, with higher depths in the open, and lower depths under the canopy.



Figure E 1 Snow depth distribution of old growth forest plot ST1OG7 showing the field (orange) and LiDAR (purple) snow depths categorized by open, edge, or under canopy for 2022 snow surveys

## Appendix F: Average snow depth results tables

Mean Snow		FIE	П			L ;D	۸D	
Deptil (cill)	ar	E E		n	ar	LID. E		n
2022	M-9	11-A	21-M	24-Jı	М-9	11-A	21-M	24-Jı
Steph 1	212.4 -		308.6	181	212.6	294.6	293.5	124.5
Ridge Run	-	290.7	281	146.1	223	284	274.5	108.4
Lower Cain	-	186	206.6	80.7	168.5	216.8	210.8	38.8
Steph 2	175.8	245.2	212.8	79.9	175.7	224.8	201.8	27.5
Steph 3	78.4	128.8	65.4		77.7	114.8	58.7	13.9
Steph 4	89.6	130.2	69.6		83.6	118.3	66.3	0.9
Steph 6	91.7	122.3	52.4		86.4	101.5	42.8	5.7
Steph 7	51.8	41.4			60.1	35.2	-2.6	24.8
Steph 8	45.4	18.6			46	7.6	-11.8	4.6

Table F 1 2022 mean snow depth from snow courses for field and LiDAR measurements. Blue highlight indicates the plot was snow free

Table F 22023 mean snow depth from snow courses for field and LiDAR measurements. Blue highlight indicates the plot was snow free

Mean Snow Depth (cm) 2023	10-Mar	4-Apr <sub>H</sub>	DTELD 29-Apr	25-May	12-Jun	10-Mar	4-Apr	iDAR 59-Apr	25-May	12-Jun
Steph1	204.4	194.4	-	81		189.5	207.4	190.4	56.4	-4
Ridge Run	-	-	-	65.9		209.7	217.2	226.9	45.4	-4.1
Lower Cain	-	-	-	22.9		171.5	173.1	172	21.5	6.1
Steph 2	163.9	158.4	169.6			160.6	156	154.7	1.3	-8.3
Steph 3	80.5	69.5	66.6			76.2	70.8	48.9	5.4	-3
Steph 4	91.4	81.2	74.9			75.1	66.9	45.5	0.1	-4.5
Steph 6	95	76.7	73.2			78	64.5	49.1	-0.5	-4.9
Steph 7	52.6	21.6				43.7	21.4	6.5	5.3	1.9
Steph 8	52.6	27.8				42.1	17.3	-2.4	-8.1	-10.1

Table F 3 Mean difference in centimeters for snow courses snow depth between field and LiDARs. Grey highlight indicates bias +/-10 cm, red is LiDAR under-estimated by more than 10 cm, and green highlight indicates LiDAR overestimated by more than 10 cm. Blue highlight indicates snow free. Significantly different average snow depths between the field and LiDAR (p<0.05) are bolded with an \*.

Mean difference	9-Mar	11-Apr <sub>10</sub>	21-May 221-May	24-Jun	10-Mar	4-Apr.o	29-Apr	25-May	12-Jun
Steph 1	0.2	-	-15.1	-56.5*	-14.9*	13	-	-24.6*	-4
Ridge Run	-	-6.7	-6.5	-38*	-	-	-	-20.5*	-4.1
Lower Cain	-	30.8*	4.2	-41.9*	-	-	-	-1.4	6.1
Steph 2	0.1	-20.4*	-11*	-52.4*	-3.3	-2.4	-14.9*	1.3	-8.3
Steph 3	0.7	-14*	-6.7	13.9	-4.3	1.3	-17.7*	5.4	-3
Steph 4	-6*	-11.9*	-3.3	0.9	-16.3*	-14.3*	-29.4*	0.1	-4.5
Steph 6	5.3	-20.8*	-9.6*	5.7	-17*	-12.2*	-24.1*	-0.5	-4.9
Steph 7	8.3*	-6.2	-2.6	24.8	-8.9*	-0.2	6.5	5.3	1.9
Steph 8	0.6	-11*	-11.8	4.6	-10.5	-10.5	-2.4	-8.1	-10.1

Table F 4 2022 mean snow depth from the cardinal plots for field and LiDAR measurements. Blue highlight indicates the plot was snow free

Mean Sno	ow Depth		Fie	eld			LiD	AR	
(ci 20	m) 22	9-Mar	11-Apr	21-May	24-Jun	9-Mar	11-Apr	21-May	24-Jun
	ST1A1	167.4	-	172.8	69.3	160.4	213.7	222.8	34.8
	ST2A2	-	-	191.5	71.1	171.3	222.9	232	61.1
Alpine	RRA1	-	-	-	206.9	218.4	302	406.1	157.7
	ST1OG3	-	-	157.6	88.1	170.9	223.1	240.1	61.6
Old	ST1OG7	163.6	229.2	201.2	94	158.8	205.9	193.2	59.8
Growth	ST10G8	146.8	223.9	210.4	94.4	151.6	198.3	185	47.2
	ST10G4		112.6	120.1	16.5	69	96.1	116.1	11.8
D. Old	ST1OG5	79.3	115.3	137.6	23	72	105	116.9	15.5
Growth	ST1OG6	93.1	125.6	140.4	25.5	79.2	107.7	112.6	19
	ST4RF1	103.6	91.4	28.1	0	143.4	147.4	65.4	162.9
	ST4RF2	84.2	150.5	48	0	191.1	216.6	147.6	118.3
Regen.	ST6GC1	64.4	104.8	14.8	0	120.4	117.3	44.1	76.8
	ST2CC1	-	167.3	147.8	27.6	169.8	196.8	150.5	68.7
Juvenile	ST2CC2	-	194.7	117.5	13.9	284	316.2	251.5	164.8

Table F 5 2023 mean snow depth (cm) from cardinal plots for field and LiDAR measurements. Blue highlight indicates the plot was snow
free

		10-Mar	4-Apr	Field 59-Apr	25-May	12-Jun	10-Mar	4-Apr	LiDAR 767-67	25-May	12-Jun
	ST1A1	165	161.2	-	15.7	0	148.4	152.5	140	11.8	-4.9
	ST2A2	208.9	216.7	-	35.6	0	183.3	197.6	172.5	33.3	0.5
Alpine	RRA1	-	-	-	198.6		291	302.8	335.6	134.9	30.9
	ST1OG3	228.2	218.6	-	24.4	0	221.9	207.7	224.1	3.3	-16.4
Old	ST1OG7	169.7	172.5	177.1	25.8	0	156.5	114.9	164.4	11.2	-14
Growth	ST1OG8	175.9	178	198.2	22.1	0	151.5	74.9	164.1	-7.2	-22.9
	ST10G4	143.9	155.2	171.2	0	0	138.3	138.6	141.2	-11.9	-9.1
D. Old	ST10G5	143.5	148.2	158.8	1.6	0	128.2	129.3	131.8	-11.8	-12.2
Growth	ST1OG6	130.3	136.5	156.1	2.2	0	118.9	116.4	122.2	-10.7	-15.6
	ST4RF1	90.8	62.9	46.4	0	0	132.8	115.9	87.7	45.3	-27.6
	ST4RF2	106	72.8	75.8	0	0	175.1	158.3	131.3	75.2	-40
Regen.	ST6GC1	59.6	36.2	29.8	0	0	98.4	80.2	59	25.4	-25
	ST2CC1	156.4	151.5	155	0	0	178.7	182	172.2	31.5	-9.8
Juvenile	ST2CC2	152.4	141.6	137.6	0	0	275.6	276.4	261.8	127.5	-27.8

Table F 6 Mean difference in centimeters for cardinal plots for snow depth between field and LiDARs. Grey highlight indicates bias +/- 10 cm, red is LiDAR under-estimated by more than 10 cm, and green highlight indicates LiDAR overestimated by more than 10 cm. Blue highlight indicates snow free. Significantly different average snow depths between the field and LiDAR (p<0.05) are bolded with an \*.

Mean d (c	ifference m)	9-Mar	11-Apr <sub>0</sub> 2	21-May	24-Jun	10-Mar	4-Apr	2023 20-702	25-May	12-Jun
	ST1A1	-6.97	-	50*	-34.5*	-16.7*	-8.7	-	-3.8*	-4.86
Alpine	ST2A2	-	-	40.5*	-9.9*	-25.5*	-19.06*	-	-2.35	0.49
	RRA1	-	-	-	-49.26*	-	-	-	-63.7*	
Old	ST1OG3	-	-	82.5*	-26.6*	-6.3	-10.9*	-	-21.1*	-16.4
	ST1OG7	-4.8	-23.4*	-8.1	-34.3*	-13.2*	-57.6*	-12.7*	-14.6*	-14
Growth	ST1OG8	4.8	-25.7*	-25.3*	-47.2*	-24.4*	-103.1*	-34.1*	-29.3*	-22.9
	ST10G4	-	-16.6*	-3.97	-4.63	-5.6*	-16.6*	-30*	-11.9	-9.1
D. Olu Growth	ST10G5	-7.3	-10.3*	-20.7*	-7.5	-15.3*	-18.9*	-27*	-13.4*	-12.2
Growth	ST1OG6	-13.9*	-17.9*	-27.9*	-6.53	-11.4*	-20.1*	-33.9*	-12.9*	-15.6
	ST4RF1	39.8*	56.1*	37.2	162.9	42*	53*	41.3*	45.3	-27.6
Regen.	ST4RF2	106.9*	66.1*	99.7	118.3	69.1*	85.5*	55.5*	75.2*	-40
	ST6GC1	56.0	12.5	29.2	76.8	38.8*	44*	29.2	25.4	-25
Tuvonilo	ST2CC1	-	29.6	2.7	41.2	22.3	30.5*	17.2	31.5	-9.8
JUVEIIIE	ST2CC2	-	121.5*	134.0*	151.0*	123.2*	134.8*	124.2*	127.5*	-27.8

## Appendix G: Bias corrections for meteorological variability

Year	Acquisition	Cover	Plot ID	Snow	Weather Station (Wx) /	Notes
	Date			depth	Game Camera (GC)	
				[cm]	station	
			ST4RF1	+5	GC: ST6GC1	Snowfall in plots
	Mar-9	Regenerating	ST4RF2	+11	GC: ST6GC1	sampled after LiDAR
	A	T	ST2CC1	+16	Wess Obsert 2	LiDAR flown after,
	Apr-11	Juvenile	ST2CC2	+16	wx: Stepn 2	plots
		Alpine	ST1A1	-14		LiDAR flown, then
	May-21	p	ST1A2	-14	Wx: Steph 1	warming prior to sampling
		Alpine	ST1A1		Wyv Steph 1	
		Alphic	ST1A2	+43		
2022			ST10G4			Delayed LiDAR
		Dense old	ST1OG5			Snow entirely
		growth		+10	GC: ST1GC1	melted at ST1GC1,
	Jun 24		GTT1000			approximation of
	Juli-24		STIOG6		Average of Wy: Steph 1 &	Delayed LiDAR
			ST1OG3	+31	GC: ST1GC1	flight, melt occurred
		Old growth	ST1OG7	+19	CC ST1CC2	
			ST1OG8		00.511005	
		Iuvenile	ST1CC1	+30	Wx: Steph 2	Delayed LiDAR
		Juvenne	ST1CC2	150	WX. Steph 2	flight, melt occurred
		dense old	ST10G4			Rapid snow melt
		growth	ST10G5	+12.5	GC: ST1GC1	sampling and
			ST1OG6			LiDAR
		11 4	ST1OG3		00 0 <b>T</b> 1002	Rapid snow melt
		old growth	ST10G7	+13	GC: STIGC3	occurred between
~			ST1OG8	15		LiDAR
2023	Apr-29		ST4RF1			no enough snow at
		raganarating	ST4RF2		CC ST1CC1	closest station
		regenerating			00.511001	change
			ST6GC1	+12.5		
			ST2CC1			Rapid snow melt
			512001		Wx: Steph 2	sampling and
		juvenile	ST2CC2	+16		LiDAR

Table G 1 Meterological bias corrections applied in the bias assessment of the cardinal plots, as shown in results section 5.4.1.2

# Appendix H: Watershed Snow Volume

Table H-1 Snow Storage in the Russell Creek watershed by cover type for the 2022 LiDAR acquisitions. Snow is shown in cubic meters, with the proportion of the watershed snow shown in brackets

Date Flown	3/9/2	2022	4/11/2	2022	5/21/2	2022	6/24/2	2022
Bare Earth	2017, BCTS	2023, ACO	2017, BCTS	2023, ACO	2017, BCTS	2023, ACO	2017, BCTS	2023, ACO
	m <sup>3</sup> (percent of volu	of total snow ime)	m <sup>3</sup> (percent o volui	f total snow me)	m³ (percent o volui	f total snow me)	m³ (percent o volui	of total snow me)
Alpine	11,814,549 (36.0%)	13,712,941 (40.1%)	14,587,480 (34 1%)	16,484,398 (37 2%)	15,258,007 (41.6%)	17,163,290 (44.4%)	8,963,691 (37 8%)	10,849,364
Old Growth	13,007,977 (39.7%)	(11,230,885 (32.9%)	16,280,662 (38.1%)	14,552,546 (32.9%)	13,875,470 (37.8%)	(31.9%) (31.9%)	9,027,503 (38.0%)	7,172,312 (28.7%)
Mature Regen.	1,299,083 (4.0%)	1,070,746 (3.1%)	4,669,245 (10.9%)	4,516,964 (10.2%)	3,077,733 (8.4%)	2,973,875 (7.7%)	1,392,165 (5.9%)	1,161,106 (4.7%)
Regenerating	4,823,783 (14.7%)	5,947,794 (17.4%)	5,330,758 (12.5%)	6,512,690 (14.7%)	3,402,653 (9.3%)	4,651,516 (12.0%)	3,301,467 (13.9%)	4,384,568 (17.6%)
Juvenile	$1,572,433 \\ (4.8\%)$	2,059,789 (6.0%)	1,600,730 (3.8%)	2,072,641 (4.7%)	910,329 (2.5%)	$1,410,716 \\ (3.6\%)$	850,146 (3.6%)	1,318,570 (5.3%)
New Harvest	195,834 (0.6%)	73,387 (0.2%)	183,021 (0.4%)	75,633 (0.2%)	126,205 (0.3%)	58,915 (0.1%)	169,395 (0.7%)	50,404 (0.2%)
FSR	87,639 (0.3%)	90,081 ( $0.3\%$ )	82,989 (0.2%)	90,624 (0.2%)	46,354 (0.1%)	55,501 (0.1%)	26,133 $(0.1%)$	33,760 (0.1%)
Total	32,801,298	34,185,623	42,734,885	44,305,496	36,696,751	38,622,767	23,730,500	24,970,084

Table H-2 Snow Storage in the Russell Creek watershed by elevation band for the 2022 LiDAR acquisitions. Snow is shown in cubic meters, with the proportion of the watershed snow shown in brackets

							:			
2022	2023, ACO	tal snow volume)	534,366 (2.1%)	3,047,727 (12.2%)	3,329,063 (13.3%)	3,147,159 (12.6%)	2,477,293 (9.9%)	5,542,991 (22.2%)	6,891,485 (27.6%)	24,970,084
6/24/	2017, BCTS	m <sup>3</sup> (percent of to	526,784 (2.2%)	3,478,685 (14.7%)	3,452,784 (14.6%)	2,817,824 (11.9%)	2,921,229 (12.3%)	5,806,577 (24.5%)	4,726,617 (19.9%)	23,730,500
2022	2023, ACO	al snow volume)	440.917 (1.1%)	3,464,926 (9.0%)	2,983,642 (7.7%)	3,874,085 (10.0%)	6,013,327 (15.6%)	11,538,073 (29.9%)	10,307,797 (26.7%)	38,622,767
5/21/2	2017, BCTS	m <sup>3</sup> (percent of tot	430,814 (1.2%)	3,513,020 (9.6%)	2,911,511 (7.9%)	3,502,837 (9.6%)	6,424,254 (17.5%)	$11,773,919 \\ (32.1\%)$	8,140,396 (22.2%)	36,696,751
2022	2023, ACO	al snow volume)	402,362 (0.9%)	5,864,185 (13.2%)	4,270,943 (9.6%)	5,922,151 (13.4%)	6,833,379 (15.4%)	11,102,671 (25.1%)	9,909,805 (22.4%)	44,305,496
4/11/2	2017, BCTS	m <sup>3</sup> (percent of tot	388,107 (0.9%)	6,057,999 $(14.2%)$	4,394,563 (10.3%)	5,577,343 (13.1%)	7,237,320 (16.9%)	11,333,253 (26.5%)	7,746,300 (18.1%)	42,734,885
022	2023, ACO	al snow volume)	438,489 (1.3%)	2,879,070 (8.4%)	3,314,036 (9.7%)	5,126,971 (15.0%)	5,231,501 (15.3%)	8,791,304 (25.7%)	8,404,252 (24.6%)	34,185,623
3/9/2	2017, BCTS	m <sup>3</sup> (percent of tot	432,489 (1.3%)	3,327,715 (10.2%)	3,425,212 (10.4%)	4,706,684 (14.3%)	5,641,676 (17.2%)	9,030,259 (27.5%)	(19.0%)	32,801,298
Date Flown	Bare Earth	Elevation Band [m]	200 - 400	400 - 600	600 - 800	800 - 1000	1000 - 1200	1200 - 1400	1400 - 1700	Total

3/10/20 017, 20 CTS A m <sup>3</sup> (percent of to volume 1,053,398 1	3, 2017, D BCTS I snow m <sup>3</sup> (percent o volui	2023 2023, ACO of total snow me) 13,669,997	4/29/. 2017, BCTS m <sup>3</sup> (percent c volu	2023 2023, ACO of total snow me) 13,933,833	5/25 2017, BCTS m <sup>3</sup> (percent voli	/2023 2023, ACO of total snow ime) 3,930,662	6/1 2017, BCTS m <sup>3</sup> (percei vv
398 1 () 54 1	968,040         11,760,305           7.6%)         (39.8%)           (00,555         12,656,902	$\begin{array}{c} 13,669,997 \\ (43.7\%) \\ 10,953,036 \end{array}$	12,027,988 (42.6%) 12,217,025	13,933,833 (46.3%) (46.3%) 10,635,542	2,009,029 (41.7%) 1,784,975		3,930,662 (56.0%) 340,755

Table H-3 Snow Storage in the Russell Creek watershed by cover type for the 2022 LiDAR acquisitions. Snow is shown in cubic kilometers, with the proportion of the watershed snow shown in brackets

144

-3,589,788

-5,991,728

7,018,933

4,813,295

30,116,482

28,232,610

31,280,394

29,581,989

34,441,880

33,384,574

Total

-1,822,858(50.8%)

-3,191,502

(53.3%)

1,893,150(27.0%)

527,137 (10.9%)

3,782,503 (12.6%)

2,523,775 (8.9%)

4,424,920 (14.2%)

3,208,766 (10.8%)

5,934,958 (17.2%)

4,816,056 (14.4%)

Regenerati

ng

-450,824 (12.6%)

-382,670 (6.4%)

50,965 (0.7%)

178,223 (3.7%)

56,104 (0.2%)

165,973

175,790(0.6%)

305,586

763,779

,131,221 (3.4%)

M. Regen.

(2.2%)

(1.0%)

(0.6%)

-826,744 (23.0%)

-1,342,496 (22.4%)

789,014 (11.2%)

244,117 (5.1%)

1,611,113(5.3%)

1,120,349(4.0%)

1,934,539(6.2%)

1,449,571 (4.9%)

2,358,069 (6.8%)

1,883,514(5.6%)

Juvenile

-21,484(0.6%)

56,506 (-0.9%)

-4,459 (-0.1%)

63,155 (1.3%)

39,308 (0.1%)

129,859(0.5%)

51,545 (0.2%)

139,569(0.5%)

116,560(0.3%)

269,670 (0.8%)

Harvest

New

-38,031(1.1%)

-47,433(0.8%)

18,846(0.3%)

6,659(0.1%)

58,079 (0.2%)

47,641 (0.2%)

70,567 (0.2%)

(0.2%)

99,919 (0.3%)

101,461(0.3%)

FSR

Table H- 4 Snow Storage in the Russell Creek watershed by cover by elevation band for the 2023 LiDAR acquisitions. Snow is shown in cubic meters, with the proportion of the watershed snow shown in brackets

6/12/2023	17, 2023, ACO TS	<sup>3</sup> (percent of total snow volume)	86,510 -271,358 1.8%) (7.6%)	582,683 -1,630,707 6.4%) (45.4%)	179,970         -1.385,459           4.7%         (38.6%)	376,815         -1,416,145           3.0%)         (39.5%)	71,459 -668,139 5.2%) (18.6%)	52,614         396,250           2.7%)         (-11.0%)	56,905         1,385,770           7.6%)         (-38.6%)	
023	2023, 201 ACO BC	total snow m <sup>3</sup> m <sup>3</sup>	3,169 -28 (0.1%) (2	471,920 -1,5 (6.7%) (2	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c cccc} 1,014,587 & -1,5 \\ (14.5\%) & (3 \\ \end{array}$	818,808 -37 (11.7%) (6	$\begin{array}{c c} 1,973,042 \\ (28.1\%) \\ (-1) \\$	1,950,138 -1,0 (27.8%) (1	
5/25/2	2017, BCTS	m <sup>3</sup> (percent of volum	-25,865 (-0.5%)	517,407 (10.8%)	754,800 (15.7%)	453,504 (9.4%)	1,144,933 (23.8%)	2,417,601 (50.2%)	-449,085 (-9.3%)	
2023	2023, ACO	f total snow me)	-45,787 (-0.1%)	681,567 (2.2%)	1,775,079 (5.7%)	4,590,145 (14.7%)	6,360,540 (20.3%)	10,061,308 (32.2%)	7,857,542 (25.1%)	201 211 202
4/29/2	2017, BCTS	m³ (percent o volui	-72,591 (-0.2%)	774,689 (2.6%)	1,891,989 ( $(6.4\%)$	4,262,719 (14.4%)	6,747,699 (22.8%)	10,389,886 (35.1%)	5,587,598 (18.9%)	
2023	2023, ACO	of total snow ime)	41,113 (0.1%)	500,897 (1.7%)	1,242.975 (4.1%)	3,736,937 (12.4%)	6,186,740 (20.5%)	10,858,248 (36.0%)	7,549,572 (25.1%)	1000010
4/4/2	2017, BCTS	m³ (percent c volu	5,327 (0.0%)	541,998 (1.9%)	1,235,261 (4.4%)	3,397,311 (12.0%)	6,592,089 (23.4%)	11,223,485 (39.8%)	5,237,139 (18.6%)	000 102 00
/2023	2023, ACO	of total snow ume)	120,090 (0.3%)	1,829,453 (5.3%)	2,925,779 (8.5%)	5,883,739 (17.1%)	6,715,517 (19.5%)	9,755,978 (28.3%)	7,211,324 (20.9%)	000 111 10
3/10.	2017, BCTS	m <sup>3</sup> (percent voli	103,995 (0.3%)	2,417,108 (7.2%)	3,254,608 (9.8%)	5,490,746 (16.4%)	7,120,985 (21.3%)	10,044,987 (30.1%)	$\begin{array}{c} 4,952,145\\ (14.8\%)\end{array}$	
Date Flown	Bare Earth		200 - 400	400 - 600	600 - 800	800 - 1000	1000 - 1200	1200 - 1400	1400 - 1700	Total

145

### Appendix I: Harvest Experiment Slash Pile Analysis

Further analysis of the cut block surface debris was prompted by the result of a positive increase in ground surface post-harvesting. A potential source of error would be a misclassification of logs and slash piles as a ground. If this occurred in numerous parts of the cut block, this would result in a false positive bias to the ground surface.

Classification of the cut block into slash and ground using a basic supervised classification of the orthoimagery. Shadow caused by the trees were classified separately and not included in the analysis. The classified raster was resampled to the LiDAR 1 meter resolution, and surface elevations were binned according to ground or slash.



Figure I lResult of classification of cut block as ground (yellow) or slash (brown)

The summary statistics and plotted histogram do not show evidence of a bias on logs compared to the ground. Both the slash and ground groups show a similar distribution and positive bias when comparing the 2023 ground surface to the 2022.



Figure I 2 Histogram of the ground surface difference between the post-harvest (2023) and pre-harvest (2022) pixels, showing the peak for both the slash and ground pixels are aligned, and slightly above zero