

SPATIO-TEMPORAL ANALYSIS OF LARGE MAGNITUDE AVALANCHES
USING DENDROCHRONOLOGY

by

Erich Hans Peitzsch

A dissertation submitted in partial fulfillment
of the requirements for the degree

of

Doctor of Philosophy

in

Earth Sciences

MONTANA STATE UNIVERSITY
Bozeman, Montana

April 2020

©COPYRIGHT

by

Erich Hans Peitzsch

2020

All Rights Reserved

DEDICATION

This dissertation is dedicated to my mother, Janice Peitzsch, for her bravery and compassion.

ACKNOWLEDGEMENTS

This work would certainly not be possible without the support from numerous individuals and institutions. First, I thank my advisor, Dr. Jordy Hendrikx, and committee members Dr. Daniel Fagre, Dr. Karl Birkeland, and Dr. Gregory Pederson for their vast amount of support, insightful discussions, and contributions to this work. I thank my colleagues at the U.S. Geological Northern Rocky Mountain Science Center for their support and tireless work ethic, specifically Daniel Stahle and Chelsea Martin-Mikle who contributed to the analysis and field work and Adam Clark, Zachary Miller, and Caitlyn Florentine who assisted with field work. I am extremely grateful for the financial support from the U.S. Geological Survey Land Resources Western Mountain Initiative program. I thank my friends who listened and always expressed (feigned?) interest. Finally, and most importantly, I extend my deepest gratitude to my incredibly encouraging and supportive wife, Laura, and sons, Reece and Soren.

TABLE OF CONTENTS

1. INTRODUCTION.....	1
Scope and Context.....	1
Research Motivation.....	4
Study Area	5
Dissertation Outline.....	8
Chapter 2.....	9
Chapter 3.....	11
Chapter 4.....	12
Chapter 5.....	13
Conceptual Model.....	13
REFERENCES	16
2. A REGIONAL SPATI-TEMPORAL ANALYSIS OF LARGE MAGNITUDE SNOW AVALANCHES USING TREE RINGS.....	17
Contribution of Author and Co-Authors	20
Manuscript Information.....	21
Abstract.....	22
1. Introduction	22
1.1 Background.....	22
1.2 Dendrochronology Techniques.....	24
1.3 Previous Dendrochronology Studies.....	26
2. Methodology.....	31
2.1 Study Site	31
2.2 Sample Collection and Processing.....	35
2.3 Avalanche Event Identification.....	39
2.4 Chronology and Return Period Calculation.....	41
2.5 Geomorphological characteristics.....	47
3. Results	47
3.1 Geomorphological Characteristics.....	49
3.2 Comparison of Two Approaches – GPD and ET.....	50
3.3 Individual Path Chronologies	52
3.4 Sub-region Chronologies	56
3.5 Regional Chronology and RAAI	59
4. Discussion.....	65
4.1 Regional Sampling Strategy and Use of Threshold Approaches.....	66
4.2 Chronologies for Individual Paths and Sub-Regions.....	68
4.3 Regional Chronologies and RAAI	70
4.4 Limitations and Future Work.....	74
5. Conclusions	75
REFERENCES	77

TABLE OF CONTENTS CONTINUED

APPENDIX	84
3. TRENDS IN REGIONAL LARGE MAGNITUDE SNOW AVALANCHE OCCURRENCE AND ASSOCIATED CLIMATE PATTERNS IN THE U.S. NORTHERN ROCKY MOUNTAINS.....	86
Contribution of Author and Co-Authors	93
Manuscript Information	94
Abstract.....	95
1. Introduction	95
2. Methodology.....	99
2.1 Study Site	99
2.2 Sample collection and processing	103
2.3 Chronology and Return Period Calculation	103
2.4 Climate data	104
2.5 Statistical analysis	106
3. Results	108
3.1 Regional Avalanche Chronology	108
3.2 Climate Conditions Characterizing Avalanche Years	110
3.3 Multivariate Analysis of Large Magnitude Avalanche Years	112
3.4 Analysis of Probability of Avalanche Years.....	115
4. Discussion.....	116
4.1 Regional Chronology and RAAI	117
4.2 Climate – Avalanche Interactions.....	118
4.3 Modeling avalanche years.....	122
5. Conclusions	125
REFERENCES	127
APPENDIX	133
4. VEGETATION CHARACTERIZATION IN AVALANCHE PATHS USING LIDAR AND SATELLITE IMAGERY.....	129
Contribution of Author and Co-Authors	139
Manuscript Information	140
Abstract.....	141
1. Introduction	141
1.1 Avalanche Effects on Vegetation Structure and Composition	142
1.2 Effects of Vegetation Cover and Structure on Avalanches	144
1.3 Characterizing vegetation using remote sensing.....	145
2. Methods	146
2.1. Study Site	146

TABLE OF CONTENTS CONTINUED

2.2 Lidar and Spectral Imagery Data Acquisition	148
2.3 Imagery and Lidar Data Processing.....	149
2.4 Ground Reference Data and Object-Based Metric Calculation.....	151
2.5 Model Selection and Image Classification	154
2.6 Dendrochronological Analysis and Return Period Reconstruction	155
3. Results	156
3.1 Lidar Field Validation.....	156
3.2 Manually Classified Objects (ROI).....	158
3.3 Random Forest Model Classification.....	158
3.4 Return Period Vegetation.....	164
4. Discussion.....	168
4.1 Vegetation Classification	168
4.2 Return Period Intervals and Vegetation Classification	170
4.3 Limitations	173
5. Conclusions	173
REFERENCES	175
APPENDIX	181
5. CONCLUSION.....	184
Summary.....	184
Limitations and Recommendations for Future Work.....	186
CUMULATIVE REFERENCES CITED.....	190

LIST OF TABLES

Table	Page
2.1 List of previous avalanche-dendrochronological work.....	27
2.2 Topographic characteristics of all avalanche paths.....	32
2.3 Regional chronologies from the ITRDB	38
2.4 Avalanche impact trauma classification ratings.....	40
2.5 Avalanche chronologies and return interval statistics for all 12 individual paths.....	54
2.6 Avalanche chronologies and return interval statistics for sub-regions.....	57
2.7 Number of avalanche events for each subregion	58
2.8 Comparison of the number of avalanche years and RI	61
2.9 Probability of Detection (POD_{year}).....	63
2.10 Probability of Detection (POD_{path}).....	64
2.S1 Results of Tukey HSD test of means	89
2.S2 Avalanche chronologies and return interval statistics for all 12 individual paths without W_{it} step.....	90
2.S3 Number of avalanche events for each sub-region and region using the GPD approach	91
2.S4 Avalanche years identified in the regional analysis and years identified in one or more paths in the individual path analysis.....	91
3.1 Descriptive statistics for 12 avalanche paths in the study site	101
3.2 NRCS snow course sites used in this study.....	105
3.3 Climate, temperature, and snow property variables.....	106

LIST OF TABLES CONTINUED

Table	Page
3.4 Avalanche chronology characteristics for the various sub-regions and overall region	110
3.S1 Results of Mann Kendall test for monotonic trend	134
3.S2 Table of climate variables tested in Wilcoxon rank-sum test between avalanche and non-avalanche years	134
3.S3 Best-fit GLARMA model results	135
4.1 Topographic characteristics of all avalanche paths	148
4.2 Class aggregation for avalanche path return period analysis	152
4.3 The number of manually identified objects in each class	158
4.4 Overall accuracies and kappa values for random forest models	161
4.5 Confusion matrices associated with the best fit model for each individual avalanche path	162
4.6 Classification accuracies for each avalanche path using different datasets	164
4.S1 Confusion matrices associated with the best fit spectral model	182
4.S2 Confusion matrices associated with the best fit lidar model	183

LIST OF FIGURES

Figure	Page
1.1 Study site	7
1.2 Conceptual model.....	15
2.1 Study site	33
2.2 A tree-ring sample illustrating multiple types of scars that are representative of our weighted classification	41
2.3 General workflow of analytical methods	42
2.4 Example of cross-section sample	48
2.5 Histograms of (A) ratings of responses, (B) sample age, and (C) species.	49
2.6 The number of avalanche years identified using the ET (circles) and GPD (triangles) approaches associated with the median return interval for each individual avalanche path	51
2.7 Median return intervals derived using the (A) GPD approach and (B) the ET approach	51
2.8 Example demographic plot of the LJA path.....	52
2.9 Number of individual avalanche paths identified per year after implementing the ET approach and subsequent W_{it} threshold process step.....	53
2.10 Boxplot of return intervals for individual paths in each sub-region.....	56
2.11 Venn diagram of avalanche years common between sub-regions	59
2.12 (A) The number of samples through time, (B) the W_{it} threshold, and (C) the RAAI.	62
2.S1 Raw number of responses from the entire dataset	85

LIST OF FIGURES CONTINUED

Figure	Page
2.S2 Demograph plots of all samples from all paths.....	86
2.S3 Aspect of all samples in the study region	87
2.S4 Correlation matrix of the number of avalanche years return intervals, starting zone slope angle, and path length	88
3.1 Study site	102
3.2 The regional avalanche activity index chronology and supporting double threshold analysis for avalanche event classification.....	109
3.3 Time series and boxplots of snowpack and precipitation	111
3.4 Boxplots of atmospheric variables and indices	112
3.5 Time series plots of select PCs.....	114
3.6 Regional avalanche probability and major contributing variables	116
3.S1 Scree plot of principal components.....	136
3.S2 Plot of PC variables in two dimensions	137
3.S3 Correlation matrix of all variables used in the PCA	138
4.1 Study site	147
4.2 General workflow of classification procedure	151
4.3 Canopy height measurements.....	157
4.4 Variable importance plots	160
4.5 Labeled vegetation mapping results for Shed 10-7, 1163 and Shed 1163 using a combination of spectral and LiDAR data.	163

LIST OF FIGURES CONTINUED

Figure	Page
4.6 Return periods and Random Forest model generated vegetation classes for return interval zones for Path 1163 and Shed 7	166
4.7 Proportions of each vegetation class for Path 1163 and Shed 7.....	167

ABSTRACT

Snow avalanches are a natural hazard to humans and infrastructure as well as an important landscape disturbance affecting mountain ecosystems. In many mountainous regions, records of avalanche frequency and magnitude are sparse or non-existent. Inferring historic avalanche patterns to improve forecasting and understanding requires the use of dendrochronological methods. In this dissertation, we examine a regional tree-ring derived large magnitude avalanche dataset from northwest Montana in the northern Rocky Mountains, USA, to produce avalanche chronologies at three distinct scales (path, sub-region, and region), assess seasonal climate drivers of years with large magnitude avalanche occurrence on a regional scale, and characterize vegetation in select avalanche paths. By implementing a strategic spatial sampling design and collecting a large dataset of tree-ring samples, we: (1) assessed scaling in the context of a regional avalanche chronology, reconstructed avalanche chronologies for 12 avalanche paths in four sub-regions, and examined the effects of two methods of sampling indexing on the resultant avalanche chronology; (2) identified specific climate drivers of large magnitude avalanche years across a region and identified trends in avalanche year probability through time; and (3) tested the feasibility of using remote sensing products to quantify vegetation types in avalanche paths and characterized the vegetation composition based on return periods within specific avalanche paths. This dissertation is organized into 3 key chapters/manuscripts (Chapters 2, 3, and 4) and two supporting chapters (Chapters 1 and 5) that address the problem of assessing large magnitude avalanche frequency at various spatio-temporal scales using a tree-ring dataset. The results contribute toward a better understanding of reconstructing regional avalanche chronologies, a more accurate assessment of avalanche-climate relationships, and improved methods to characterize vegetation characteristics within avalanche path return periods. This work has applications for regions with sparse avalanche records.

CHAPTER 1

INTRODUCTION

Scope and Context

Snow avalanches are a natural hazard to humans and infrastructure (Mock et al., 2016; Schweizer, 2003; Voight et al., 1990) as well as an important landscape disturbance affecting mountain ecosystems (Bebi et al., 2009). A snow avalanche (hereafter avalanche) is a mass movement of snow down a slope that takes place predominantly in mountainous terrain. There are two types of avalanches: slab avalanches and loose snow avalanches. Either of those can be a dry or wet snow avalanche. Slab avalanches, in particular, are the most destructive and hazardous. A slab avalanche requires four primary ingredients to occur: a sufficiently steep slope (typically 30° to 45°), a weak layer within the snowpack, a slab of snow above that weak layer, and a trigger. A trigger can be additional loading from new snow, wind, a human, or, in the case of avalanche mitigation, an explosive. Numerous factors influence the likelihood of avalanche occurrence including precipitation type and rate, temperature, wind speed and direction, existing snowpack structure, slope angle and aspect, terrain, and vegetation.

Over the last 10 years in the United States an average of 27 people died in avalanche accidents each winter (CAIC, 2018). Avalanches also affect transportation corridors and settlements throughout the world. For example, avalanches impact numerous roadways in the western United States (Armstrong, 1981; Blattenberger and Fowles, 1994; Hendrikx et al., 2014; Reardon et al., 2004; Wayand et al., 2015). In

Glacier National Park, Montana, USA, specifically, avalanches impact road clearing operations and a major transportation corridor (Peitzsch et al., 2012; Reardon and Fagre, 2006). Large magnitude avalanches, in particular, are destructive and cause disruptions to society and commerce (Reardon et al., 2004). Therefore, identifying return periods of large magnitude avalanches can help decision makers and land managers with infrastructure planning and the implementation of protective measures or structures.

Long term, reliable, and consistent avalanche observation records are important for calculating avalanche return periods. However, in many mountainous regions, including areas with existing transportation corridors, such records are sparse or non-existent. Thus, inferring avalanche patterns requires the use of dendrochronological methods. Even in regions with historical records, tree-ring dating methods can be used to extend or validate uncertain historical avalanche records (Corona et al., 2012; Favillier et al., 2018; Schläppy et al., 2014), particularly large-magnitude events. Accordingly, the use of dendrochronology to document geomorphic response has been used rather extensively in numerous regions throughout the world (Butler and Sawyer, 2008; Shroder, 1980; Stoffel and Bollschweiler, 2008).

Advances in dendrochronological methods for developing avalanche chronologies have allowed for a more comprehensive account of avalanche activity in any given area. While the fundamental concepts of using tree-ring data to infer avalanche activity remain the same, recent incremental improvements and applications help reduce noise and, ultimately, improve large magnitude avalanche forecasting. Two such examples include the identification of traumatic resin ducts (TRDs) as avalanche signals (Stoffel et al.,

2010) and the use of a double threshold based on changing sample size for determining avalanche events (Corona et al., 2012). From an application perspective, tree ring derived avalanche chronologies have been used to examine avalanche and climate/weather relationships (Germain et al., 2009; Martin and Germain, 2016) and to identify avalanche return periods and create spatially explicit maps in specific avalanche paths (Favillier et al., 2018; Meseşan et al., 2018; Reardon et al., 2008). Despite these advances, using tree-ring methods to reconstruct avalanche activity has limitations. The greatest limitation of using tree-ring records is the underestimation of avalanche activity (Corona et al., 2012). The successive damage and removal of trees from events size D2 (Greene et al., 2010) or greater impacts the future potential to record subsequent events of similar magnitude. In other words, if a large magnitude avalanche removes a large swath of trees in one year, then there are fewer trees available to record a large magnitude avalanche in subsequent years. However, dendrochronological avalanche research continues to improve and contributes to our understanding of avalanche activity on a variety of spatio-temporal scales.

Dendrochronological techniques can be used to infer regional avalanche chronologies to provide context for long term avalanche activity and trends across a large spatial extent. Sample size and sampling strategy, spatial extent, and representation of avalanche path morphology are necessary considerations when attempting to reconstruct a regional avalanche chronology. An avalanche chronology from one path is insufficient to infer avalanche frequency for an entire region due to scaling and spatial variability constraints. Therefore, a regional avalanche chronology should consist of a sufficient

number of samples and representative avalanche paths relative to the extent of the study region.

Research Motivation

Forecasting large magnitude avalanche frequency is challenging on a multitude of spatial scales (Schweizer et al., 2008; Schweizer et al., 2009). There are numerous drivers of large magnitude avalanches with often complex interactions. A better understanding of spatio-temporal relationships of large magnitude avalanche events will fill a gap in avalanche science. By knowing the avalanche chronology of a region, we can more thoroughly assess current and future trends in avalanche activity and, ultimately, improve public safety and protect resources.

In this work, we examine a regional tree-ring derived large magnitude avalanche dataset to produce avalanche chronologies at three distinct scales (path, sub-region, and region), assess seasonal climate drivers of years with large magnitude avalanche occurrence on a regional scale, and characterize vegetation in select avalanche paths. We address the following objectives through several related questions, which are addressed in three manuscripts (objectives 1,2 and 3 in Chapter 2, objectives 4 and 5 in Chapter 3, and objectives 6 and 7 in Chapter 4):

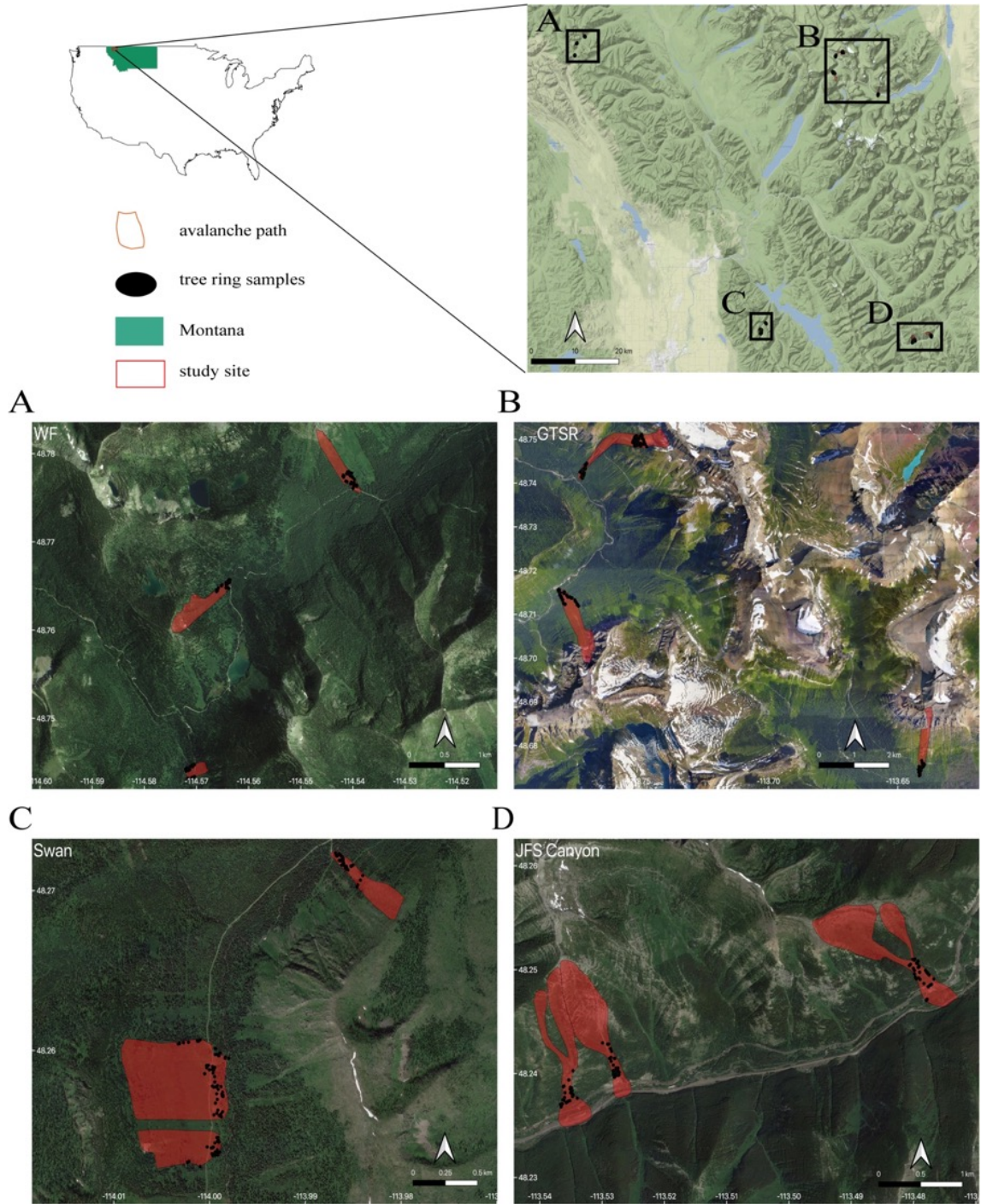
1. Determine the regional, sub-regional, and path specific frequency of large magnitude avalanches in the U.S. northern Rocky Mountains of northwest Montana.
2. Identify how the spatial extent of the study site affects the resultant avalanche chronology.

3. Examine the effect of two different methods of sampling indexing on the resultant avalanche chronology.
4. Identify specific contributory seasonal climate or atmospheric variables to large magnitude avalanche events across the U.S. northern Rocky Mountains of northwest Montana.
5. Investigate any trend of annual regional avalanche activity in the U.S. northern Rocky Mountains of northwest Montana.
6. Test the efficacy of lidar and aerial imagery to characterize and quantify the various types of vegetation throughout three select avalanche paths in southern Glacier National Park, Montana, USA.
7. Accurately map avalanche return periods using a tree-ring derived avalanche chronology and subsequently characterize the vegetation composition within those return periods.

Study Area

The study area of this dissertation encompasses transportation corridors as well as popular recreation destinations in the northern U.S. Rocky Mountains in northwest Montana, USA (Figure 1). This region provides an ideal natural setting for studying avalanches due to its geography, inclusion of transportation and recreation corridors potentially impacted by avalanches, relative accessibility, and minimal artificial avalanche hazard mitigation. Northwest Montana is classified as both coastal transition and intermountain avalanche climate (Mock and Birkeland, 2000), and, as such, exhibits characteristics of both continental and coastal climates. This study area is representative

of the geological, ecological, and climatic characteristics of the northern most extent of the spine of this continental mountain range (Finklin, 1986). However, the entirety of the U.S. northern Rocky Mountains extends south into Wyoming. Here, we use the term U.S. northern Rocky Mountains to describe the northern-most extent of the mountain range.



In this study region, the Flathead Avalanche Center (FAC), a regional U.S. Forest Service backcountry avalanche center, records all avalanches observed and reported to the center. However, given the approximately 3500 km² advisory area comprised of five mountain ranges the center covers, not all avalanches are observed or reported. The Burlington-Northern Santa Fe Railway (BNSF) Avalanche Safety Program records most avalanches observed in their program area; 16 km with over 40 avalanche paths adjacent to Highway 2, in John F. Stevens Canyon in southern Glacier National Park. While their observational record is more consistent, it is temporally limited. Systematic operational observations commenced in 2005. Observations available prior to this time are reliable, but temporally and spatially inconsistent. Large magnitude avalanches were recorded with some consistency due to the adjacent transportation corridor providing a record of avalanches causing disruption to road and rail travel, but the record is still incomplete, particularly further back in time. In this region avalanche mitigation is conducted on an infrequent and inconsistent basis only in emergency situations. Mitigation measures are not conducted every year and typically only once a year, so the record is proximal to a natural avalanche record.

Dissertation Outline

The following chapters of this dissertation address large magnitude avalanche frequency at varying spatio-temporal scales using a large and robust tree-ring based dataset, a strategic spatial sampling design, a suite of climate and atmospheric variables, and a novel approach to vegetation classification in avalanche paths. Each chapter builds upon and utilizes the foundational methods and procedures developed in Chapter 2 to

reconstruct an avalanche chronology. Chapter 3 uses this reconstructed regional chronology to examine associations of large magnitude avalanche years with climate and atmospheric drivers. Chapter 4 uses the spatial component of the tree-ring dataset to examine the composition of vegetation in various return period zones. Overall, the dissertation ties together various components of infrequent, but impactful, events on varying spatio-temporal scales to bolster our understanding of the avalanche phenomenon.

Chapter 2

The foundational component of this chapter uses a tree-ring based dataset to reconstruct a large magnitude avalanche chronology (Peitzsch et al., 2019). We utilize a novel strategic sampling design using the concepts of scale triplet (Blöschl and Sivapalan, 1995) to examine large magnitude avalanche frequency. We strategically sampled 12 avalanche paths in four distinct sub-regions of the U.S. northern Rocky Mountains of northwest Montana to examine spatial differences at a regional scale. The concept of scale triplet (Blöschl and Sivapalan, 1995) is important when trying to extrapolate a process (i.e. avalanche frequency and magnitude) from a single point, such as an avalanche path, to across a region. Tree-ring avalanche research is resource and time intensive. Like numerous other scientific fields of study, it is rarely feasible to completely sample the variable of interest with infinite detail due to logistical and financial constraints (Skoien and Blöschl, 2006). A strategic spatial sampling method can be used to collect robust data that limits the influence of those constraints. Here, we strategically sampled 12 avalanche paths in four distinct sub-regions of the U.S. northern

Rocky Mountains of northwest Montana to examine spatial differences at a regional scale. The sampling strategy is founded on the concept of scale triplet (Blöschl and Sivapalan, 1995) which is important when trying to extrapolate a process (e.g. avalanche frequency and magnitude) from a single point, such as an avalanche path, across a region. Incorporating the concept of scale triplet helps us to more fully understand the nature of the problem, the scale at which we should measure, and how we can estimate the measurements across space. Often, the scale at which we collect samples differs from the scale necessary for predictive purposes (Blöschl, 1999). For example, if we collect tree-ring samples at an avalanche path scale and are interested in avalanche frequency relationships with regional climate patterns, then we need to aggregate to a regional scale. This is only feasible by sampling more than a few paths and certainly more than one path. More simply, by sampling one path we are unable to accurately portray the natural variability of regional avalanche activity over time.

Scale triplet can be implemented at three different scales: a process scale that represents a spatial dimension, a measurement scale that relates to measurement structure, and a model scale that relates to a spatial dimension of a predictive model or aggregated data (Blöschl, 1999). For each scale, the scale triplet is comprised of the spacing, extent, and support. In our study, the extent is the entire region and sub-regions, the spacing is the distance between avalanche paths and sub-regions, and the support is the size of the area being sampled. In addition, the process scale is the natural variability of avalanche frequency, the measurement scale is the tree-ring proxies used to represent

avalanche occurrence on an annual temporal scale, and the model scale relates to aggregating all of the sample areas to derive a regional avalanche chronology.

Here, we aim to answer these specific questions:

- *What is the regional, sub-regional, and path specific frequency of large magnitude avalanches in the U.S. northern Rocky Mountains of northwest Montana?*
- *How does the spatial extent of the study site affect the resultant avalanche chronology?*
- *How do two different methods of sampling indexing affect the resultant avalanche chronology?*

To our knowledge, this is the first study to compare various spatial scales to reconstruct a regional avalanche chronology from dendrochronological data on a large dataset (of over 600 samples) and utilize a regional dendrochronological record to derive return periods over a large ($\sim 3500 \text{ km}^2$) spatial extent.

Chapter 3

Understanding the spatiotemporal behavior of avalanches and the contributory climate factors is important for understanding climate variability, interpreting historical avalanche variability, and improving avalanche forecasting. The complexity of associating climate drivers or changes in climate and subsequent effects on large magnitude avalanching warrants careful analysis and cautious inference. However, with no data or a sparse observer network, large magnitude avalanche occurrence can be inferred from tree-ring data. This technique not only allows for a temporal (annual)

resolution of large magnitude frequency, but also a spatial reconstruction if sampled appropriately and strategically. Using a tree-ring-generated spatio-temporal avalanche dataset, we address the following questions:

- *Are there specific seasonal climate or atmospheric circulation variables that contribute to years with large magnitude avalanche events across the U.S. northern Rocky Mountains of northwest Montana?*
- *What is the long-term temporal trend of annual regional avalanche activity in the northern U.S. Rocky Mountains?*

Chapter 4

Avalanches not only pose a major hazard to people and infrastructure, but also act as an important ecological disturbance (Bebi et al., 2009; Walsh et al., 1994). Several studies investigating the vegetation composition of avalanche paths were completed in Glacier National Park (Butler et al., 1992; Malanson and Butler, 1986; Walsh et al., 2004), but the emergence of high resolution topographic capabilities like light detection and ranging (lidar) allows for a more detailed and robust characterization of avalanche terrain and vegetation structure. The fourth chapter in this dissertation utilizes lidar to characterize the vegetation structure in large avalanche paths that span from alpine terrain to riparian zones. In this chapter, we aim to address the following questions:

- *Can we effectively use lidar and aerial imagery to characterize and quantify the various types of vegetation throughout three avalanche paths?*

- *Are there differences in vegetation composition in various avalanche return period zones?*

This chapter details a novel approach using remote sensing products in combination with dendrochronological techniques to classify vegetation and characterize vegetation classes within various return periods across several avalanche paths.

Chapter 5

This chapter discusses linkages between and connects the preceding chapters in this dissertation. In this chapter we present a summary of Chapters 2, 3, and 4, and the overall body of work, and link the science and practical motivation to the final results. Finally, we also explain the limitations of our research as well as provide recommendations for future research.

Conceptual Model

Throughout this work, we examined various spatio-temporal scales in the context of a regional large magnitude avalanche chronology (Figure 2). In Chapter 2 we provide the foundational tree-ring record and reconstructed regional large magnitude avalanche chronology. This chapter encompasses a large spatial extent ($\sim 3500 \text{ km}^2$) and long-term temporal scale (1867 to 2017 C.E.). In Figure 2 we show the spatial and temporal extent of the work completed in this chapter. Tree-ring records provide an annual resolution for avalanche signals but cannot resolve intra-annual avalanche events. Therefore, the shaded gray box does not extend fully to 0 on the x- or y-axis. In Chapter 3, we examine the avalanche-climate relationships on a regional scale. This requires examining long term

and spatially extensive datasets due to the nature of climate drivers and their effects on avalanche frequency and magnitude across a region. Therefore, the blue ellipse covers longer term and greater spatial extents, but not quite the length of the full chronology because of the temporally limited climate datasets. Finally, in Chapter 4, we investigate vegetation patterns that span a smaller spatial extent (e.g. an individual avalanche path), and a shorter time scale due to changes in vegetation because of disturbances, such as avalanche or other exogenous factors (e.g. fire).

Though each component of this dissertation contains uncertainty (z-axis), we capture this to the best of our ability by reporting associated error and accuracy values. However, as we progress from reconstructing a large magnitude avalanche chronology from tree-ring data in Chapter 2 to examining avalanche-climate associations in Chapter 3 the uncertainty propagates because of the use of additional tools and inferred data at each step. We inherently introduce uncertainty in Chapter 2 because tree-ring data are a proxy for observational records. This uncertainty, however, is at a conceptually minimal value respective to the overall dissertation. By incorporating climate records and using statistical inference tools in Chapter 2, we introduce more uncertainty. Finally, in Chapter 4 we inherently introduce additional uncertainty by using remote sensing products. This error combined with the original uncertainty from the tree-ring record results in the largest amount of uncertainty throughout the dissertation. The use of remotely sensed products creates inherent uncertainty and error when compared to in-situ observations, such as the climate data.

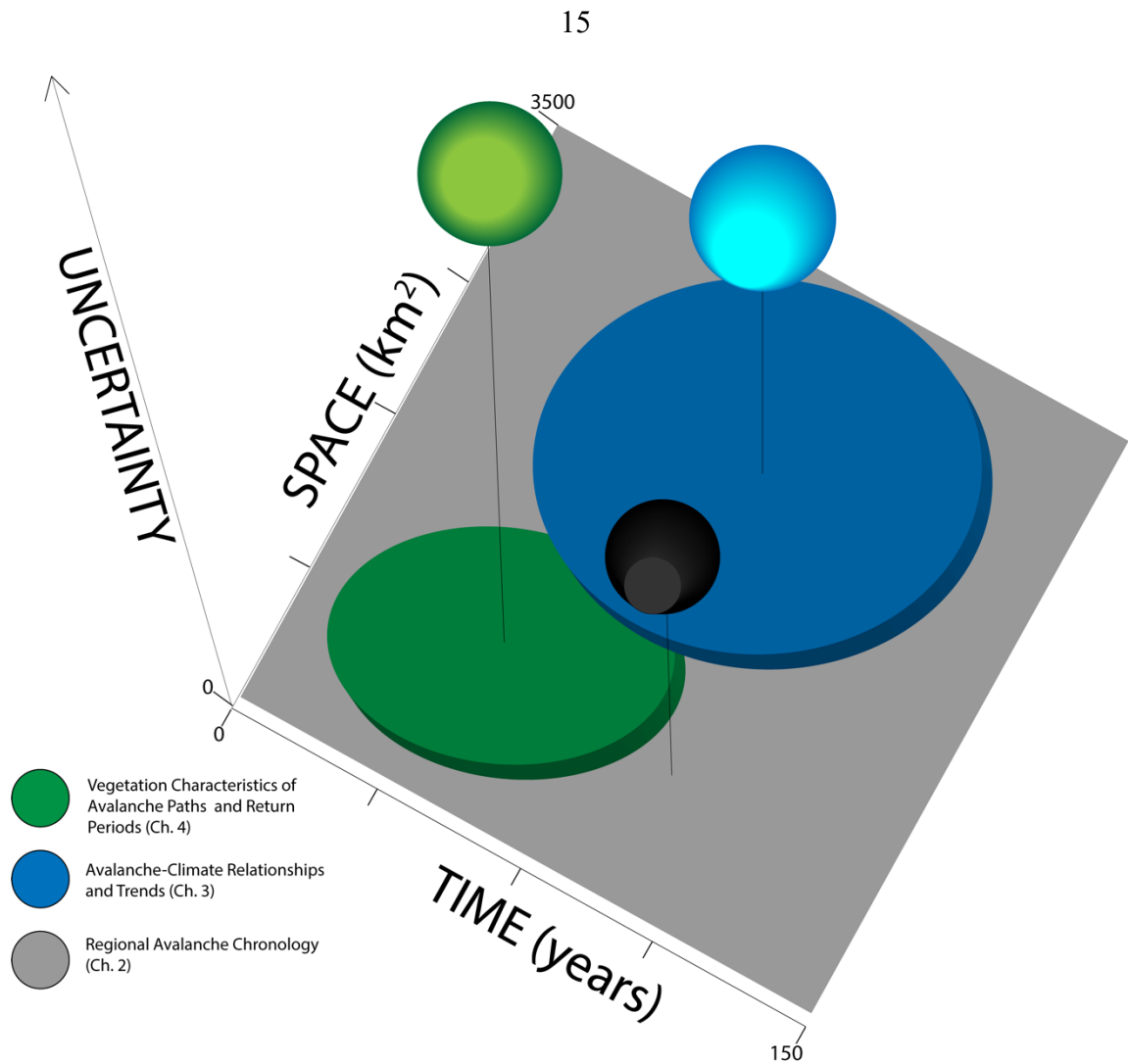


Figure 2: Conceptual model relating the spatial and temporal scales to the uncertainty in each section/chapter of this dissertation.

REFERENCES

- Armstrong, B.R., 1981. A quantitative analysis of avalanche hazard on U.S. Highway 550, southwestern Colorado, Proceedings of the Western Snow Conference, St. George, Utah, April 14-16, 2017, St. George, Utah, pp. 95-104.
- Bebi, P., Kulakowski, D. and Rixen, C., 2009. Snow avalanche disturbances in forest ecosystems-State of research and implications for management. Elsevier Science Bv, pp. 1883-1892.
- Blattenberger, G. and Fowles, R., 1994. The Road Closure Decision in Little Cottonwood Canyon, Proceedings of the 1994 International Snow Science Worskhop, October 30-November 3, 1994, Snowbird Utah, Snowbird, Utah, pp. 537-547.
- Blöschl, G. and Sivapalan, M., 1995. Scale issues in hydrological modelling: A review. *Hydrological Processes*, 9: 251-290.
- Butler, D.R., Malanson, G.P. and Walsh, S.J., 1992. Snow-avalanche paths: conduits from the periglacial-alpine to the subalpine depositional zone. In: J.C. Dixon and A.D. Abrahams (Editors), *Periglacial Geomorphology*. John Wiley and Sons Ltd., pp. 185-202.
- Butler, D.R. and Sawyer, C.F., 2008. Dendrogeomorphology and high-magnitude snow avalanches: a review and case study. *Natural Hazards and Earth System Sciences*, 8(2): 303-309.
- CAIC, 2018. Colorado Avalanche Information Center Statistics and Reporting. <http://avalanche.state.co.us/accidents/statistics-and-reporting/>.
- Corona, C., Lopez Saez, J., Stoffel, M., Bonnefoy, M., Richard, D., Astrade, L. and Berger, F., 2012. How much of the real avalanche activity can be captured with tree rings? An evaluation of classic dendrogeomorphic approaches and comparison with historical archives. *Cold Regions Science and Technology*.
- Favillier, A., Guillet, S., Trappmann, D., Morel, P., Lopez-Saez, J., Eckert, N., Zenhäusern, G., Peiry, J.-L., Stoffel, M. and Corona, C., 2018. Spatio-temporal maps of past avalanche events derived from tree-ring analysis: A case study in the Zermatt valley (Valais, Switzerland). *Cold Regions Science and Technology*, 154: 9-22.
- Finklin, A.I., 1986. A Climatic Handbook for Glacier National Park - with Data for Waterton Lakes National Park. INT-204, U.S.D.A. Forest Service Intermountain Research Station, Ogden.

- Germain, D., Fillion, L. and Hétu, B., 2009. Snow avalanche regime and climatic conditions in the Chic-Choc Range, eastern Canada. *Climatic Change*, 92(1-2): 141-167.
- Greene, E., Atkins, D., Birkeland, K., Elder, K., Landry, C., Lazar, B., McCammon, I., Moore, M., Sharaf, D., Sternenz, C., Tremper, B. and Williams, K., 2010. Snow, weather and avalanches: observation guidelines for avalanche programs in the United States, Pagosa Springs, CO.
- Hendrikx, J., Murphy, M. and Onslow, T., 2014. Classification trees as a tool for operational avalanche forecasting on the Seward Highway, Alaska. *Cold Regions Science and Technology*, 97: 113-120.
- Malanson, G.P. and Butler, D.R., 1986. Floristic patterns on avalanche paths in the Northern Rocky Mountains, USA. *Physical Geography*, 7(3): 231-238.
- Martin, J.P. and Germain, D., 2016. Dendrogeomorphic reconstruction of snow avalanche regime and triggering weather conditions: A classification tree model approach. *Progress in Physical Geography*.
- Meseşan, F., Gavrilă, I.G. and Pop, O.T., 2018. Calculating snow-avalanche return period from tree-ring data. *Natural Hazards*, 94(3): 1081-1098.
- Mock, C.J. and Birkeland, K.W., 2000. Snow avalanche climatology of the western United States mountain ranges. *Bulletin of the American Meteorological Society*, 81(10): 2367-2392.
- Mock, C.J., Carter, K.C. and Birkeland, K.W., 2016. Some Perspectives on Avalanche Climatology. *Annals of the American Association of Geographers*: 1-10.
- Peitzsch, E.H., Hendrikx, J., Fagre, D.B. and Reardon, B., 2012. Examining spring wet slab and glide avalanche occurrence along the Going-to-the-Sun Road corridor, Glacier National Park, Montana, USA. *Cold Regions Science and Technology*, 78: 73-81.
- Peitzsch, E.H., Stahle, D.K., Fagre, D.B., Clark, A.M., Pederson, G.T., Hendrikx, J. and Birkeland, K.W., 2019. Tree ring dataset for a regional avalanche chronology in northwest Montana, 1636-2017. U.S. Geological Survey. <https://doi.org/10.5066/P9TLHZAI>.
- Reardon, B. and Fagre, D.B., 2006. Reassessing a troublesome fact of mountain life: avalanches in Glacier National Park. *Park Science*, 24(1): 37-39.
- Reardon, B.A., Fagre, D.B. and Steiner, R.W., 2004. Natural avalanches and transportation: a case study from Glacier National Park, Montana, USA,

- Proceedings of the International Snow Science Workshop, Sept. 19-24, 2004, Jackson, WY, U.S.A., pp. 582-597.
- Reardon, B.A., Pederson, G.T., Caruso, C.J. and Fagre, D.B., 2008. Spatial reconstructions and comparisons of historic snow avalanche frequency and extent using tree rings in Glacier National Park, Montana, U.S.A. *Arctic, Antarctic, and Alpine Research*, 40(1): 148-160.
- Schlappy, R., Eckert, N., Jomelli, V., Stoffel, M., Grancher, D., Brunstein, D., Naaim, M. and Deschatres, M., 2014. Validation of extreme snow avalanches and related return periods derived from a statistical-dynamical model using tree-ring techniques. *Cold Regions Science and Technology*, 99: 12-26.
- Schweizer, J., 2003. Snow avalanche formation. *Reviews of Geophysics*, 41(4).
- Schweizer, J., Kronholm, K., Jamieson, J.B. and Birkeland, K.W., 2008. Review of spatial variability of snowpack properties and its importance for avalanche formation. *Cold Regions Science and Technology*, 51(2-3): 253-272.
- Schweizer, J., Mitterer, C. and Stoffel, L., 2009. On forecasting large and infrequent snow avalanches. *Cold Regions Science and Technology*, 59(2-3): 234-241.
- Shroder, J.F., 1980. Dendrogeomorphology: review and new techniques of tree-ring dating. *Progress in Physical Geography*, 4(2): 161-188.
- Stoffel, M. and Bollschweiler, M., 2008. Tree-ring analysis in natural hazards research - an overview. *Natural Hazards and Earth System Science*, 8: 15.
- Stoffel, M., Bollschweiler, M., Butler, D.R. and Luckman, B.H. (Editors), 2010. *Tree Rings and Natural Hazards - A State of the Art*. Springer Science and Business Media, 505 pp.
- Voight, B., Armstrong, R.R., Armstrong, R.L., Bachman, D., Bowles, D., Brown, R.L., Faisant, R.D., Ferguson, S.A., Fedston, J.A., Kennedy, J.L., Kiusalaas, J., LaChapelle, E., McFarlane, R.C., Newcomb, R., Penniman, R. and Perla, R., 1990. *Snow Avalanche Hazards and Mitigation in the United States*. National Academy Press, Washington, D.C.
- Walsh, S.J., Butler, D.R., Allen, T.R. and Malanson, G.P., 1994. Influence of snow patterns and snow avalanches on the alpine treeline ecotone. *Journal of Vegetation Science*, 5: 657-672.

- Walsh, S.J., Weiss, D.J., Butler, D.R. and Malanson, G.P., 2004. An assessment of snow avalanche paths and forest dynamics using Ikonos satellite data. *Geocarto International*, 19(2).
- Wayand, N.E., Massmann, A., Butler, C., Keenan, E., Stimberis, J. and Lendquist, J.D., 2015. A meteorological and snow observational data set from Snoqualmie Pass (921 m), Washington Cascades, USA. *Water Resources Research*, 51: 10092-10103.

CHAPTER TWO

A REGIONAL SPATIO-TEMPORAL ANALYSIS OF LARGE MAGNITUDE SNOW
AVALANCHES USING TREE RINGS

Contribution of Author and Co-Authors

Manuscript in Chapter 2

Author:	Erich H. Peitzsch
Contributions	Responsible for designing sampling technique, leading data collection campaign, the development of analysis, the majority of the writing, and figure development.
Author:	Jordy Hendrikx
Contributions	Provided extensive discussion of the development of methods used in the study and contributed to the editing of the manuscript throughout its development.
Author:	Daniel K. Stahle
Contributions	Assisted with data collection, responsible for laboratory processing, assisted with methodology writing.
Author:	Gregory T. Pederson
Contributions	Provided extensive discussion of the development of methods used in the study, field site visits, and contributed to the editing of the manuscript throughout its development.
Author:	Karl W. Birkeland
Contributions	Provided technical input to the development of methods used in the study and contributed to the editing of the manuscript throughout its development.
Author:	Daniel B. Fagre
Contributions	Provided technical input to the development of methods used in the study and contributed to the editing of the manuscript throughout its development.

Manuscript Information

Peitzsch, E.H.^{1,2}, Hendrikx, J.², Stahle, D.K.¹, Pederson, G.T.¹, Birkeland, K.W.^{3,2}, and Fagre, D.B.¹. A regional spatio-temporal analysis of large magnitude snow avalanches using tree rings. Manuscript for submittal to Natural Hazards and Earth Systems Sciences

¹ U.S. Geological Survey Northern Rocky Mountain Science Center, West Glacier, Montana, USA

² Snow and Avalanche Lab, Department of Earth Sciences, Montana State University, Bozeman, Montana, USA

³ U.S.D.A. Forest Service National Avalanche Center, Bozeman, Montana, USA

Journal: Natural Hazards and Earth Systems Sciences (NHESS)

Status of manuscript

- ☒ Prepared for submission to a peer-reviewed journal
- ☐ Officially submitted to a peer-reviewed journal
- ☐ Accepted by a peer-reviewed journal
- ☐ Published in a peer-reviewed journal

Publisher: European Geophysical Union

Anticipated date of submission: May 2020

Abstract

Snow avalanches, especially those of large magnitude, affect transportation corridors and settlements worldwide. In many mountainous regions, despite the hazards avalanches pose, records of avalanche frequency and magnitude are sparse or non-existent. Thus, inferring historic avalanche patterns to improve forecasting and understanding requires the use of dendrochronological methods. In this study, we developed an avalanche chronology for large magnitude avalanche events using dendrochronological techniques for a region in the northern United States Rocky Mountains. We implemented a strategic sampling design that allowed us to examine avalanche activity through time and across spatial scales spanning single avalanche paths, multiple paths in four sub-regions, and region wide. We analyzed a total of 673 total samples from 647 suitable trees. We collected 614 cross sections and 59 cores, identifying 2304 tree growth disturbances from 1636 to 2017 Common Era (C.E.). We compared two different indexing approaches to discriminate avalanche signals from noise in the tree-ring record and developed a regional avalanche activity index. Large magnitude events that were common across the region occurred in 30 individual years, and the median return interval for regional large magnitude avalanches was three years (mean = 5.21 years). Throughout the four sub-regions, the large magnitude avalanche return interval (3-8 years) and the total number of avalanche years (12-18) vary suggesting the important influence of local terrain and weather factors. Testing subsampling routines for regional representation, we found that sampling eight out of a total of 12 avalanche paths in the region captures 83% of the regional chronology, whereas four paths capture anywhere from 43% to 73%. In our dataset, the greatest value probability of detection for any given path is 40% suggesting that if, by chance, we sampled this path we would have captured the regional avalanche activity 40% of the time. Our work emphasizes the importance of sample size, scale, and spatial extent when attempting to derive a regional large magnitude avalanche event chronology from tree-ring records.

1. Introduction

1.1 Background

Snow avalanches are a natural hazard to human safety and infrastructure (Mock et al., 2016; Schweizer, 2003) as well as an important landscape disturbance affecting mountain ecosystems (Bebi et al., 2009). In the United States an average of 27 people die in avalanche accidents each winter (CAIC, 2018). Avalanches, especially large

magnitude events, also affect transportation corridors and settlements throughout the world. For example, avalanches impact numerous roadways in the western United States (Armstrong, 1981; Hendrikx et al., 2014; Reardon et al., 2008). Consequently, understanding general avalanche processes and associated large magnitude avalanche return intervals is critical for local and regional avalanche forecasters, transportation agencies, and land use planners.

Long-term, reliable, and consistent avalanche observation records are necessary for calculating avalanche return intervals which can be used in infrastructure planning and avalanche forecasting operations. However, in many mountainous regions, including areas with existing transportation corridors, such records are often sparse or non-existent. Thus, inferring avalanche frequency requires the use of dendrochronological methods. Even in regions with historical records, tree-ring dating methods can be used to extend or validate uncertain historical avalanche records, particularly large-magnitude events (Corona et al., 2012; Favillier et al., 2018; Schläppy et al., 2014). Accordingly, dendrochronology has been used extensively to document geomorphic response in numerous regions throughout the world (Shroder, 1980; Stoffel and Bollschweiler, 2008).

In the United States, reconstructing avalanche chronologies using tree-ring methods has been ongoing for decades (Burrows and Burrows, 1976; Butler et al., 1987; Carrara, 1979; Potter, 1969; Rayback, 1998). Butler and Sawyer (2008) provided a review of avalanche dendrochronological studies by assessing the current state of general methodologies and the type of tree-ring responses used. In addition, they used a case study to illustrate the potential impact of sample size on reconstructing an avalanche

chronology. Favillier et al. (2018) provide a more recent comprehensive graphical summary of dendrochronological avalanche studies throughout the world. Numerous studies used dendrochronological techniques to develop avalanche chronologies for remote regions without historical avalanche records or areas with inconsistent avalanche observations (Butler and Malanson, 1985a; Germain et al., 2009; Reardon et al., 2008; Šilhán and Tichavský, 2017; Voiculescu et al., 2016).

1.2 Dendrochronology Techniques

The major limitation of using dendrochronological methods to reconstruct avalanche chronologies is that tree-ring records may underestimate natural avalanche activity (Schläppy et al., 2015). Corona et al. (2012) examined the ability of dendrochronological methods to capture avalanche occurrence by comparison with historical observations. To achieve this, they developed a novel approach to determine optimal thresholds to discriminate avalanche signals from noise in the tree-ring record by using a double threshold of minimum absolute number of growth disturbances (GD) combined with a minimum index (I_t) each year based on sample size: $N = 10-20$ ($GD \geq 3$ and $I_t \geq 15\%$), $N = 21-50$ ($GD \geq 5$ and $I_t \geq 10\%$), and $N \geq 51$ ($GD \geq 7$ and $I_t \geq 7\%$). Their results suggest an optimal sample size of ~ 100 trees, and when compared to an historical record highlight that dendrochronological methods underestimate the frequency of natural avalanche activity by $\sim 60\%$ because large avalanches remove trees and evidence of past events.

Germain (2016) used a generalized Pareto distribution (GPD) approach to calculate a minimum index threshold that discriminates large magnitude avalanche years

from years without large magnitude events. Since large magnitude avalanche events display low-frequency patterns characteristic of the tail-end of Gaussian distributions, least-squared regression approaches may not be adequate to capture such events. A threshold based on the original distribution using a Pareto or generalized extreme value distribution may also allow for a more robust assessment of return period intervals. Germain (2016) compared this approach to other threshold values and found substantial variability among the different methods and suggests implementing a peaks-over-threshold or GPD model-based index in conjunction with a minimum sample size.

Using a weighted growth disturbance index factor is another technique often used to discriminate avalanche years from noise (Kogelnig-Mayer et al., 2011). This method assigns a greater weight (i.e. stronger influence) to higher quality growth disturbances. The quality of growth disturbances or intensities is often rated on a scale of 1-4 (or 5) (Favillier et al., 2018; Kogelnig-Mayer et al., 2011; Reardon et al., 2008). The weighted index factor incorporates both the number of trees (samples) and the intensity of the growth disturbances, and it adds substantial confidence to dating snow avalanches as a complement to the percentage and minimum GD index factor. Chiroui et al. (2015) illustrates the value of using this method as well as the use of traumatic resin ducts as an avalanche signal. They also compare the conventional method of using $I_t \geq 10\%$ with the more modern approaches devised by Corona et al. (2012) and Kogelnig-Mayer (2011). These recent advances help refine optimal sample sizes and reduce uncertainty in avalanche chronologies using dendrochronological reconstruction and provide a foundation to assess historical avalanche activity throughout a given region.

1.3 Previous Dendrochronology Studies

Most dendrochronological snow avalanche studies use samples from a relatively small spatial extent and small number of avalanche paths by design (Table 1). This is understandable, given that most of these studies intentionally focused on an individual path or small group of paths. However, this makes extrapolating to a regional context challenging, and likely inappropriate. Understanding long-term avalanche frequency and magnitude at a regional scale allows for associations with large-scale synoptic weather patterns. In one example, Hebertson and Jenkins (2003) examined climate variables and the probability of large magnitude avalanches throughout 16 paths in the Wasatch Plateau. In another regional analysis, Germain et al. (2009) computed a regional avalanche activity index for 12 avalanche paths in close proximity ($< \sim 30$ km) to each other in the Chic Choc Range of Québec, Canada.

Tree-ring avalanche research is resource and time intensive. Like numerous other scientific fields of study, it is rarely feasible to completely sample the variable of interest with infinite detail due to logistical and financial constraints (Skoien and Blöschl, 2006). A strategic spatial sampling method can be used to collect robust data that limits the influence of those constraints. Here, we strategically sampled 12 avalanche paths in four distinct sub-regions of the U.S. northern Rocky Mountains of northwest Montana to examine spatial differences at a regional scale. The sampling strategy is founded on the concept of scale triplet (Blöschl and Sivapalan, 1995) which is important when trying to extrapolate a process (e.g. avalanche frequency and magnitude) from a single point, such as an avalanche path, across a region. Using scale triplet as a framework in our strategic sampling allows us to take a process from a point measurement and robustly extrapolate

to a larger spatial footprint. Incorporating scale triplet helps us to more fully understand the nature of the problem, the scale at which we should measure, and how we can estimate the measurements across space. Often, the scale at which we collect samples differs from the scale necessary for predictive purposes (Blöschl, 1999). For example, if we collect tree-ring samples at an avalanche path scale and are interested in avalanche frequency relationships with regional climate patterns, then we need to aggregate to a regional scale. This is only feasible by sampling more than a few paths and certainly more than one path. More simply, by sampling one path we are unable to accurately portray the natural variability of regional avalanche activity over time. The scale triplet is comprised of the spacing, extent, and support. In our study, the extent is the entire region and sub-regions, the spacing is the distance between avalanche paths and sub-regions, and the support is the size of the area being sampled. In addition, the process scale is the natural variability of avalanche frequency, the measurement scale is the tree-ring proxies used to represent avalanche occurrence on an annual temporal scale, and the model scale relates to aggregating all of the sample areas to derive a regional avalanche chronology.

Table 1: List of previous avalanche-dendrochronological work *with more than one avalanche path* in study – to place our regional work in context with other regional/multiple path studies. Number of samples, paths, GD, and spatial extent (linear distance between most distant avalanche paths in study area) are included. For spatial extent, *NA* is reported in studies where spatial extent is not reported or could not be inferred from maps in the published work. Where spatial extent is not reported directly in previous work, it is estimated by using maps from the published work and Google Earth.

Authors	Location	# Trees	# Samples	# Paths	Spatial Extent	# GD
Gratton et al. (2019)	Northern Gaspé Peninsula, Québec, Canada	82	177 cores 65 x- sec	5	~20 km	Not provided

Favillier et al. (2019)	Zermatt valley, Switzerland	307	620 cores 60 x-sec	3	~1 km	2570
Meseşan et al. (2019)	Parâng Mountains, Carpathians, Romania	232	430 cores 39 x-sec 4 wedges	3	~16 km	Not provided
Ballesteros-Canovas (2018)	Kullu district, Himachal Pradesh, India	114	Not Provided	1 slope (multiple paths)	~ 1 km	521
Pop et al.(2018)	Piatra Craiului Mountains, Romania	235	402 cores 34 x-sec	2	~ 2 km	789
Martin and Germain (2016)	White Mountains, New Hampshire	450	350 cores 456 x-sec	7	~10 km	2251
Voiculescu et al. (2016)	Făgăras massif, Carpathians, Romania	293	586 cores	4	NA	853
Schläppy et al. (2015)	French Alps, France	967	1643 cores 333 x-sec	5	~100 km	3111
Schläppy et al. (2014)	French Alps, France	297	375 cores 63 x-sec	2	~100 km	713
Schläppy et al. (2013)	French Alps, France	587	1169 cores 122 x-sec	3	~100 km	1742
Casteller et al. (2011)	Santa Cruz, Argentina	95	~95 x-sec	9	~2 km	Not provided
Köse et al. (2010)	Katsomonu, Turkey	61	Not provided	2	~ 500 m	Not provided
Muntán et al. (2009)	Pyrenees, Catalonia	NA	448	6	~150 km	Not provided
Germain et al. (2009)	Northern Gaspé Peninsula, Québec, Canada	689	1214 x-sec	12	~30 km	2540
Butler and Sawyer (2008)	Lewis Range, Glacier National Park, Montana, USA	22	22 x-sec	2	~5 km	Not provided
Casteller et al. (2007)	Grisons, Switzerland	145	122 x-sec 52 cores 10 wedges	2	~ 20 km	Not provided

Germain et al. (2005)	Northern Gaspé Peninsula, Québec, Canada	142	142 x-sec	5	NA	420
Dube et al.(2004)	Northern Gaspé Peninsula, Québec, Canada	110	170 x-sec	3	~9 km	Not provided
Hebertson and Jenkins (2003)	Wasatch Plateau, Utah, USA	261	Not provided	16	NA	Not provided
Rayback (1998)	Front Range, Colorado, USA	98	58 trees cored (2-5 cores /tree) 31 x-sec 9 wedges	2	~7 km	Not provided
Bryant et al. (1989)	Huerfano Valley, Colorado, USA	180	Not provided	3	~2 km	Not provided
Butler and Malanson (1985a)	Lewis Range, Glacier National Park, Montana, USA	78	Not provided	2	~6 km	Not provided
Butler (1979)~	Glacier National Park, Montana, USA	NA	36 x-sec 17 cores	12	~15 km	Not provided
Smith (1973)	North Cascades, Washington, USA	NA	Not provided	11	~ 35 km	Not provided
Potter (1969)	Absaroka Mountains, Wyoming, USA	50	Not provided	5	~ 2 km	50

We adopt Germain's (2016) definition that large magnitude avalanches are events characterized by low and variable frequency with a high capacity for destruction. This generally translates to a size 3 or greater on the destructive classification scale (Greene et al., 2016) - ability to bury or destroy a car, damage a truck, destroy a wood frame house, or break a few trees.

Understanding the spatiotemporal behavior of large magnitude avalanches on the regional scale will, ultimately, improve avalanche forecasting efforts, especially for operations involving avalanche terrain that impacts transportation corridors. Here, we aim to answer three specific questions:

- 1) What is the regional, sub-regional, and path specific frequency of large magnitude avalanches in the U.S. northern Rocky Mountains of northwest Montana?
- 2) How does the spatial extent of the study region affect the resultant avalanche chronology?
- 3) How do two different methods of sampling indexing affect the resultant avalanche chronology?

To our knowledge, this is the first study to look at how various spatial scales compare when reconstructing a regional avalanche chronology from dendrochronological data on a large dataset ($N > 600$ samples). Further, we believe this is the first study that utilizes a regional dendrochronological record to derive return periods over a large spatial extent. Aggregating the paths into sub-region and then again into a full region allows us to potentially minimize the limitation of tree-ring avalanche chronologies underestimating avalanche years at these scales.

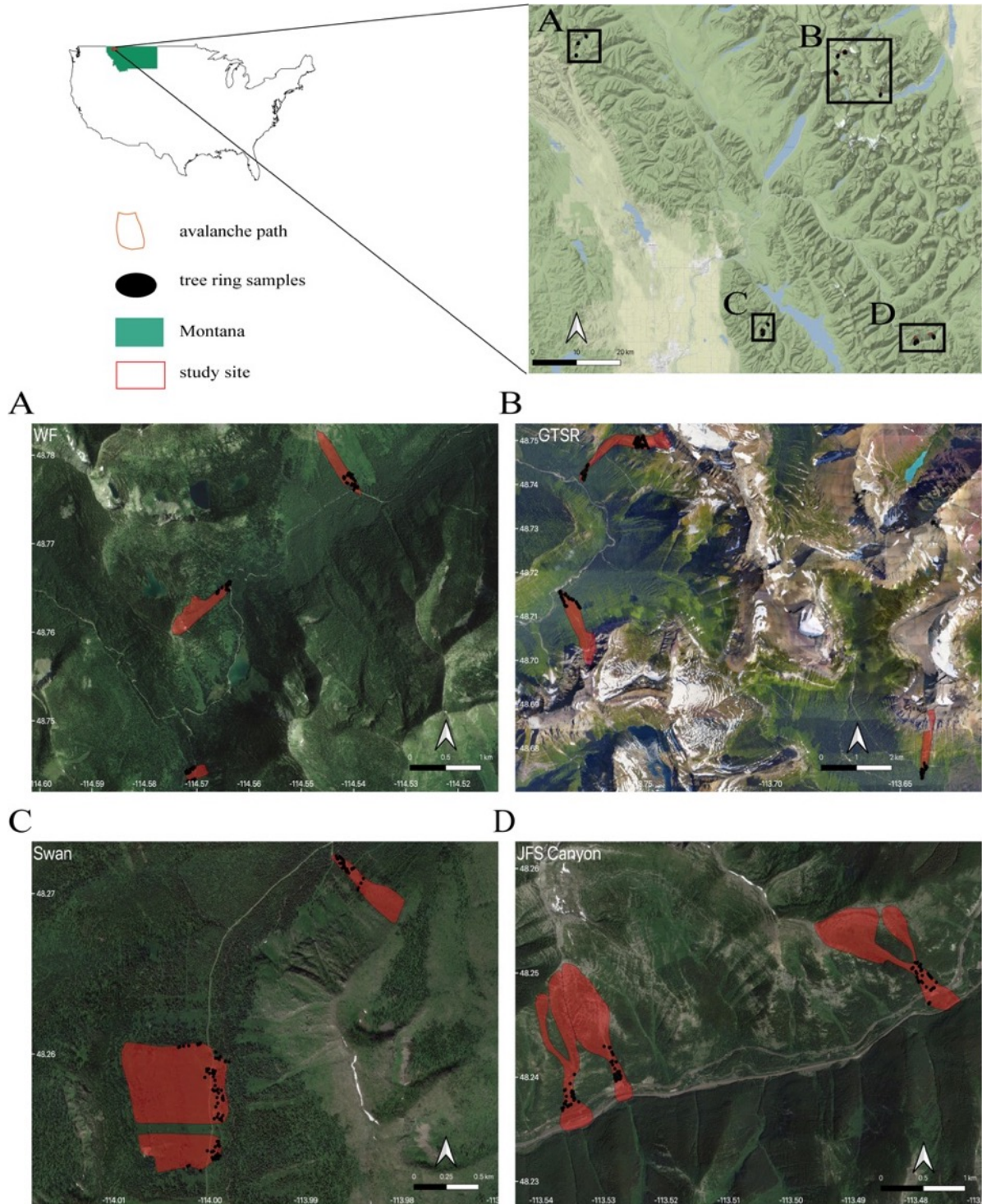
2. Methodology

2.1 Study Site

Our study site consists of 12 avalanche paths in the Rocky Mountains of northwest Montana, USA (Table 2 and Figure 1). We sampled sets of three avalanche paths in four distinct sub-regions within three mountain ranges: the Whitefish Range (WF, Red Meadow Creek) and Swan Range (Swan, Lost Johnny Creek) on the Flathead National Forest, and two sub-regions within the Lewis Range in Glacier National Park (GNP), Montana. The avalanche paths in each sub-region encompass a range of spatial extents from adjacent (i.e. 0 m apart) to ~10 km apart. The sites in GNP are along two major transportation corridors through the park: the Going-to-the-Sun Road (GTSR) and U.S. Highway 2 in John F. Stevens (JFS) Canyon. These two areas have been utilized for previous dendrochronological avalanche research (Butler and Malanson, 1985a; Butler and Malanson, 1985b; Butler and Sawyer, 2008; Reardon et al., 2008). A robust regional avalanche chronology reconstruction will help place the previous work in context of the wider region. The other two sites, WF and Swan, are popular backcountry recreation areas with access via snowmachine in the winter along a U.S. Forest Service road. Overall, this study site provides an ideal natural setting for studying avalanches due to its geography, inclusion of transportation and recreation corridors potentially impacted by avalanches, relative accessibility, and no artificial avalanche hazard mitigation.

Table 2: Topographic characteristics of all avalanche paths. Different colors indicate sub-regions. * denotes two major starting zones for one runout in Shed 10-7 and Shed 7 paths.

Subregion-Path	n	Full Path Elev. (mean) (m)	Full Path Elev. (range) (m)	Starting Zone Elev. (mean) (m)	Full Path Slope (mean) (°)	Starting Zone Slope (mean) (°)	Median Aspect (°)	Area (km ²)	Length (m)	Vertical (m)	Years of previous fire or logging
WF-Red Meadow A (RMA)	41	1651	1462 - 1957	1774	26	32	155	0.32	1004.97	495.20	1952
WF-Red Meadow B (RMB)	40	1870	1643 - 2164	1965	31	37	53	0.13	1041.98	521.27	1967
WF-Red Meadow C (RMC)	42	1650	1582 - 1742	1692	28	33	257	0.08	326.14	160.46	1962
GTSR - 54-3	56	1501	1080 - 2149	1708	31	40	327	0.44	2063.61	1068.49	NA
GTSR-Little Granite (LGP)	109	1770	1109 - 2314	2170	24	34	250	0.78	2940.29	1205.07	NA
GTSR-Jackson Glacier Overlook (JGO)	41	1863	1500 - 2660	2090	32	42	180	0.70	1793.13	1159.84	NA
Swan-Lost Johnny A (LJA)	53	1619	1441 - 1896	1731	29	38	77	0.41	811.50	455.27	1971-72
Swan-Lost Johnny B (LJB)	26	1633	1478 - 1879	1721	32	39	76	0.57	617.52	401.80	1971-72
Swan-Lost Johnny C (LJC)	42	1550	1344 - 1750	1670	34	36	326	0.39	667.88	405.66	1957, 2003
JFS-Shed 10-7 (S10.7)*	109	1644	1233 - 2193	1910 - 1964	31	35 - 39	176	0.13	1745.66	959.74	1910
JFS-Shed 7 (S7)*	46	1712	1310 - 2078	1935 - 1837	29	34 - 36	152	0.57	1686.96	768.01	1910
JFS-1163	50	1718	1250 - 2217	1861	38	42	158	0.17	1636.52	966.82	1910
All Paths	655	1690	1080 - 2660	1869	-0.17	0.14	31	37	Spatial footprint = 3500 km ²		



We eliminated or minimized influence from exogenous disturbance factors such as logging and wildfire throughout our study site by referencing wildfire maps extending back to the mid-20th century. We selected sites undisturbed by wildfire since this time except for one path, Lost Johnny C, which was purposeful as this area burned most recently in 2003. We also minimized the influence of logging by selecting sites not previously logged or not logged within the previous three decades. Using historical logging parcel spatial data, we determined logging in those sites was limited to very small parcels adjacent to the farthest extent of the runout zones.

The historical observational record in this region is limited. In this study region, the Flathead Avalanche Center (FAC), a regional U.S. Forest Service backcountry avalanche center, records all avalanches observed and reported to the center. However, given the approximately 3500 km² advisory area comprised of five mountain ranges, not all avalanches are observed or reported. The Burlington-Northern Santa Fe Railway (BNSF) Avalanche Safety Program records most avalanches observed in their program area, 16 km with over 40 avalanche paths adjacent to Highway 2, in John F. Stevens Canyon in southern Glacier National Park. While their observational record is more consistent, systematic operational observations commenced in 2005. Observations prior to this time are reliable, but inconsistent. Large magnitude avalanches were recorded with some consistency due to the adjacent transportation corridor providing a record of avalanches causing disruption to road and rail travel, but the record is still incomplete. Reardon et al. (2008) developed as complete a record as possible from the Department of Transportation and railroad company records, National Park Service ranger logs, and

popular media archives. In this region avalanche mitigation is conducted on an infrequent and inconsistent basis only in emergency situations. Mitigation measures are typically conducted only once a year, if at all, so the record approximates a natural avalanche record. We compared the reconstructed avalanche chronology of the JFS sub-region to the historical record (see section 2.4).

Northwest Montana's avalanche climate is classified as both a coastal transition and intermountain avalanche climate (Mock and Birkeland, 2000), but it can exhibit characteristics of both continental or coastal climates, and specific areas within the region are more representative of such climates more frequently than the overall regional classification. The WF and Swan Ranges represent coastal climates while the GTSR and JFS Canyon regions represent more of an intermountain climate. The elevation of avalanche paths within the study sites range from approximately 1100 m to 2700 m and the starting zones of these paths are distributed among all aspects (Table 2).

2.2 Sample Collection and Processing

Given the specific research questions targeting large magnitude avalanche events, our sampling was strategic and stratified. Thus, our sampling strategy targeted an even number of samples collected from both lateral trimlines at varying elevations and trees located in the main lower track and runout zone of the selected paths. This adequately captured trees that were destroyed and transported, as well as those that remained in place.

Sample size for avalanche reconstruction using tree-ring data requires careful consideration. Butler and Sawyer (2008) suggest that a few damaged trees may be

sufficient for avalanche chronologies, but larger target sample sizes increase the probability of detecting avalanche events. Germain (2010) examined cumulative distribution functions of avalanche chronologies and reported only slight increases in the probability of extending chronologies with sample size greater than 40. Thus, given the large spatial footprint ($\sim 3500 \text{ km}^2$) of this study and feasibility of such a large sample size, we sampled between 26-109 samples per avalanche path resulting in 673 total samples from 655 trees. Only eight trees were unsuitable for analysis, leaving us with 647 total trees to analyze. Of the 673 total samples, we collected 614 cross sections and 59 cores. Two paths (Shed 10.7 and Little Granite (LGP)) were collected prior to the main data collection campaign. The Shed 10.7 path (Reardon et al., 2008) was the focus of previous work and the dendrochronological record extends to 2005 ($n=109$ trees). LGP was collected in the summer of 2009 ($n=109$ trees). We sampled the remaining 10 paths (437 of the 655 total trees) in the summer of 2017.

We collected cross-sectional wood samples from dead (both downed and standing dead) trees, and the cores were collected from live trees. We emphasized the selection of trees with obvious external scars and considered location, size, and potential age of tree samples. A limitation of all dendrochronology studies in avalanche paths is that large magnitude events cause extensive damage and high tree mortality, thereby reducing subsequent potential tree-ring records. We utilized predominantly cross-sections in this study for a more robust analysis as events can potentially be missed or incorrectly identified in cores.

We sampled cross-sections at the location of an external scar or just above the root buttress from downed and dead tree stems, standing dead trees, and from stumps of trees that suffered topping from avalanche damage. We collected tree-ring core samples from live trees using a 5 mm diameter increment borer. We extracted core samples from live trees with obvious scarring or flagging along the avalanche path margins and runout zone. We sampled a minimum of two and up to four cores per tree (two in the uphill-downhill direction and two perpendicular to the slope). We photographed each sample at each location and recorded species, GPS coordinates (accuracy 1-3 m), amount of scarring on the cambium of the tree, relative location of the tree in the path and upslope direction (Peitzsch et al., 2019). We also recorded location characteristics that identified the tree to be in-place vs. transported from its original growth position (i.e. presence or absence of roots attached to the ground or the distance from an obvious excavated area where the tree was uprooted).

To prevent radial cracking and further rot, we dried and stabilized the cross sections with a canvas backing. We sanded the samples using a progressively finer grit of sandpaper (up to 1200 grit) to expose the anatomy of each growth ring, and cross-dated cores and cross sections against each other using the visual skeleton plot method to account for missing and false-rings (Stokes and Smiley, 1996). We developed a site composite chronology using live-tree core samples and dead tree cross-sections. Cross-dating with preexisting regional chronologies confirmed the exact calendar dating of each tree-ring (Table 3) (ITRDB, 2018). We measured the widths of the dated tree-rings to 0.001mm precision using a sliding stage micrometer, and statistically verified the ring-

width measurements for each sample using the dating quality control software

COFECHA (Grissino-Mayer, 2001; Holmes, 1983). For further details on cross dating methods and accuracy calculation for this dataset see Peitzsch et al. (2019).

Table 3: Regional chronologies from the International Tree-Ring Database used for cross-dating.

MT Avalanche Project Site	ITRDB Tree-Ring Chronology	Originator	Date Range	Species	Coordinates	Elevation	NOAA data set ID
Little Granite Path (LGP)	Going to the Sun Road (GTS)	Gregory T. Pederson Jeremy S. Littell	1337 - 2002	PSME	48.42- 113.5167	1860M	noaa-tree- 27540_MT1 59
Site 54-3 (54-3)	Going to the Sun Road (GTS)	Gregory T. Pederson Jeremy S. Littell	1337 - 2002	PSME	48.42- 113.5167	1860M	noaa-tree- 27540_MT1 59
Jackson Glacier Overlook (JGO)	Going to the Sun Road (GTS)	Gregory T. Pederson Jeremy S. Littell	1337 - 2002	PSME	48.42- 113.5167	1860M	noaa-tree- 27540_MT1 59
John F. Stevens Canyon Site Shed 7 (S7)	Doody Mountain (DOO)	Gregory T. Pederson Blase Reardon	1660 - 2001	PSME	48.3833- 113.6167	1890M	noaa-tree- 27536_MT1 55
John F. Stevens Canyon Site 1163 (1163)	Doody Mountain (DOO)	Gregory T. Pederson Blase Reardon	1660 - 2001	PSME	48.3833- 113.6167	1890M	noaa-tree- 27536_MT1 55
Lost Johnny Creek Sites ABC (LJ_ABC)	Preston Park (PP)	Bekker, M.F.; Tikalsky, B.P.; Fagre, D.B.; Bills, S.D.	1766 - 2006	ABLA	48.43-113.39	2150M	noaa-tree- 5993_MT11 7
Red Meadow Lakes Sites ABC (RM ABC)	Numa Ridge Falls (NRF)	Gregory T. Pederson Brian Peters	1645 - 2001	PSME	48.51-114.12	1695M	noaa-tree- 27550_MT1 68

2.3 Avalanche Event Identification

We analyzed the cross-sections for signs of traumatic impact events that could be caused by snow avalanches. We designed and adapted a system of classification ratings ranked 1 through 5 from previous dendrogeomorphological studies to qualify the severity of the trauma and tree growth response, where 1 is the most severe (Reardon et al., 2008). Using this classification scheme allowed us to remain consistent with previous work done in this region and classified more prominent signals with higher quality scores (Corona et al., 2012; Favillier et al., 2018) (Table 4).

Table 4: Avalanche impact trauma classification ratings.

Classification	Description
C ₁	• Clear impact scar associated with well-defined reaction wood, growth suppression or major traumatic resin duct development. • Or, the strong presence of some combination of these major anatomical markers of trauma and growth response recorded in multiple years of growth and occurring at a year that multiple samples from other trees at the site record similar trauma and scarring. • C₁ events are also assigned to the death date of trees killed by observed avalanche mortality at the collection site; the presence of earlywood indicates an early spring, or late avalanche season, event killed the tree.
C ₂	• Scar or small scar recorded in the first ten years of tree growth without associated reaction wood, growth suppression or traumatic resin ducts. • Or, obvious reaction wood, growth suppression or significant presence of traumatic resin ducts that occur abruptly after normal growth that lasts for 3 or more years.
C ₃	• The presence of reaction wood, growth suppression, or traumatic resin ducts recorded in less than 3 successive growth years.
C ₄	• Poorly defined reaction wood, growth suppression or minimal presence of traumatic resin ducts lasting 1-2 years. • Or, a C₃ class event occurring in the first 10 years of tree growth where the cause of damage could result from various biological and environmental conditions.
C ₅	• Very poorly defined reaction wood, growth suppression, or minimal presence of traumatic resin ducts isolated in one growth year. • Or, a C₄ class event occurring in the first 10 years of tree growth where the cause of damage could result from various biological and environmental conditions.

We recorded a range of anatomical markers with the most prominent being the presence of a cambial scar where avalanche debris impacted and/or tore away the bark killing the cambium. Often times a debris impact will result in the formation of dense reaction wood within the growth rings on the opposite side of the tree from the scar or

direction of impact. This is due to the tree's response to being partially bent over by the avalanche. Other anatomical markers identified included rows of traumatic resin ducts, subsequent years of radial growth suppression, and growth ring eccentricities related to scar healing or stem dislodging (Figure 2).

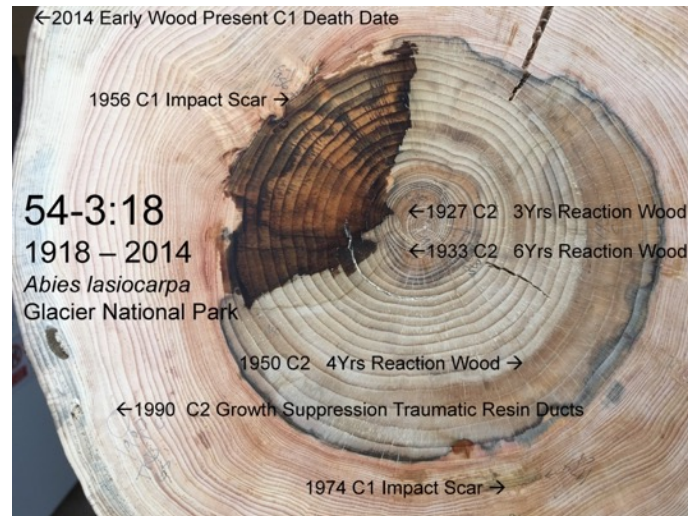


Figure 2: A tree-ring sample illustrating multiple types of scars that are representative of our weighted classification methodology.

2.4 Chronology and Return Period Calculation

To generate avalanche event chronologies and estimate return periods for each path and for the entire study site, we utilized *R* statistical software and the package *slideRun*, an extension of the *burnR* library for forest fire history data (Malevich et al., 2018). We calculated the age of each tree sampled and the number of responses per year and computed descriptive statistics for the entire dataset. We note that using dendrochronological methods for establishing avalanche path return intervals should be viewed as maximum return interval values because of the inherent loss of samples and decreasing sample size going back in time.

We employed a multi-step process to reconstruct a regional avalanche chronology and a regional avalanche activity index (RAAI) (Figure 3). First, we tested two different approaches to reconstructing an avalanche chronology. Each approach was implemented on three different spatial scales: individual path, sub-region, and entire region. Both approaches involve calculating the ratio of trees exhibiting a GD over the number of samples alive at year t to provide the index I_t (Shroder, 1978):

$$I_t = \left(\frac{\sum_{i=1}^n (R_t)}{\sum_{i=1}^n (A_t)} \right) \times 100 \quad (1)$$

where R is the number of trees recording a GD at year t with A_t representing the number of trees alive in our sample at year t . Each approach resulted in a threshold of I_t from which we derived avalanche years and subsequent return intervals.

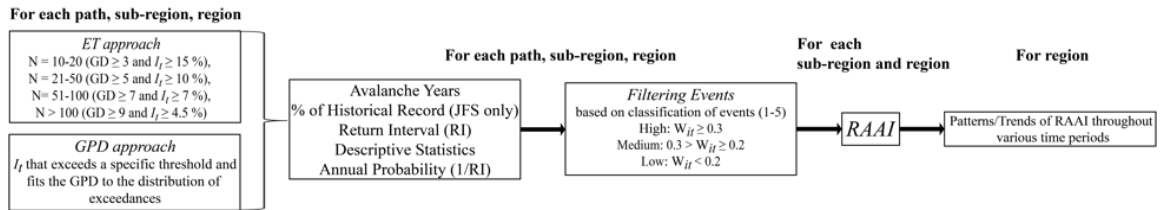


Figure 3: General workflow of analytical methods to reconstruct regional avalanche chronology and regional avalanche activity index.

The first approach (hereafter the established thresholds, or ET, approach) used established double thresholds for minimum absolute number of GD and a minimum percentage of samples exhibiting GD per year (I_t) based on sample size, as per Corona et al. (2012) and Favillier et al. (2018): $N = 10-20$ ($GD \geq 3$ and $I_t \geq 15\%$), $N = 21-50$ ($GD \geq 5$ and $I_t \geq 10\%$), $N = 51-100$ ($GD \geq 7$ and $I_t \geq 7\%$), and $N > 100$ ($GD \geq 9$ and $I_t \geq 4.5\%$).

The second approach used a peaks-over-threshold method based on a generalized Pareto distribution (hereafter the GPD approach), a type of extreme value distribution, as per Germain (2016). This method determined an index I_t that exceeds a specific threshold and fit the GPD to the distribution of exceedances. Before we fit the GPD, we also tested the fit of a Weibull distribution to the data using a Kolmogorov-Smirnov nonparametric test to determine if the data fit that distribution for comparison to the GPD. We used an Anderson-Darling goodness-of-fit test for the GPD (Choulakian and Stephens, 2001). Then, we set a sequence of thresholds for I_t (1-45) specific to each group of data (i.e. path, sub-region, region) and ran 1000 bootstrapped replicates for each to determine the optimal threshold. This provided a set of p-values and test statistics from which we selected the threshold with the highest p-value and the lowest statistic to minimize the distance from the GPD. We applied this approach to each path, each sub-region, and the overall region. As Germain (2016) mentions, a strong knowledge of the geomorphic process and local conditions are necessary to recognize if the resultant threshold is accurate. This is our impetus for comparing these two methods with a large dataset where we have substantial familiarity of local conditions and avalanche paths.

For each approach, we calculated the percentage of historical events captured for each path in the JFS sub-region and the sub-region itself as this is the only sub-region with a long-term historical record. We also calculated the number of avalanche years, descriptive statistics for return intervals (RI), and the annual probability ($1/RI$) for each path, sub-region, and region.

We then used the chronologies derived from the ET approach to calculate a weighted index factor (W_{it}). We chose the ET approach as it has been used consistently in the literature and allows comparability of our final chronology to chronologies from other studies. We adapted Eq. (2) from (Kogelnig-Mayer et al., 2011) to our 5-scale classification scheme to derive the W_{it} :

$$W_{it} = \left(\left(\sum_{i=1}^n T_{C_1} * 7 \right) + \left(\sum_{i=1}^n T_{C_2} * 5 \right) + \left(\sum_{i=1}^n T_{C_3} * 3 \right) + \left(\sum_{i=1}^n T_{C_4, C_5} \right) \right) * \frac{\sum_{i=1}^n R_t}{\sum_{i=1}^n A_t} \quad (2)$$

where the sum of trees with scars or injuries (C_1) was multiplied by a factor of 7, the sum of trees with C_2 signals by a factor of 5, the sum of trees classified C_3 by a factor of three, and the sum of trees with weak or poorly defined signals (C_4 or C_5) a factor of 1 (Kogelnig-Mayer et al., 2011).

Then, we classified W_{it} into high, medium, and low confidence events using the thresholds detailed in Favillier et al. (2018), where High: $W_{it} \geq 0.3$, Medium: $0.3 > W_{it} \geq 0.2$, Low: $W_{it} < 0.2$. This provides yet another step to discriminate the signal of avalanche events/years from the noise. We chose all events with medium to high confidence to advance to the next analysis step. For these higher-quality events, we again calculated the number of avalanche years, descriptive statistics for return intervals, and annual probability for each avalanche path, sub-region, and overall region. We then compared return intervals of all individual paths and sub-regions using analysis of variance (ANOVA) and Tukey's Honest Significant Difference (HSD) (Ott and Longnecker, 2016).

We compared the number of avalanche years and return periods identified in the full regional chronology to subsets of the region to determine the number of paths required to replicate a full 12-path regional chronology. We compared the full chronology with 11 paths by sequentially removing the three paths with the greatest sample size. Then, we randomly sampled two paths from each sub-region for a total of eight paths, then four paths by choosing the path in each sub-region with the greatest sample size, and, finally, a random sample of one path from each sub-region.

Next, we used I_t from each path to calculate a regional avalanche activity index (RAAI) for the sub-regions and overall region (Germain et al., 2009). The RAAI for each year across the sub-regions and region provides a more comprehensive assessment of avalanche activity within the spatial extent. For each year t , we calculated RAAI:

$$RAAI_t = \left(\sum_{i=1}^n I_t \right) / \left(\sum_{i=1}^n P_t \right) \quad (3)$$

where I is the index factor as per (Eq. 1) for a given avalanche path for year t and P is the number of paths that could potentially record an avalanche for year t . Each path must contain a sample size of ≥ 10 trees with a minimum number of three paths for year t , and a minimum of one path from each sub-region for the calculation of the overall RAAI. We performed a sensitivity test to establish the minimum number of paths necessary to calculate an RAAI value for any given year. We also calculated the probability of detecting an avalanche year identified in the regional chronology if we had sampled any given individual path. The probability of detection for a given year (POD_{year}) is defined as:

$$POD_{year} = \frac{a}{a + b} \quad (4)$$

where a is the number of individual avalanche paths that identify any given avalanche year in the regional chronology and b is the total number of avalanche paths ($n=12$). We calculated POD_{year} for every year in the regional avalanche chronology. We then compared the POD_{year} of individual paths to the number of active avalanche paths as defined in Eq. 3.

We also calculated the probability of detection for each path for the period of record (POD_{path}):

$$POD_{path} = \frac{c}{c + d} \quad (4)$$

where c is the number of years identified in any given path that is included in the regional chronology and d is the number of years in the regional chronology that are not identified in the chronology for the given path.

Finally, we examined trends of RAAI through time using the non-parametric modified Mann-Kendall test for trend (Hamed and Rao, 1998; Mann, 1945). We parsed the dataset into various periods to allow comparability due to a loss of evidence and a decreasing sample size going back in time: the entire period of record, 1933 to 2017, 1950 to 2017, and 1990 to 2017. We chose these time periods based on the years with greatest responses and RAAI values as well as visual inspection of the overall RAAI time series.

2.5 Geomorphological characteristics

Using a 10m digital elevation model (DEM), we calculated a number of geomorphological characteristics for each path, including mean elevation (m, full path and starting zone), elevation range (m), eastness $\sin(\text{aspect})$ and northness $\cos(\text{aspect})$ (radians), slope (degrees, full path and starting zone), curvature (index (0-1), profile and planform), roughness (index, full path and starting zone), perimeter (km²), area (km²), length (m), and vertical distance from starting zone to runout zone (m). We also calculated the mean of these characteristics for all paths in the region. The geomorphological characteristics allowed us to determine the representativeness of the region as a whole (i.e. are the paths similar across the region?) as well as compare the return interval for each path in the context of these characteristics. Finally, we calculated the Pearson correlation coefficients between path length, starting zone slope angle, the number of avalanche years, and median return interval for each individual path.

3. Results

Through the cross-dating and avalanche event identification procedures, we noted that had we collected only cores instead of nearly all cross sections, there would have likely been numerous missed events and a greater proportion of low-quality growth disturbance classifications (Figure 4). This suggests that our results are mostly comparable to other studies that utilized all or mostly cross section samples. We analyzed 673 total samples from 647 suitable trees. Of those 673 samples, we collected 614 cross sections (91%) and 59 cores (9%). Within these samples we identified 2304 GD, of which 1279 were classified as C₁ and C₂ (Figure 5A). The oldest tree we sampled was

367 years old and the mean age of the sampled trees was 73 years (Figure 5B). The period of record of sampled trees extended from 1636 to 2017 C.E. The most common species in our dataset was *Abies lasiocarpa* (*ABLA*, sub-alpine fir) (46%) followed by *Pseudotsuga menziesii* (*PSME*, Douglas-fir) (37%) and *Picea engelmannii* (*PIEN*, Engelmann spruce) (14%) (Figure 5C). The oldest response was from 1655. In the entire dataset, the five years with the greatest number of raw responses were 2002 (165 responses), 2014 (151 responses), 1990 (93 responses), 1993 (90 responses), 1982 (75 responses) (Figure S1 and S2).

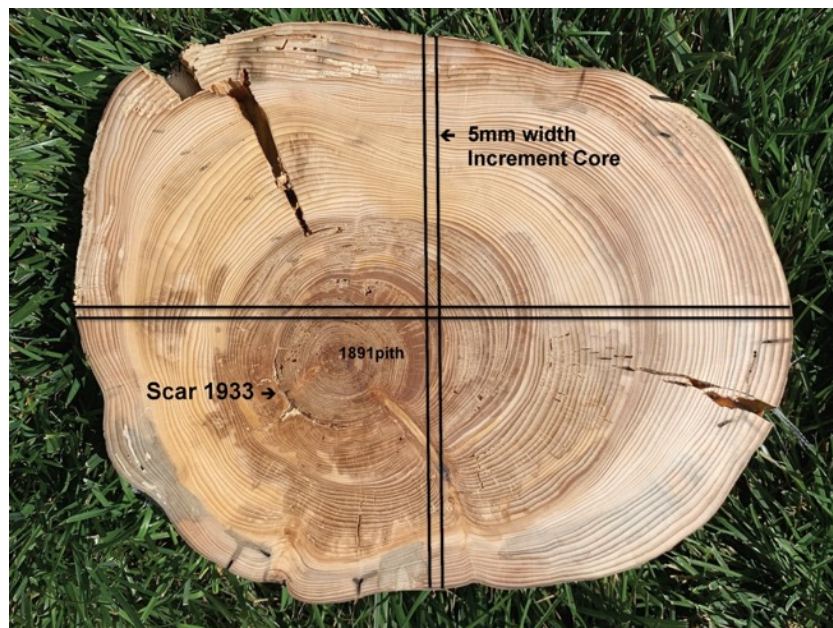


Figure 4: Example of cross section sample where 4 cores taken on uphill, downhill, and perpendicular (2) would have missed at least one scar (1933) and potentially the pith of the tree. The black lines indicate the potential cores using a 5 mm width increment borer.

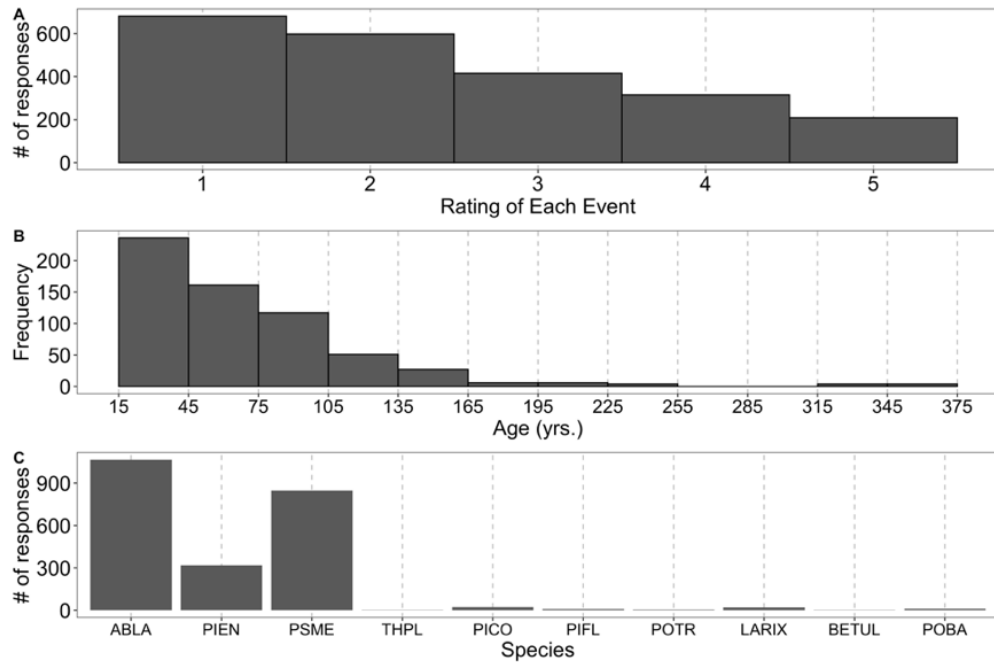


Figure 5: Histograms of (A) ratings of responses, (B) sample age, and (C) species. For species: ABLA=*Abies Lasciocarpa*, PIEN = *Picea engelmannii*, PSME = *Pseudotsuga menziesii*, THPL = *Thuja plicata*, PICO = *Pinus contorta*, POTR = *Populus tremuloides*, LARIX = *Larix* Mill., BETUL = *Betula* L., POBA = *Populus balsamifera*.

3.1 Geomorphological Characteristics

The avalanche paths encompassed all aspects and a range of elevations representative of avalanche paths in the region, but with the fewest on north to northeast aspects (Table 2 and Figure S3). All paths fell within ± 1 standard deviation of the mean for elevation and slope angle. The paths in the GTSR sub-region were the largest, highest in elevation, and had the greatest path length and vertical fall. The mean slope angle of the starting zones for all paths was 37 degrees with a range of 32 to 34 degrees.

3.2 Comparison of Two Approaches – GPD and ET

We compared two approaches prior to applying the W_{it} threshold for low, medium, and high confidence signals. The historical observation record for JFS was incomplete and inconsistent prior to 2005, even for large magnitude avalanches. Thus, the comparison should not reflect the ability of either method to capture all historical events. The ET approach captured 10-50% of the historical record for all three paths in JFS (Table S2). The GPD consistently captured 23-55% of the historical events. The number of avalanche years captured in the JFS sub-region varied as compared to the other regions, where the ET approach consistently identified fewer years (Figure 6). Overall, the GPD approach identified a greater number of avalanche years compared to the ET approach, which produced the fewest number of events in the chronologies of all individual paths. There was no consistent spatial pattern of RI or annual probability based on the approach used for most of the individual paths across the study area (Figure 7). However, the three individual paths in the WF sub-region had consistent RIs across the paths and across both approaches. The record reaching furthest back in time is LJA with signals identified as far back as 1636 (Figure 8). However, the ET threshold filters those out as noise given the minimum GD requirement.

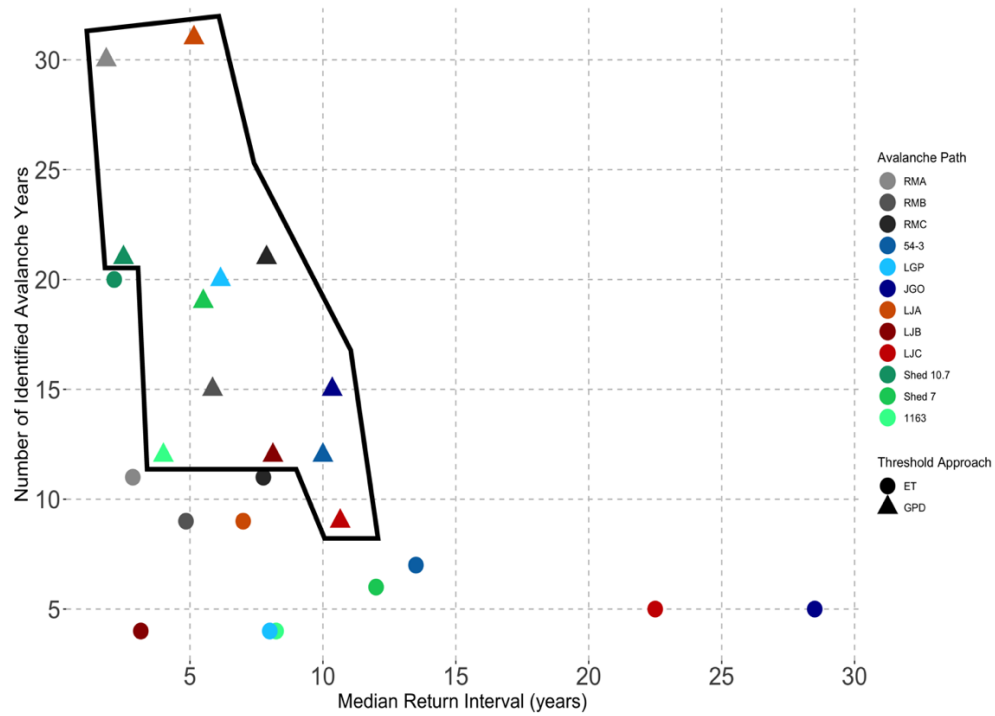


Figure 6: The number of avalanche years identified using the ET (circles) and GPD (triangles) approaches associated with the median return interval for each individual avalanche path (denoted by colors, color band represents sub-region). The black polygon demarcates the GPD approach from the ET approach. See Table S2 for descriptive statistics comparing each approach.

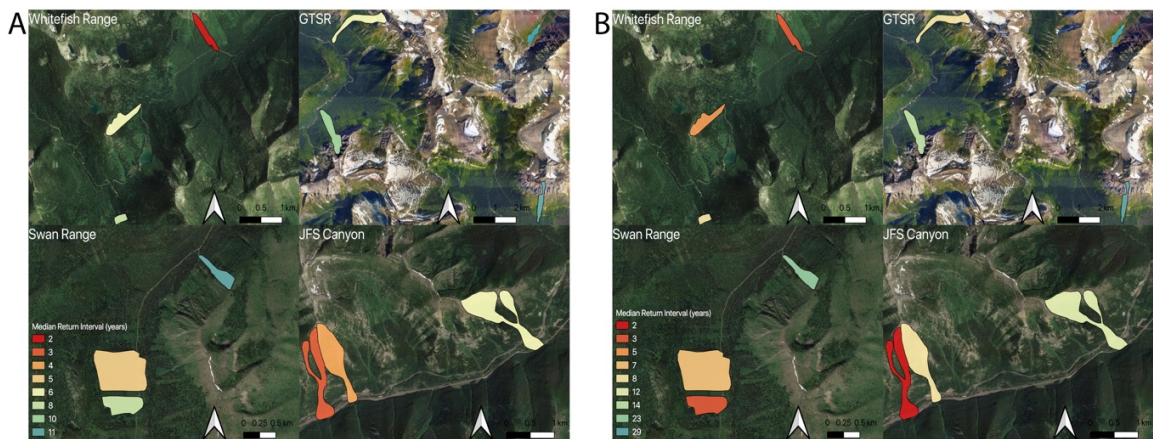


Figure 7: Median return intervals derived using the (A) GPD approach and (B) the ET (established thresholds) approach.

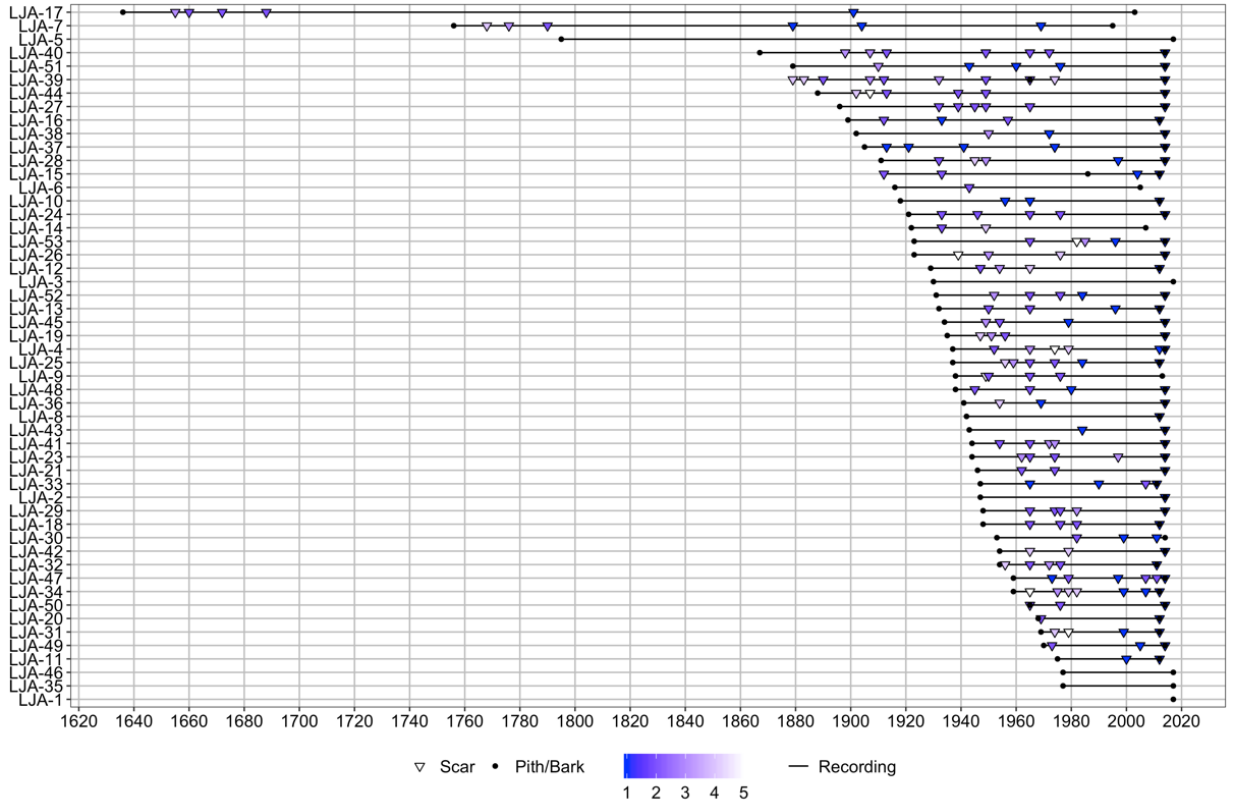


Figure 8: Example demographic plot of the LJA path, the path with the oldest recording trees, in the Swan sub-region. Sample ID is on the y-axis. Inverted triangles represent scars or signals with a color gradient representing the event classification of each signal. The black dot represents the pith or bark of each tree, and the solid line indicates the time the tree was able to record avalanche signals. Demographic plots for all paths are in Figure S2.

3.3 Individual Path Chronologies

Results hereafter reflect avalanche chronologies derived by applying the ET approach and the W_{it} process step to the dataset to allow comparability across recent avalanche-dendrochronological studies in other regions. When we apply the W_{it} process step to more heavily weight higher quality signals, the number of identified avalanche years does not change for any individual avalanche path. The avalanche years most common throughout all of the individual path chronologies are 2014 (7 paths), 1982 and 1990 (5 paths), 1933,

1950, 1972, and 1974 (4 paths), (Figure 9 and Table 5). The year with the greatest number of raw responses (2002) was identified in 3 paths. Two of these paths were in the JFS sub-region as well as the RMA path in the WF sub-region. There is no clear pattern that paths closer in proximity to each other have more similarly identified avalanche years.

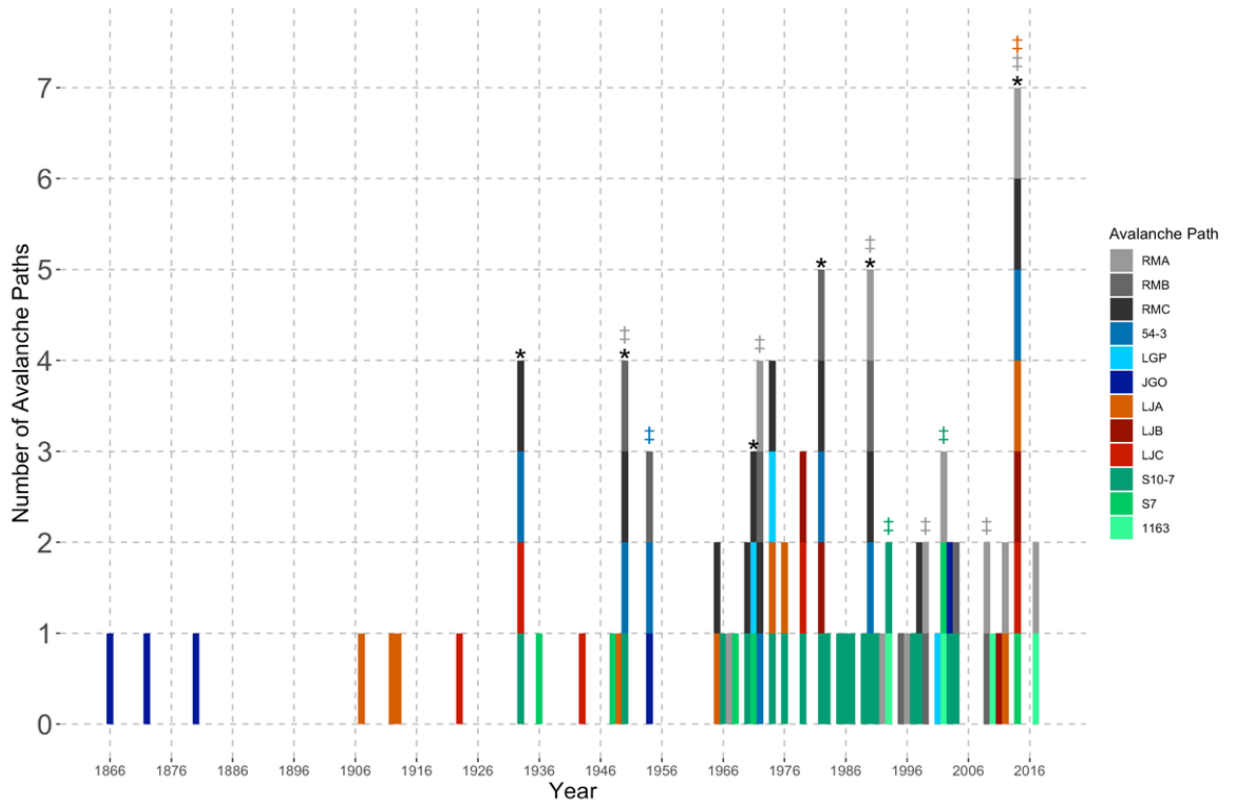


Figure 9: Number of individual avalanche paths identified per year after implementing the ET approach and subsequent W_{it} threshold process step. Avalanche years with ‡ (gray=WF, dark blue = GTSR, orange = Swan, green= JFS) indicate years identified in at least two avalanche paths in the sub-region. * represents avalanche years in common in at least 1 path from at least three of the four sub-regions. See Table S3 for full descriptive statistics of individual paths after applying ET and W_{it} approaches.

Table 5: Avalanche chronologies and return interval (RI) statistics of all 12 avalanche paths in the region after implementing the ET approach and subsequent W_{it} threshold process step. Avalanche years in bold indicate years identified in at least two avalanche paths in the sub-region. Underlined avalanche years indicate years in common in at least 1 path from at least three of the four sub-regions.

	RMA	RMB	RMC	54-3	LGP	JGO	LJA	LJB	LJC	Shed 10-7	Shed 7	1163
Aval Years	1967 1972 1990 1992 1996 1999 2002 2009 2012 2014 2017	1950 1954 1972 1982 1990 1995 1999 2004 2009	<u>1933</u> 1950 1965 1970 <u>1971</u> 1972 1974 <u>1982</u> <u>1990</u> <u>1998</u> 2014	<u>1933</u> <u>1950</u> 1954 1972 <u>1982</u> <u>1990</u> <u>2014</u>	<u>1971</u> 2001 2009	1866 1872 1880 1954 2003	1907 1912 1913 1949 1965 1974 1976 2012 2014	1979 <u>1982</u> 2011 2014	1923 <u>1933</u> 1943 1979 2014	<u>1933</u> <u>1950</u> 1966 1970 1974 1976 1979 <u>1982</u> 1983 1985 1986 1987 1989 1990 1991 1993 1997 1998 2003 2004	1936 1948 1968 <u>1971</u> 2002 <u>2014</u>	1993 2002 2010 2017
# of aval. years	11	9	11	7	4	5	9	4	5	20	6	4
RI - median	3	5	8	14	8	8	7	3	22.5	2	12	8
RI - mean	5	7.38	8.1	13.5	12.67	34.25	13.38	11.67	22.75	3.74	15.6	8
RI - min.	2	4	1	4	3	6	1	3	10	1	3	7
RI - max.	18	18	17	24	27	74	36	29	36	17	31	9
1/RI	0.33	0.20	0.13	0.07	0.13	0.13	0.14	0.33	0.04	0.50	0.08	0.13
σ	4.81	4.78	6.12	7.42	12.66	33.09	14.79	15.01	14.73	4.68	10.50	1.00

JGO, located in the GTSR sub-region, exhibited the greatest spread in return intervals, followed by LJB (Figure 10A and 10C). The avalanche paths within the GTSR sub-region have the most similar return intervals of any of the sub-regions while the individual paths in the JFS sub-region exhibit substantial variability in median return interval values (Figure 10B and 10D). The number of documented return intervals is

relatively small for all the avalanche paths. The return interval for JGO differs significantly from several other paths: RMA, RMB, RMC, and Shed 10-7 ($p < 0.01$, $p = 0.01$, $p < 0.01$, $p < 0.01$, respectively). However, when we relax a strict cutoff of $p = 0.05$, intervals from JGO differ from 1163 ($p = 0.07$) and LJA ($p = 0.08$) and intervals from Shed 10-7 differ from LJC ($p = 0.07$). The paths within the WF sub-region produced the most similar number of large magnitude avalanche years. Return interval was significantly correlated with path length ($r = 0.65$, $p = 0.02$, Figure S4) among all of the geomorphic characteristics we examined.

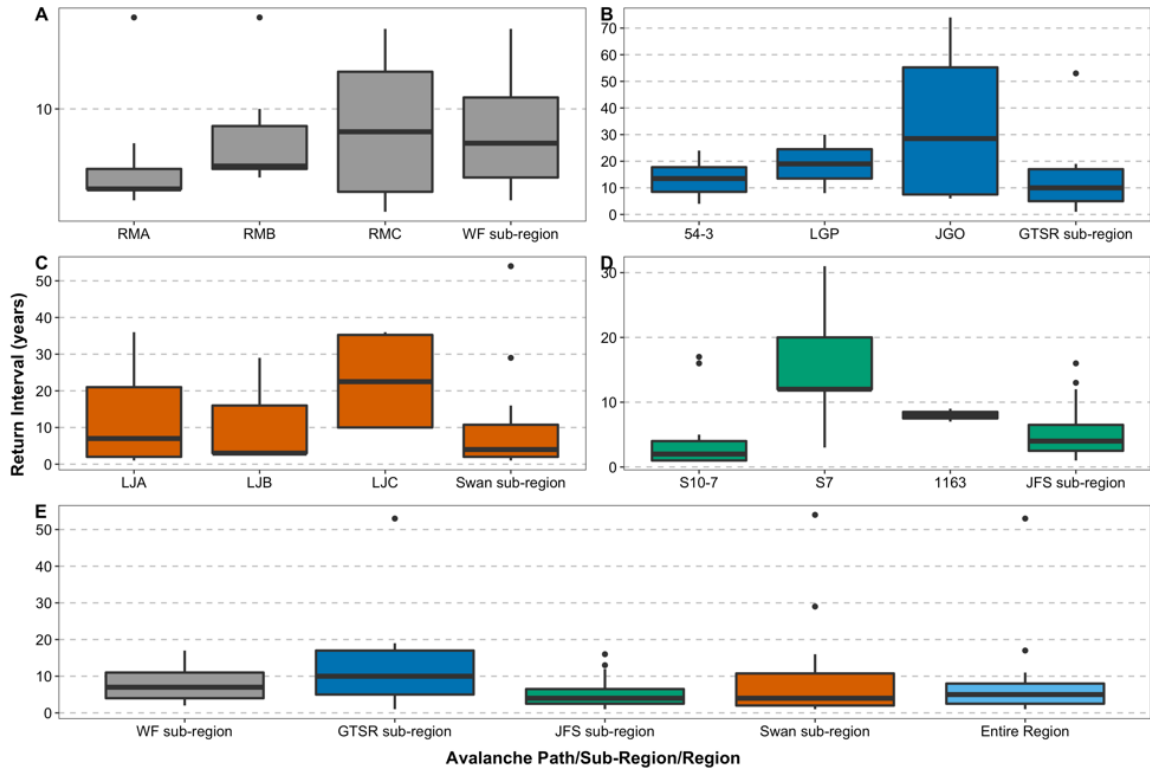


Figure 10: Boxplot of return intervals for individual avalanche paths in each sub-region: (A) WF, (B) GTSR, (C) Swan, and (D) JFS. (E) shows the median return intervals for the sub-regions and the overall region.

3.4 Sub-region Chronologies

When the paths were aggregated into sub-regions (three paths per sub-region) and the ET and Wit process steps were applied, the median return periods for each sub-region were similar and all less than 10 years (Figure 10E and Table 6). The number of avalanche years for all of the sub-regions ranges from 12-18 with the greatest number of identified years in the JFS sub-region and the fewest in the WF sub-region. The JFS sub-region has the shortest median return interval followed by the Swan, WF, and GTSR sub-regions, but the GTSR and Swan sub-regions have similar mean return intervals of 11.35 and 11.25, respectively. The number of avalanche years for each aggregated sub-region is greater than the number of avalanche years for any individual path within each sub-

region except for the JFS sub-region where 18 avalanche years were identified but Shed 10-7 totaled 20 avalanche years (Table 7).

Table 6: Avalanche chronologies and return interval (RI) statistics of all four sub-regions after implementing the ET approach and subsequent Wit threshold process step.

	WF	GTSR	Swan	JFS	Region
Aval Years					1866
					1872
					1880
					1933
					1936
					1945
				1933	1948
				1936	1950
				1948	1954
	1945	1866			
	1950	1872	1879	1950	1956
	1954	1880	1933	1966	1965
	1965	1933	1949	1970	1970
	1972	1950	1954	1971	1971
	1974	1954	1956	1974	1972
	1982	1968	1965	1982	1974
	1990	1971	1974	1983	1976
	1997	1972	1976	1985	1982
	1999	1982	1979	1990	1990
	2012	1987	1982	1993	1993
	2014	2001	2011	1997	1997
	2017	2003	2012	2002	1998
		2014	2014	2003	1999
				2004	2002
				2017	2003
					2004
					2009
					2011
					2012
					2014
					2017
# of aval. years	12	14	13	18	30
RI – median	7	8	4	3	3
RI – mean	6.27	11.35	11.25	4.94	5.21
RI – min.	2	1	1	1	1
RI – max.	13	53	54	16	53
1/RI	0.14	0.13	0.25	0.33	0.33
σ	3.69	13.48	15.70	4.60	9.53

Table 7: Number of avalanche events for each subregion, the mean of three individual paths in each region, and the overall aggregated region.

<u># of avalanche events</u>		
Sub-region	3 individual paths	Aggregated sub-region
WF	11,9,11	12
GTSR	7,3,5	14
Swan	9,4,5	13
JFS	20,6,4	18
Region	30	

In terms of commonality of years between the sub-regions, 1982 is the only year identified in all of the four sub-regions (Figure 11). Avalanche years commonly identified in three sub-regions are 1950, 1954, 1974 and 2014. The JFS sub-region identified the greatest number of years exclusive to that sub-region (10 years). The WF sub-region shared the greatest number of years with other regions (11 years) followed by JFS (9 years), GTSR (8 years), and the Swan (7 years).

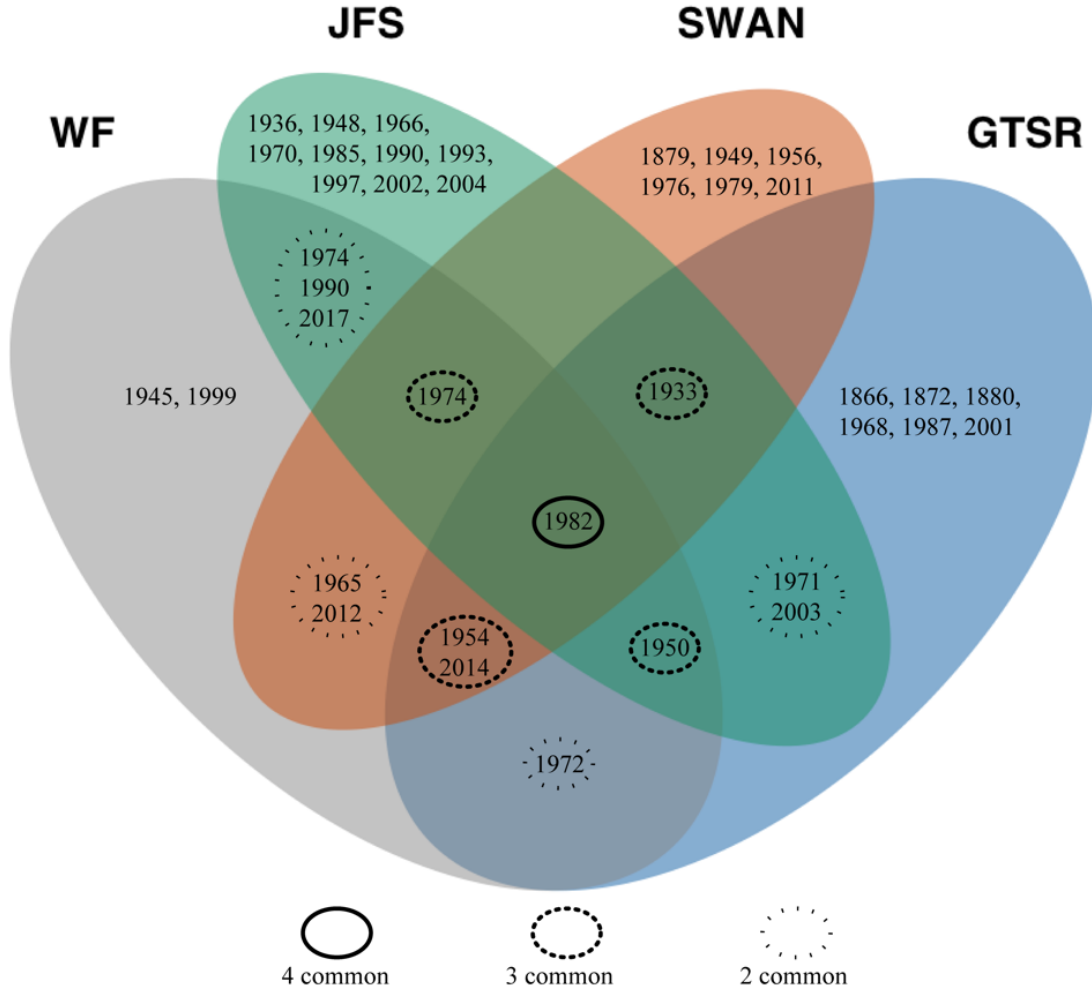


Figure 11: Venn diagram of avalanche years common between sub-regions. Overlapping areas of each ellipse indicate years in common with each sub-region.

3.5 Regional Chronology and RAAI

Using the ET and W_{it} workflow we identified 30 avalanche years in the overall region, a median return interval of 3 years, and a mean return interval of 5.21 years (Table 6). The number of samples increases through time to a peak during 2005 C.E. and the number of GD also increases through time (Figure 12A). The W_{it} index also increases,

particularly from 2000 C.E. onward with the largest spikes in 2014 and 2017 (Figure 12B). The regional assessment of avalanche years identified fewer years ($n=30$) than the simple aggregation of all unique avalanche years identified in the individual paths ($n=49$) (Table S4).

When we included all paths but Shed 10.7 (one of two paths with the greatest sample size), we captured 80% of all avalanche years and introduced one new year (Table 8). When we removed LGP (the other path with the greatest sample size), we still captured all of the years in the regional chronology but introduced four years into the chronology for a total of 34 years. A random sample of eight (two from each sub-region) of the 12 avalanche paths captured 83% of the years in the chronology and identified two new avalanche years. Finally, when using only one path from each sub-region with the largest samples size (Shed 10-7, 54-3, LJA, and RMA), we captured 73% of the avalanche years identified in the full regional chronology. When using a random sample of one path from each sub-region (1163, LGP, LJC, RMB), we captured only 43% of the years included in the regional chronology.

Table 8: Comparison of the number of avalanche years and RI when including all 12 paths in region to using a combination of fewer paths to define the region.

Paths	Region (All Paths)	All but Shed 10-7	All but LGP	All but 54-3	S7, 1163, LGP, JGO, RMB, RMC, LJB, LJC	S107, Path543, LJA, RMA	Path1163, LGP, LJC, RMB
# Paths	12	11	11	11	8	4	4
Sample Size (n)	635	528	526	581	382	253	239
# of Aval Years	30	27	34	31	27	34	17
# matches with regional	NA	24	30	29	25	22	13
# not in regional	NA	1	4	2	2	11	4
% captured in regional	NA	80	100	97	83	73	43
Median RI	3	3	3	3	3	2	3.5
# years removed using only W_{it} =HLC instead of W_{it} =MLC and HLC	10	3	9	7	1	1	1

The RAAI is insensitive (no significant difference, $p > 0.05$) to the number of paths when tested using a minimum number of paths recording an avalanche in year t . The years with the largest RAAI are 2014 and 2017 followed by 2002, 1950 and 1933 (Figure 9C). There is serial autocorrelation in our data, and, therefore, we implemented the modified Mann-Kendall test for trend. The full period of record of RAAI (1867-2017) exhibits a positive trend ($\tau = 0.186$, Sens slope = -0.01, $p = 0.006$). The two other periods analyzed, 1950-2017 and 1990-2017, exhibit neither a positive nor a negative trend ($p = 0.36$ and $p = 0.95$, respectively).

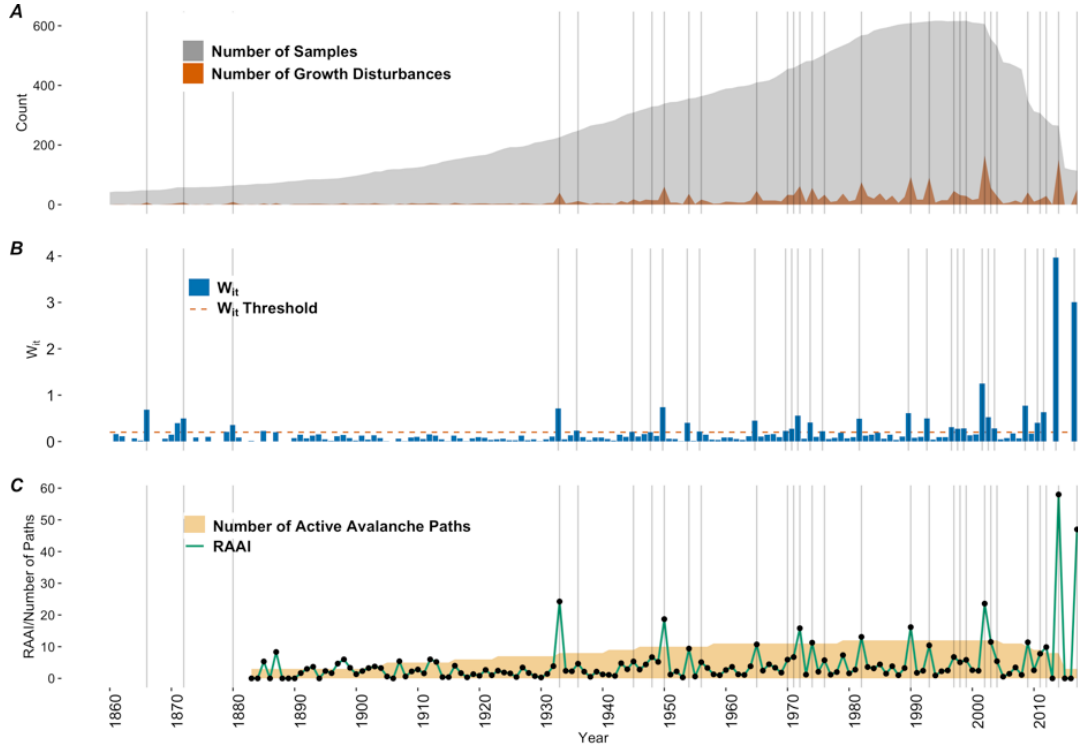


Figure 12: (A) The number of samples (gray shaded area) increases through time, but the number of responses (dark orange shaded area) varies. (B) The W_{it} threshold (0.2, red dashed line) provides a means of discriminating between high and low confidence signals in the tree ring record. (C) The RAAI (green line, black points) is a measure of regional avalanche activity based on the I_t of each path and the number of active avalanche paths (yellow shaded area).

The probability of detection (POD) for the avalanche years identified in the regional chronology ranged from 8 to 58% when we examined individual paths after applying ET and W_{it} thresholds (Table 9). The year with the highest POD was 2014. The mean POD for all years was 21%. When we examined avalanche paths that exhibited at least one scar during avalanche years identified in the regional chronologies, the POD is generally greater.

Table 9: Probability of Detection (POD_{year}). Avalanche years identified in the regional chronology and associated POD by analyzing individual paths with and without ET and W_{it} thresholds.

Avalanche Year in Regional Chronology	POD (%) with thresholds	POD (%) without thresholds
1866	8	8
1872	8	8
1880	8	17
1933	33	58
1936	8	25
1945	NA	58
1948	8	33
1950	33	58
1954	25	67
1956	NA	58
1965	17	67
1970	17	50
1971	25	50
1972	33	83
1974	33	75
1976	17	50
1982	42	92
1990	42	83
1993	17	50
1997	8	92
1998	17	50
1999	17	58
2002	25	75
2003	17	33
2004	17	75
2009	17	33
2011	8	33
2012	17	42
2014	58	58
2017	17	25
Mean	21	52

Finally, the probability of capturing all of the avalanche years identified in the regional chronology by each individual path ranges from 7% to 40% (Table 10). The greatest POD value from any given path is Shed 10-7 ($POD = 40\%$) in the JFS sub-

region followed by RMC in the Whitefish sub-region ($POD = 37\%$). In general, the paths within the Whitefish sub-region capture the regional chronology most consistently.

Table 10: Probability of Detection (POD) of each individual path to the regional avalanche chronology.

Path	POD (%)
RMA	27
RMB	27
RMC	37
54-3	23
LGP	7
JGO	17
LJA	17
LJB	10
LJC	7
Shed 10-7	40
Shed 7	17
1163	10

4. Discussion

The processing and analysis of 673 samples spanning a large spatial extent allowed us to create a robust regional large magnitude avalanche chronology reconstructed from dendrochronological methods. Cross-sections provided a more robust and complete story to each sample compared to cores. Due to the reduced information value of working only with cores, Favillier et al. (2017) includes a discriminatory step in their methods to distinguish avalanche signals in the tree-ring record from exogenous factors, such as abnormal climate signals or response to insect disturbance. By using cross sections to develop our avalanche chronologies, we were able to view the entire ring growth and potential disturbance around the circumference of the tree as opposed to the limited view provided by cores. This allowed us to place signals in context to both climate and insect disturbance without the need for this processing step. We identified 2304 GD from our samples, which is similar to Martin and Germain (2016) in a study where they collected 458 cross sections and 350 cores, and reported 2251 GD.

We targeted areas in the runout zones and along the trim line where large magnitude avalanches occurred in recent years. However, we also sampled into the bottom of the track at some sites. Therefore, some of the noise in the signal could be due to avalanches that may have been on the margin of our large magnitude criteria. The age of our trees reached as far back as the mid 17th century but the application of the ET and W_{it} processing steps filtered many of the older signals out as they failed to meet the minimum number of GD threshold or a given year. With decreasing evidence back in time inherent in avalanche path tree-ring studies it is difficult to place much confidence in

these older recorded events. Therefore, we chose to examine more recent time periods with a larger sample size and more consistent number of sites and individual series when considering return intervals and RAAI.

All of the paths in the study are capable of producing large magnitude avalanches with path lengths greater than 100 m (typical length for avalanche destructive size 2, D2), and all but RMC have a typical path length of close to or greater than 1000 m (for avalanche destructive size 3, D3) (Greene et al., 2010). As Corona et al. (2012) note, the avalanche event must be large enough to create an impact on the tree, and size D2 or greater will be evident from the tree-ring record (Reardon et al., 2008). However, the successive damage and removal of trees from events size D2 or greater also impacts the future potential to record subsequent events of similar magnitude. In other words, if a large magnitude avalanche removes a large swath of trees in one year, then there are fewer trees available to record a slightly smaller magnitude avalanche in subsequent years. Therefore, dendrochronology methods inherently underestimate avalanche events by up to 60% (Corona et al., 2012), and our results suggest these methods captured about 10-50% of the historical record.

4.1 Regional Sampling Strategy and Use of Threshold Approaches

By examining three different spatial scales (individual path, sub-region, and region) we are able to produce a chronology of large magnitude avalanches for the region that is captured in several paths. This sampling may also alleviate the issue of recording large magnitude avalanches within a region in the successive years following a major

destructive avalanche event that removed large number of trees within specific paths but not others.

Our results illustrate the importance and necessity of careful consideration when choosing an approach for discriminating between the signal and the noise in tree-ring avalanche samples (Figure 6). Overall, the GPD method produced shorter return intervals and identified more avalanche years in all paths within the study area than the ET approach. These differences between approaches would influence the outcome of subsequent analyses (e.g. avalanche-climate associations). Therefore, we opted for the more robust approach by using ET as it discriminates against a small number of GD when sample sizes within a given path are small or moderate.

The GPD approach captured slightly more historical events in our record for the JFS sub-region than the ET approach, but confidence in the completeness of the historical record is low. Therefore, caution should be used when considering the ability of these methods to capture the historical record in our dataset. Because both methods performed relatively similarly in capturing the historical record, except in the Shed 7 path where the GPD captured 25% and the ET only captured 10%, we chose to use the ET approach in the subsequent sub-regional and regional analysis. This approach is also more widely used in recent literature (Favillier et al., 2018) so it allows comparability between studies. The GPD method, however, clearly captures more events in the past due to the omission of the minimum number GD threshold. Without an observational record for the entire region, it is unknown whether these past events with a small number of GD are indeed avalanches or noise. This issue cannot be resolved by simply collecting more samples due

to the nature of the highly reduced total number of samples available at a site from further back in time.

4.2 Chronologies for Individual Paths and Sub-Regions

The number of identified avalanche years does not change for any individual avalanche path when we applied the W_{it} process. This suggests that many of the signals in our samples were ranked as high-quality signals (i.e. C₁-C₂). This can be attributed to the use of cross sections which allowed for a more complete depiction and assessment of the tree-ring signal (Carrara, 1979).

The path with the greatest number of identified avalanche years, Shed 10-7, contains two major starting zones that are both steeper (35 and 39 degrees) than Shed 7, which also contains two separate starting zones. Reardon et al. (2008) collected a substantial number of samples at higher elevations in the avalanche path. However, the location data were not available. Many of those samples were the living stumps that captured smaller annual events. This is likely the root of the difference and the reason Shed 10-7 contains the largest numbers of avalanche years in this analysis.

The range of return intervals across all paths (2 – 22.5) is similar to those reported for 12 avalanche paths across a smaller spatial extent in the Chic Choc Mountains of Quebec, Canada (2 – 22.8) (Germain et al., 2009). Although the authors in that study used a different avalanche signal index, this still suggests considerable variation in avalanche frequency across avalanche paths within a region.

The return intervals for LJC in the Swan sub-region were the greatest and this is likely due to wildfire activity in this path. In 2003, a wildfire impacted the Lost Johnny

Creek in the Swan Range. LJC was heavily burned, and this created a steep slope with few trees that was once moderately to heavily forested. A lack of anchoring and snowfall interception likely created an avalanche path without many large magnitude avalanches for decades, and slope forestation plays a substantial role in runout distance and avalanche frequency in forested areas (Teich et al., 2012). Wildfires in 1910 burned a majority of the JFS sub-region as well and the higher frequency of avalanche years recorded between 1910 and 1940 in Shed 10-7 suggests this may also be a contributor to the high frequency of avalanche events in that location (Reardon et al., 2008).

Our results also suggest that return interval increases as path length increases, though the sample size for this correlation analysis on individual paths is small ($n=12$). This differs from a group of avalanche paths in Rogers Pass, British Columbia, Canada, where path length was not significantly correlated with avalanche frequency (Smith and McClung, 1997). However, the authors in that study used all observed avalanches, including artillery-initiated avalanches, as opposed to a tree-ring reconstructed dataset.

JGO contains the maximum return interval for any path in the study, and the return intervals are significantly different than numerous other paths. It is difficult to interpret this as it is neither the longest path nor the steepest. Again, a lack of recording data after one large avalanche event could easily skew this value. Another potential explanation is that this path is the only one located east of the Continental Divide where the snowpack is often much shallower, particularly at lower elevations (Selkowitz et al., 2002), thus inhibiting frequent large magnitude events from impacting the sampled runout zone. The fetch upwind of this avalanche path is characterized by steep, rocky

terrain harboring scoured slopes. This limits the amount of snow available for transport to the JGO starting zone which may also influence the load and stress placed upon this starting zone and subsequent large magnitude avalanches.

The greatest number of identified avalanche years is in the JFS sub-region. The avalanche paths in this sub-region are all south or southeasterly facing whereas the other sub-regions span a greater range of aspects. This may cause a bias toward a more unified representation of that aspect compared to the inclusion of other aspects in the JFS sub-region.

The differences between sub-regions are likely due to localized terrain and weather factors and the interaction of the two. For example, Birkeland (2001) demonstrated significant variability of slope stability across a small mountain range dependent upon terrain and weather. Slope stability and subsequent large magnitude avalanching are likely to be highly heterogeneous across not only the sub-region, but across a large region. This is also consistent with findings by Schweizer et al. (2003) that suggest substantial differences in stability between sub-regions despite the presence of widespread weak layers.

4.3 Regional Chronologies and RAAI

The regional chronology we developed through the use of tree-ring analysis using 12 avalanche paths suggests, unsurprisingly, that the inclusion of more avalanche paths across a large spatial extent produces a more robust identification of major avalanche winters. When we aggregate all 12 paths together and apply established thresholds to discriminate the signal from the noise, we identified 30 avalanche years throughout the

region. This allows us to place each year in context of the region, or full extent of the scale triplet, rather than simply collating all of the major avalanche winters identified in each individual path or sub-region. However, we also account for the support and spacing by including adjacent avalanche paths within a sub-region and multiple sub-regions throughout the region. This sampling strategy combined with the large sample size collected throughout the region allows for a robust assessment of regional avalanche chronology derived from tree-ring records.

We tested the sensitivity of the term regional by removing specific and random paths. Our results suggest that removing paths from this structure, and subsequently compromising the sampling strategy, introduces noise. By reducing the sample size, we reduce the ability of the ET thresholds to filter out noise, increase the actual number of avalanche years in the region, but reduce the number of identified avalanche winters common to the full 12 path regional record (Table 8). Our results emphasize the importance of sampling more paths spread throughout the region of interest as well as a large dataset across the spatial extent.

Avalanche path selection is clearly important when trying to assess avalanche frequency (de Bouchard d'Aubeterre et al., 2019), and is supported by our results suggesting that Shed 10-7 is more influential than any other path in our study (Table 8). However, selecting multiple paths throughout the region representing a wide range of geomorphic characteristics and potentially influenced by local weather patterns provides a reasonable assessment of regional avalanche activity in areas without historical records. By quantifying the sensitivity of the number of avalanche paths within a given region, we

illustrate that sampling a greater number of avalanche paths dramatically increases the probability of identifying more avalanche years as well as increases the ability to reconstruct major avalanche cycle chronologies. However, as previously noted, dendrochronological techniques tend to underestimate avalanche frequency, which implies that caution should be used when interpreting a regional avalanche signal using this technique, particularly as sample numbers and qualities (e.g. cores vs. cross sections) decline.

Interestingly, the difference in median return interval throughout the “region” using 12 paths compared to using four or eight paths changes only slightly. This suggests that fewer paths are still able to capture the major avalanche intervals across a region. However, choosing fewer paths appears to introduce more noise - years not identified in a regional chronology with more avalanche paths.

The RAAI provides a measure of avalanche activity scaled to the number of active avalanche paths across the region through time. The years with the greatest RAAI value coincide with substantial activity provided in the historical record as well as previous dendrochronological studies from the JFS sub-region (Butler and Malanson, 1985a; Butler and Malanson, 1985b; Reardon et al., 2008). The winter of 1932-33 was characterized by heavy snowfall and persistent cold temperatures leading to extensive avalanche activity that destroyed roadway infrastructure in the JFS sub-region, 1950 saw a nearly month-long closure of U.S. Highway 2 due to avalanche activity, and in 2002, an avalanche caused a train derailment. While these are all confined to the JFS sub-region, with the exception of 2002, they are also years shared by at least two other sub-regions.

We examined the probability of detecting an avalanche year throughout the region by sampling any one given path. In seven of 30 years, the *POD* is only 8% and in all but three years the *POD* is less than 40%. The low *POD* values are distributed throughout the time series suggesting decreasing sample size back in time or the number of active avalanche paths is not an influential factor. The *POD* is likely reflective of the spatial variability of large magnitude avalanche occurrence across a region. It also aligns with the observational findings of Mears (1992). During a major storm in 1986 throughout much of the western United States that deposited 30-60 cm of snow water equivalent, Mears (1992) reports that less than 40% of avalanche paths produced avalanches and less than 10% produced avalanches approaching the 100-year return interval. This also confirms the wide variability of avalanche years between sub-regions recorded in our tree-ring record. Additionally, some of the avalanches in a given cycle may not be large enough to be reflected in the tree ring record. Therefore, low values of POD_{year} when considering only one avalanche path and identifying only one common year of large magnitude avalanche activity amongst the sub-regions through dendrochronology is not surprising. Paths with at least one scar (i.e. without applying thresholds) during avalanche years identified in the regional chronology exhibit a greater POD_{year} , but this greater POD_{year} comes at the expense of introducing more noise if we were to simply use one scar for path.

Our results also suggest that our sampling design using scale triplet increases the probability of detecting avalanche activity across an entire region. We note that we are only able to scale our probability calculations to our dataset with an historical

observational record. However, our results illustrate the importance of sampling more paths if the goal is to reconstruct a regional chronology. In our dataset, the greatest value of POD_{path} is 40% suggesting that if by chance, we sampled this path we would have captured the regional avalanche activity 40% of the time.

The trends in RAAI over the entire period of record are likely influenced by the decreasing number of samples available to record an event further back in time. Despite the RAAI accounting for the number of avalanche paths (minimum of $n = 3$), the small sample size from the late 19th century precludes us from suggesting there is a true increase in regional avalanche activity from 1636 to 2017. This is also supported by the absence of positive or negative trend from 1950 to 2017 and 1990 to 2017.

4.4 Limitations and Future Work

Overall, our results strongly suggest that sampling one path, or multiple paths in one sub-region, is insufficient to extrapolate avalanche activity beyond those paths. Multiple paths nested within sub-regions is necessary to glean information regarding avalanche activity throughout those sub-regions as well as the overall region. Our study is still limited by the underrepresentation of dendrochronological techniques in identifying all avalanche events. While we analyzed 673 samples over the extent of the region, some of the paths in our study had relatively small sample sizes per individual path as compared to recent suggestions (Corona et al., 2012). This may have influenced the number of avalanche years identified and subsequent RIs per individual path. However, we attempted to limit the influence of sample size by using full cross-sections from trees, robust and critical identification of signals in the tree-rings, and appropriate established

threshold techniques. We also recognize, based on the results of our study, that the selection of more avalanche paths in our region would certainly provide a more robust regional avalanche chronology, but time, cost, and resource constraints require an optimized strategy. Finally, our study would undoubtedly have benefited from a longer and more accurate historical record for comparisons and verification of the tree-ring record in all of the sub-regions. Overall, our study illustrates the importance of consideration of spatial scale and extent when designing regional avalanche studies using tree-ring records.

5. Conclusions

In this study, we developed a large magnitude avalanche chronology using dendrochronological techniques for a region in the northern U.S. Rocky Mountains. We implemented a strategic sampling design that allowed us to examine avalanche activity through time in single avalanche paths, four sub-regions, and throughout the region. By analyzing 673 samples from 12 avalanche paths, we identified 30 years with large magnitude events across the region and a median return interval of 3 years. Throughout the sub-regions, the large magnitude avalanche return interval and number of avalanche years vary suggesting the importance of local terrain and weather factors. Our work emphasizes the importance of sample size, scale, and spatial extent when attempting to derive a regional large magnitude avalanche chronology from tree-ring records. In our dataset, the greatest value of POD_{path} is 40% suggesting that if by chance, we sampled this path we would have captured the regional avalanche activity 40% of the time. In other words, one single path cannot provide a robust and reliable regional avalanche

chronology. Specifically, our results emphasize the importance of sampling more paths spread throughout the region of interest as well as a large dataset scaled to the spatial extent. Future work should include conducting a similar study with a number of paths in the same sub-regions for verification or in an area with a robust regional historical record for verification.

REFERENCES

- Armstrong, B.R., 1981. A quantitative analysis of avalanche hazard on U.S. Highway 550, southwestern Colorado, Proceedings of the Western Snow Conference, St. George, Utah, April 14-16, 2017, St. George, Utah, pp. 95-104.
- Ballesteros-Canovas, J.A., Trappmann, D., Madrigal-Gonzalez, J., Eckert, N. and Stoffel, M., 2018. Climate warming enhances snow avalanche risk in the Western Himalayas. *Proc Natl Acad Sci U S A*, 115(13): 3410-3415.
- Bebi, P., Kulakowski, D. and Rixen, C., 2009. Snow avalanche disturbances in forest ecosystems-State of research and implications for management. Elsevier Science Bv, pp. 1883-1892.
- Birkeland, K.W., 2001. Spatial patterns of snow stability throughout a small mountain range. *Journal of Glaciology*, 47(157): 176-186.
- Blöschl, G. and Sivapalan, M., 1995. Scale issues in hydrological modelling: A review. *Hydrological Processes*, 9: 251-290.
- Blöschl, G., 1999. Scaling issues in snow hydrology. *Hydrological Processes*, 13: 2149-2175.
- Bryant, C.L., Butler, D.R. and Vitek, J.D., 1989. A Statistical-Analysis of Tree-Ring Dating in Conjunction With Snow Avalanches - Comparison of on-Path Versus Off-Path Responses. *Environmental Geology and Water Sciences*, 14(1): 53-59.
- Burrows, C.J. and Burrows, V.L., 1976. Procedures for the study of snow avalanche chronology using growth layers of woody plants, Institute of Arctic and Alpine Research, University of Colorado, Boulder, CO.
- Butler, D.R., 1979. Snow avalanche path terrain and vegetation, Glacier National Park, Montana. *Arctic and Alpine Research*, 11(1): 17-32.
- Butler, D.R. and Malanson, G., P., 1985a. A history of high-magnitude snow avalanches, southern Glacier National Park, Montana, U.S.A. *Mountain Research and Development*, 5(2): 175-182.
- Butler, D.R. and Malanson, G.P., 1985b. A reconstruction of snow-avalanche characteristics in Montana, U.S.A., using vegetative indicators. *Journal of Glaciology*, 31(108): 185-187.

- Butler, D.R., Malanson, G.P. and Oelfke, J.G., 1987. Tree-ring analysis and natural hazard chronologies: minimum sample sizes and index values. *Professional Geographer*, 39(1): 41-47.
- Butler, D.R. and Sawyer, C.F., 2008. Dendrogeomorphology and high-magnitude snow avalanches: a review and case study. *Natural Hazards and Earth System Sciences*, 8(2): 303-309.
- CAIC, 2019. Colorado Avalanche Information Center Statistics and Reporting. <http://avalanche.state.co.us/accidents/statistics-and-reporting/>.
- Carrara, P.E., 1979. The determination of snow avalanche frequency through tree-ring analysis and historical records. *Geological Society of America Bulletin*, 90: 773-780.
- Casteller, A., Stoeckli, V., Villalba, R. and Mayer, A.C., 2007. An evaluation of dendroecological indicators of snow avalanches in the Swiss Alps. *Arctic Antarctic and Alpine Research*, 39(2): 218-228.
- Chiroui, P., Stoffel, M., Onaca, A. and Urdea, P., 2015. Testing dendrogeomorphic approaches and thresholds to reconstruct snow avalanche activity in the Făgăraș Mountains (Romanian Carpathians). *Quaternary Geochronology*, 27: 1-10.
- Choulakian, V. and Stephens, M.A., 2001. Goodness-of-fit tests for the Generalized Pareto distribution. *Technometrics*, 43(4): 478-484.
- Corona, C., Lopez Saez, J., Stoffel, M., Bonnefoy, M., Richard, D., Astrade, L. and Berger, F., 2012. How much of the real avalanche activity can be captured with tree rings? An evaluation of classic dendrogeomorphic approaches and comparison with historical archives. *Cold Regions Science and Technology*.
- de Bouchard d'Aubeterre, G., Favillier, A., Mainieri, R., Lopez Saez, J., Eckert, N., Saulnier, M., Peiry, J.L., Stoffel, M. and Corona, C., 2019. Tree-ring reconstruction of snow avalanche activity: Does avalanche path selection matter? *Science of The Total Environment*, 684: 496-508.
- Dube, S., Fillion, L. and Hetu, B., 2004. Tree-Ring Reconstruction of High-Magnitude Snow Avalanches in the Northern Gaspé Peninsula, Quebec, Canada. *Arctic, Antarctic, and Alpine Research*, Vol. 36(No. 4): 555-564.
- Favillier, A., Guillet, S., Morel, P., Corona, C., Lopez Saez, J., Eckert, N., Ballesteros Cánovas, J.A., Peiry, J.-L. and Stoffel, M., 2017. Disentangling the impacts of exogenous disturbances on forest stands to assess multi-centennial tree-ring

reconstructions of avalanche activity in the upper Goms Valley (Canton of Valais, Switzerland). *Quaternary Geochronology*, 42: 89-104.

- Favillier, A., Guillet, S., Trappmann, D., Morel, P., Lopez-Saez, J., Eckert, N., Zenhäusern, G., Peiry, J.-L., Stoffel, M. and Corona, C., 2018. Spatio-temporal maps of past avalanche events derived from tree-ring analysis: A case study in the Zermatt valley (Valais, Switzerland). *Cold Regions Science and Technology*, 154: 9-22.
- Germain, D., 2016. A Statistical Framework for Tree-Ring Reconstruction of High-Magnitude Mass Movements: Case Study of Snow Avalanches in Eastern Canada. *Geografiska Annaler: Series A, Physical Geography*, 98(4): 303-311.
- Germain, D., Filion, L. and Hétu, B., 2005. Snow avalanche activity after fire and logging disturbances, northern Gaspé Peninsula, Quebec, Canada. *Can. J. Earth Sci.*, 42: 2103-2116.
- Germain, D., Filion, L. and Hétu, B., 2009. Snow avalanche regime and climatic conditions in the Chic-Choc Range, eastern Canada. *Climatic Change*, 92(1-2): 141-167.
- Germain, D., Hétu, B. and Filion, L., 2010. Tree-ring based reconstruction of past snow avalanche events and risk assessment in Northern Gaspé Peninsula (Québec, Canada). In: M. Stoffel, M. Bollschweiler, D.R. Butler and B.H. Luckman (Editors), *Tree Rings and Natural Hazards - A State-of-the-Art. Advances in Global Change Research*. Springer, London.
- Gratton, M., Germain, D. and Boucher, É., 2019. Meteorological triggering scenarios of tree-ring-based snow avalanche occurrence on scree slopes in a maritime climate, Eastern Canada. *Physical Geography*: 1-18.
- Greene, E., Atkins, D., Birkeland, K., Elder, K., Landry, C., Lazar, B., McCammon, I., Moore, M., Sharaf, D., Sternenz, C., Tremper, B. and Williams, K., 2010. *Snow, weather and avalanches: observation guidelines for avalanche programs in the United States*, Pagosa Springs, CO.
- Greene, E., Birkeland, K.W., Elder, K., McCammon, I., Staples, M. and Sharaf, D., 2016. *Snow, weather, and avalanches: Observation guidelines for avalanche programs in the United States* (3rd ed). American Avalanche Association, Victor, ID, pp. 104.
- Grissino-Mayer, H., 2001. Evaluating crossdating accuracy: A manual and tutorial for the computer program COFECHA. *Tree-Ring Research*, 57(2): 205-221.

- Hamed, K.H. and Rao, A.R., 1998. A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology*, 204(1-4): 182-196.
- Hebertson, E.G. and Jenkins, M.J., 2003. Historic climate factors associated with major avalanche years on the Wasatch Plateau, Utah. *Cold Regions Science and Technology*, 37(3): 315-332.
- Hendrikx, J., Murphy, M. and Onslow, T., 2014. Classification trees as a tool for operational avalanche forecasting on the Seward Highway, Alaska. *Cold Regions Science and Technology*, 97: 113-120.
- Holmes, R.L., 1983. Analysis of tree rings and fire scars to establish fire history. *Tree-Ring Bulletin*, 43: 51-67.
- ITRDB, 2018. International Tree Ring Data Bank (ITRDB).
- Kogelnig-Mayer, B., Stoffel, M., Schneuwly-Bollschweiler, M., Hübl, J. and Rudolf-Miklau, F., 2011. Possibilities and Limitations of Dendrogeomorphic Time-Series Reconstructions on Sites Influenced by Debris Flows and Frequent Snow Avalanche Activity. *Arctic, Antarctic, and Alpine Research*, 43(4): 649-658.
- Köse, N., Aydın, A., Akkemik, Ü., Yurtseven, H. and Güner, T., 2010. Using tree-ring signals and numerical model to identify the snow avalanche tracks in Kastamonu, Turkey. *Natural Hazards*, 54(2): 435-449.
- Malevich, S.B., Guiterman, C.H. and Margolis, E.Q., 2018. burnr : Fire history analysis and graphics in R. *Dendrochronologia*, 49: 9-15.
- Mann, H.B., 1945. Nonparametric tests against trend. *Econometrica*, 13(3): 245-259.
- Martin, J.P. and Germain, D., 2016. Dendrogeomorphic reconstruction of snow avalanche regime and triggering weather conditions: A classification tree model approach. *Progress in Physical Geography*.
- Mears, A.I., 1992. Snow-Avalanche Hazard Analysis for Land-use Planning and Engineering. *Colorado Geological Survey Bulletin*, 49.
- Meseşan, F., Gavrilă, I.G. and Pop, O.T., 2018. Calculating snow-avalanche return period from tree-ring data. *Natural Hazards*, 94(3): 1081-1098.
- Mock, C.J. and Birkeland, K.W., 2000. Snow avalanche climatology of the western United States mountain ranges. *Bulletin of the American Meteorological Society*, 81(10): 2367-2392.

- Mock, C.J., Carter, K.C. and Birkeland, K.W., 2016. Some Perspectives on Avalanche Climatology. *Annals of the American Association of Geographers*: 1-10.
- Muntan, E., Garcia, C., Oller, P., Marti, G., Garcia, A. and Gutierrez, E., 2009. Reconstructing-snow-avalanches-in-the-Southeastern-Pyrenees. *Natural-Hazards-and-Earth-System-Science*, 9: 1599-1612.
- Ott, R.L. and Longnecker, M.T., 2016. *An Introduction to Statistical Methods and Data Analysis*. Cengage Learning, Boston, MA.
- Peitzsch, E.H., Stahle, D.K., Fagre, D.B., Clark, A.M., Pederson, G.T., Hendrikx, J. and Birkeland, K.W., 2019. Tree ring dataset for a regional avalanche chronology in northwest Montana, 1636-2017. U.S. Geological Survey. <https://doi.org/10.5066/P9TLHZAI>.
- Pop, O.T., Munteanu, A., Flaviu, M., Gavrilă, I.-G., Timofte, C. and Holobacă, I.-H., 2018. Tree-ring-based reconstruction of high-magnitude snow avalanches in Piatra Craiului Mountains (Southern Carpathians, Romania). *Geografiska Annaler: Series A, Physical Geography*, 100(2): 99-115.
- Potter, N., 1969. Tree-ring dating of snow avalanche tracks and the geomorphic activity of avalanches, Northern Absaroka Mountains, Wyoming. *Geological Society of America Special Papers*(123): 141-165.
- Rayback, S.A., 1998. A dendrogeomorphological analysis of snow avalanches in the Colorado Front Range, USA. *Physical Geography*, 19(6): 502-515.
- Reardon, B.A., Pederson, G.T., Caruso, C.J. and Fagre, D.B., 2008. Spatial reconstructions and comparisons of historic snow avalanche frequency and extent using tree rings in Glacier National Park, Montana, U.S.A. *Arctic, Antarctic, and Alpine Research*, 40(1): 148-160.
- Schläppy, R., Eckert, N., Jomelli, V., Stoffel, M., Grancher, D., Brunstein, D., Naaim, M. and Deschatres, M., 2014. Validation of extreme snow avalanches and related return periods derived from a statistical-dynamical model using tree-ring techniques. *Cold Regions Science and Technology*, 99: 12-26.
- Schläppy, R., Jomelli, V., Eckert, N., Stoffel, M., Grancher, D., Brunstein, D., Corona, C. and Deschatres, M., 2015. Can we infer avalanche-climate relations using tree-ring data? Case studies in the French Alps. *Regional Environmental Change*, 16(3): 629-642.
- Schläppy, R., Jomelli, V., Grancher, D., Stoffel, M., Corona, C., Brunstein, D., Eckert, N. and Deschatres, M., 2013. A New Tree-Ring-Based, Semi-Quantitative Approach

for the Determination of Snow Avalanche Events: use of Classification Trees for Validation. *Arctic, Antarctic, and Alpine Research*, 45(3): 383-395.

Schweizer, J., 2003. Snow avalanche formation. *Reviews of Geophysics*, 41(4).

Schweizer, J., Kronholm, K. and Wiesinger, T., 2003. Verification of regional snowpack stability and avalanche danger. *Cold Regions Science and Technology*, 37(3): 277-288.

Selkowitz, D.J., Fagre, D.B. and Reardon, B.A., 2002. Interannual variations in snowpack in the Crown of the Continent Ecosystem. *Hydrological Processes*, 16(18): 3651-3665.

Shroder, J.F., 1978. Dendrogeomorphological analysis of mass movement on Table Cliffs Plateau, Utah. *Quaternary Research* 9, 168(18.5).

Shroder, J.F., 1980. Dendrogeomorphology: review and new techniques of tree-ring dating. *Progress in Physical Geography*, 4(2): 161-188.

Šilhán, K. and Tichavský, R., 2017. Snow avalanche and debris flow activity in the High Tatras Mountains: New data from using dendrogeomorphic survey. *Cold Regions Science and Technology*, 134: 45-53.

Smith, L., 1973. Indication of snow avalanche periodicity through interpretation of vegetation patterns in the North Cascades, Washington. , *Methods of Avalanche Control on Washington Mountain Highways: Third Annual Report*. Washington State Highway Commission Department of Highways, Olympia, Washington, USA.

Smith, M.J. and McClung, D.M., 1997. Avalanche frequency and terrain characteristics at Rogers' pass, British Columbia, Canada. *Journal of Glaciology*, 43(143): 165-171.

Stoffel, M. and Bollschweiler, M., 2008. Tree-ring analysis in natural hazards research - an overview. *Natural Hazards and Earth System Science*, 8: 15.

Stokes, M.A. and Smiley, T.L., 1996. *An Introduction to Tree-Ring Dating*. The University of Arizona Press, Tucson.

Teich, M., Bartelt, P., Grêt-Regamey, A. and Bebi, P., 2012. Snow Avalanches in Forested Terrain: Influence of Forest Parameters, Topography, and Avalanche Characteristics on Runout Distance. *Arctic, Antarctic, and Alpine Research*, 44(4): 509-519.

Voiculescu, M., Onaca, A. and Chiroiu, P., 2016. Dendrogeomorphic reconstruction of past

snow avalanche events in Bâlea glacial valley–Făgăraș massif (Southern Carpathians), Romanian Carpathians. *Quaternary International*, 415: 286-302.

APPENDIX

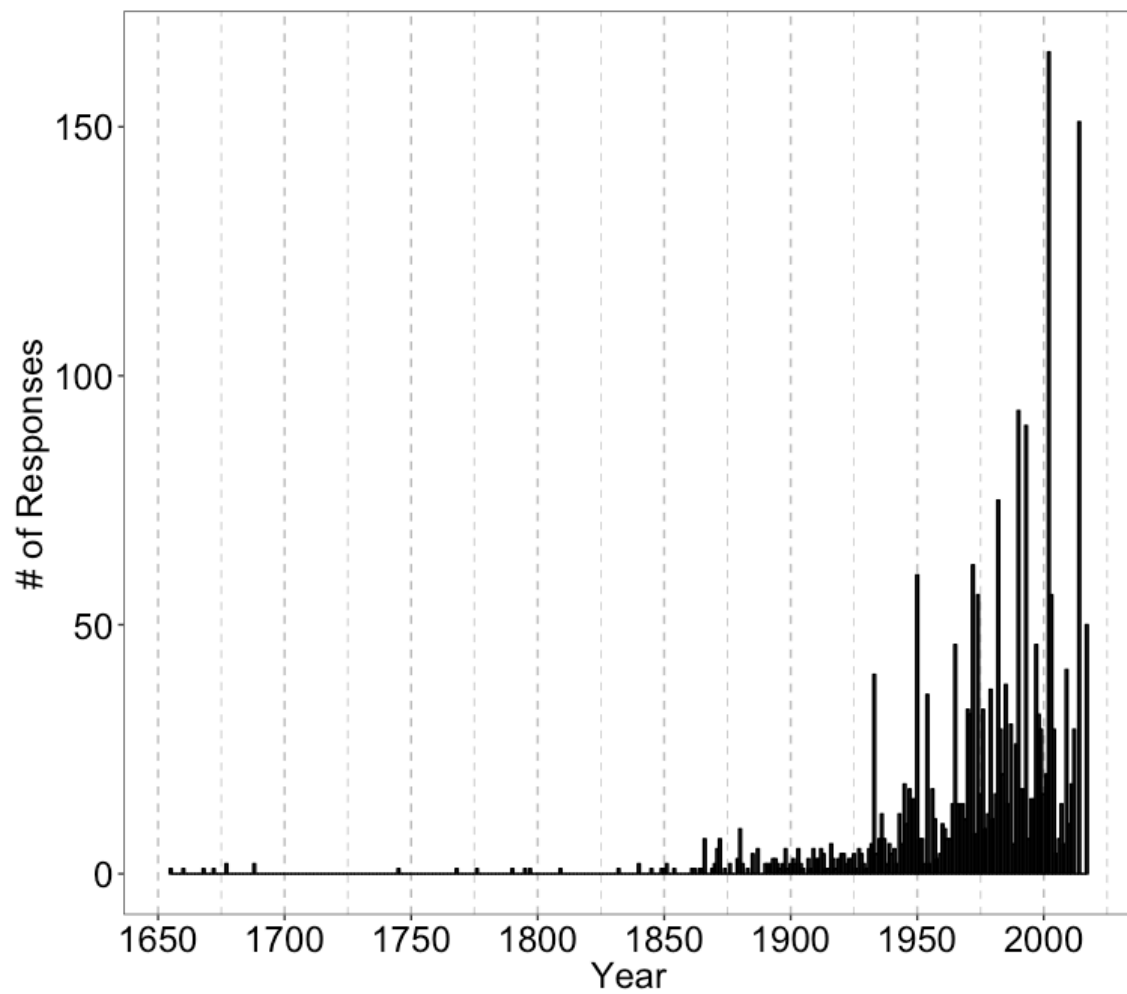


Figure S1: Raw number of responses from the entire dataset.



Figure S2: Demograph plots of all samples from all paths. Row 1: JFS, Row 2: GTSR, Row 3: Swan, Row 4: WF. Inverted triangles represent scars or signals with a color gradient representing the event classification of each signal. The black dot represents the pith or bark of each tree, and the solid line indicates the time the tree was able to record avalanche signals.

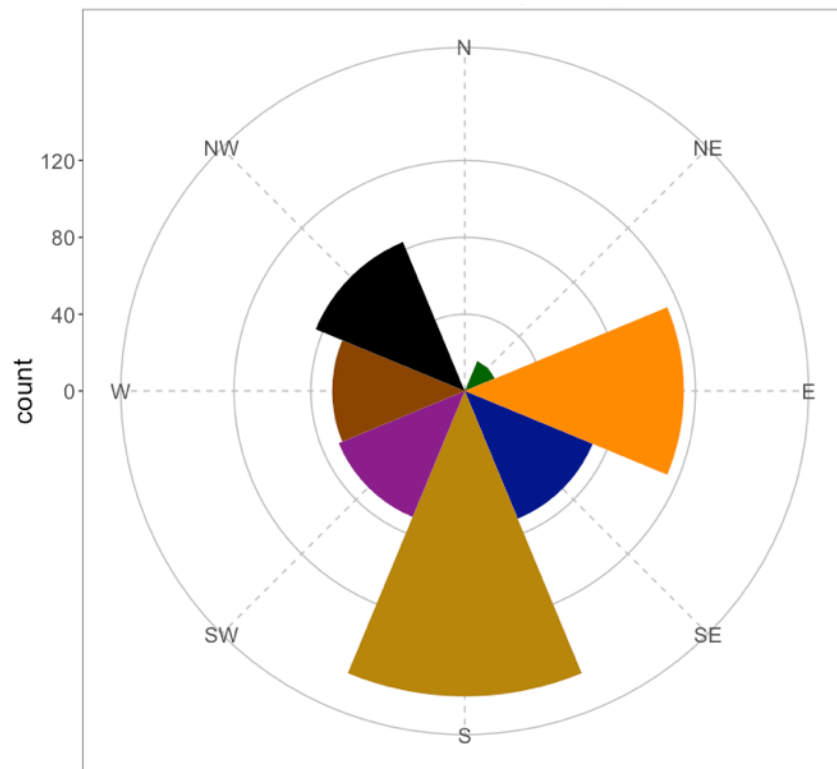


Figure S3: Aspect of all samples in the study region.

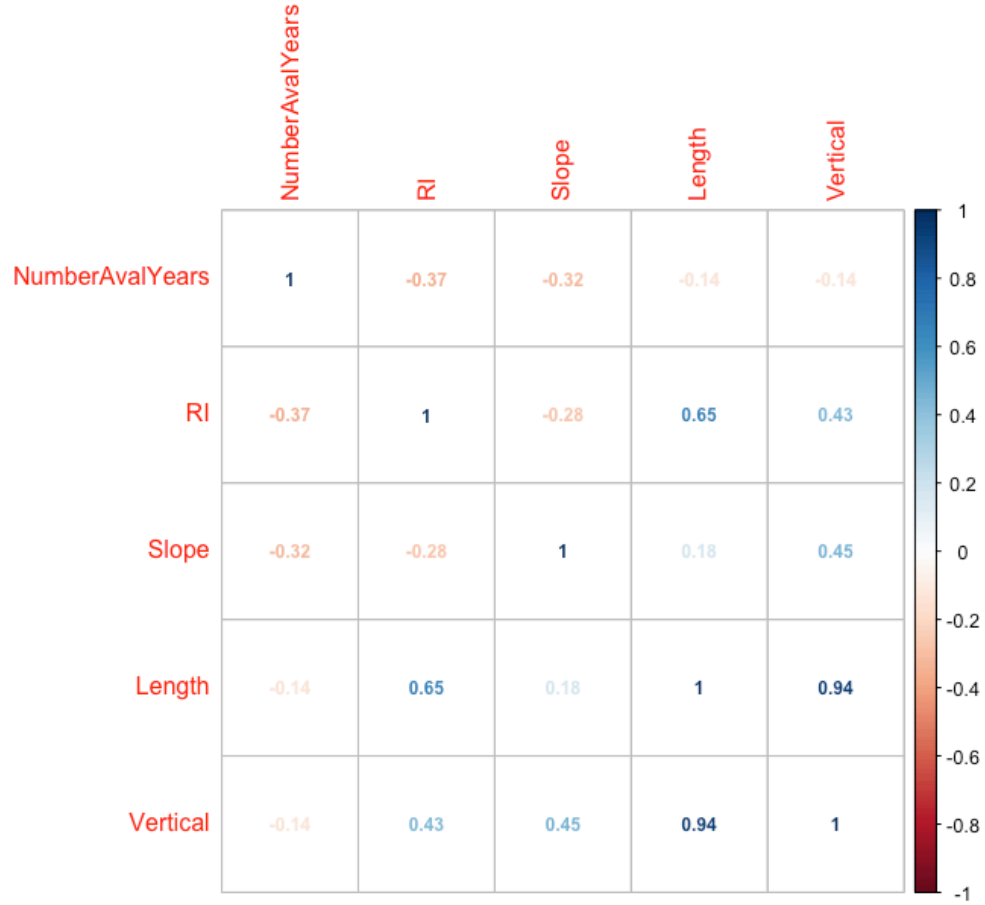


Figure S4: Correlation matrix (Pearson correlations coefficients) of the number of avalanche years, return interval (RI), starting zone slope angle (Slope), and path length (Length).

Table S1: Results of Tukey HSD test of means for each path in the dataset. Diff. = the difference in mean values. lwr. = lower end point of the interval. upr. upper end point. p-adj. = the p-value after adjustment for the multiple comparisons.

Paths	Diff.	lwr.	upr.	p-adj.	Paths	Diff.	lwr.	upr.	p-adj.
54-3-1163	5.50	-19.95	30.95	1.00	RMA-LGP	-7.67	-31.36	16.03	0.99
JGO-1163	26.25	-1.24	53.74	0.07	RMB-LGP	-5.29	-29.66	19.08	1.00
LGP-1163	4.67	-24.72	34.06	1.00	RMC-LGP	-4.57	-28.26	19.13	1.00
LJA-1163	5.38	-19.00	29.75	1.00	S10-7-LGP	-8.93	-31.29	13.43	0.97
LJB-1163	3.67	-25.72	33.06	1.00	S7-LGP	2.93	-23.36	29.22	1.00
LJC-1163	14.75	-12.74	42.24	0.81	LJB-LJA	-1.71	-26.08	22.66	1.00
RMA-1163	-3.00	-26.70	20.70	1.00	LJC-LJA	9.38	-12.67	31.42	0.95
RMB-1163	-0.63	-25.00	23.75	1.00	RMA-LJA	-8.38	-25.45	8.70	0.88
RMC-1163	0.10	-23.60	23.80	1.00	RMB-LJA	-6.00	-24.00	12.00	0.99
S10-7-1163	-4.26	-26.63	18.10	1.00	RMC-LJA	-5.28	-22.35	11.80	1.00
S7-1163	7.60	-18.69	33.89	1.00	S10-7-LJA	-9.64	-24.81	5.53	0.59
JGO-54-3	20.75	-2.49	43.99	0.12	S7-LJA	2.23	-18.30	22.75	1.00
LGP-54-3	-0.83	-26.29	24.62	1.00	LJC-LJB	11.08	-16.41	38.58	0.97
LJA-54-3	-0.13	-19.57	19.32	1.00	RMA-LJB	-6.67	-30.36	17.03	1.00
LJB-54-3	-1.83	-27.29	23.62	1.00	RMB-LJB	-4.29	-28.66	20.08	1.00
LJC-54-3	9.25	-13.99	32.49	0.97	RMC-LJB	-3.57	-27.26	20.13	1.00
RMA-54-3	-8.50	-27.09	10.09	0.92	S10-7-LJB	-7.93	-30.29	14.43	0.99
RMB-54-3	-6.13	-25.57	13.32	1.00	S7-LJB	3.93	-22.36	30.22	1.00
RMC-54-3	-5.40	-23.99	13.19	1.00	RMA-LJC	-17.75	-39.05	3.55	0.20
S10-7-54-3	-9.76	-26.62	7.09	0.72	RMB-LJC	-15.38	-37.42	6.67	0.45
S7-54-3	2.10	-19.70	23.90	1.00	RMC-LJC	-14.65	-35.95	6.65	0.47
LGP-JGO	-21.58	-49.08	5.91	0.27	S10-7-LJC	-19.01	-38.82	0.79	0.07
LJA-JGO	-20.88	-42.92	1.17	0.08	S7-LJC	-7.15	-31.30	17.00	1.00
LJB-JGO	-22.58	-50.08	4.91	0.21	RMB-RMA	2.38	-14.70	19.45	1.00
LJC-JGO	-11.50	-36.95	13.95	0.93	RMC-RMA	3.10	-13.00	19.20	1.00
RMA-JGO	-29.25	-50.55	-7.95	0.00	S10-7-RMA	-1.26	-15.33	12.80	1.00
RMB-JGO	-26.88	-48.92	-4.83	0.01	S7-RMA	10.60	-9.12	30.32	0.80
RMC-JGO	-26.15	-47.45	-4.85	0.00	RMC-RMB	0.73	-16.35	17.80	1.00
S10-7-JGO	-30.51	-50.32	-10.71	0.00	S10-7-RMB	-3.64	-18.81	11.53	1.00
S7-JGO	-18.65	-42.80	5.50	0.29	S7-RMB	8.23	-12.30	28.75	0.97
LJA-LGP	0.71	-23.66	25.08	1.00	S10-7-RMC	-4.36	-18.43	9.70	1.00
LJB-LGP	-1.00	-30.39	28.39	1.00	S7-RMC	7.50	-12.22	27.22	0.98
LJC-LGP	10.08	-17.41	37.58	0.98	S7-S10-7	11.86	-6.23	29.96	0.54

Table S2: Avalanche chronologies and return interval (RI) statistics of all 12 avalanche paths in the region using two approaches to developing a chronology *without implementing the subsequent W_{it} threshold step*. GPD = generalized Pareto distribution approach, ET = established thresholds approach (as per Corona et al. 2012).

Path	RMA	RMA	RMB	RMB	RMC	RMC	54-3	54-3	LGP	LGP	JGO	JGO
Approach	GPD	ET	GPD	ET	GPD	ET	GPD	ET	GPD	ET	GPD	ET
threshold	3%	varies	11%	varies	14%	varies	8%	varies	6%	varies	10%	varies
% of historical	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
# of aval. years	30	11	15	9	21	11	12	7	20	4	15	5
RI - median	2	3	6	5	8	8	10	13.5	6	8	10.5	28.5
RI - mean	2.7	5	7.79	7.38	8.7	8.1	9.55	13.5	7.63	12.67	15.43	34.25
RI – min.	1	2	2	4	1	1	2	4	1	3	1	6
RI – max.	8	18	17	18	35	17	24	24	26	27	49	74
1/RI	0.50	0.33	0.17	0.20	0.13	0.13	0.10	0.07	0.17	0.13	0.10	0.04
σ	1.82	4.81	4.98	4.78	7.54	6.12	6.61	7.42	6.68	12.67	14.37	33.09
Path	LJA	LJA	LJB	LJB	LJC	LJC	Shed 10.7	Shed 10.7	Shed 7	Shed 7	1163	1163
Approach	GPD	ET	GPD	ET	GPD	ET	GPD	ET	GPD	ET	GPD	ET
threshold	10%	varies	14%	varies	15%	varies	11%	varies	5%	varies	4%	varies
% of historical	NA	NA	NA	NA	NA	NA	55%	50%	25%	10%	23%	17%
# of aval. years	31	9	12	4	9	5	21	20	19	6	12	4
RI - median	5	7	8	3	10.5	22.5	2.5	2	5.5	12	4	8
RI - mean	11.97	13.38	13.91	11.67	43.63	22.75	3.65	3.74	7	15.6	7.09	8
RI – min.	1	1	3	3	3	10	1	1	1	3	2	7
RI – max.	89	36	55	29	235	36	16	17	21	31	33	9
1/RI	0.20	0.14	0.13	0.33	0.10	0.04	0.40	0.50	0.18	0.08	0.25	0.13
σ	20.78	14.79	16.46	15.01	78.31	7.78	3.59	4.68	5.22	10.50	8.90	1.00

Table S3: Number of avalanche events for each subregion and overall region for the GPD approach. Note that this differs from Table 7, which shows the same information using the ET approach.

# of avalanche events		
Sub-region	# of years identified in individual paths	Aggregated sub-region
WF	19,23,21	14
GTSR	11,18,15	29
Swan	31,12,8	19
JFS	16,21,9	18
Region	30	

Table S4: Avalanche Years identified in the regional analysis (Region, n=29) and avalanche years identified in one or more paths in the individual avalanche path analysis (Ind. Paths Unique Years, n=49). Years in bold indicate years in common between the two sets (n=27).

Region	Ind. Paths Unique Years
1866	1866
1872	1872
1880	1880
	1907
	1912
	1913
	1923
1933	1933
1936	1936
	1943
1945	
1948	1948
	1949
1950	1950
1954	1954
1956	
1965	1965
	1966
	1967
	1968
1970	1970

1971	1971
1972	1972
1974	1974
1976	1976
	1979
1982	1982
	1983
	1985
	1986
	1987
	1989
1990	1990
	1991
	1992
1993	1993
	1995
	1996
1997	1997
1998	1998
	1999
	2001
2002	2002
2003	2003
2004	2004
2009	2009
	2010
2011	2011
2012	2012
2014	2014
2017	2017

CHAPTER THREE

TRENDS IN REGIONAL LARGE MAGNITUDE SNOW AVALANCHE
OCCURRENCE AND ASSOCIATED CLIMATE PATTERNS IN THE U.S.
NORTHERN ROCKY MOUNTAINS

Contribution of Author and Co-Authors

Manuscript in Chapter 3

Author:	Erich H. Peitzsch
Contributions	Responsible for data acquisition, the development of analysis, the majority of the writing, and figure development.
Author:	Gregory T. Pederson
Contributions	Provided extensive discussion of climate processes, the development of methods used in the study, and contributed to the editing of the manuscript throughout its development.
Author:	Jordy Hendrikx
Contributions	Provided extensive discussion of the development of methods used in the study and contributed to the editing of the manuscript throughout its development.
Author:	Karl W. Birkeland
Contributions	Provided technical input to the development of methods used in the study and contributed to the editing of the manuscript throughout its development.
Author:	Daniel B. Fagre
Contributions	Provided technical input to the development of methods used in the study and contributed to the editing of the manuscript throughout its development.

Manuscript Information

Peitzsch, E.H.^{1,2}, Pederson, G.T.¹, Hendriks, J.², Birkeland, K.W.^{3,2}, and Fagre, D.B.¹. Trends in regional large magnitude snow avalanche occurrence and associated climate patterns in the U.S. northern Rocky Mountains. Manuscript for submittal to Geophysical Research Letters.

¹ U.S. Geological Survey Northern Rocky Mountain Science Center, West Glacier, Montana, USA

² Snow and Avalanche Lab, Department of Earth Sciences, Montana State University, Bozeman, Montana, USA

³ U.S.D.A. Forest Service National Avalanche Center, Bozeman, Montana, USA

Journal: Journal of Climate

Status of manuscript

☒ Prepared for submission to a peer-reviewed journal

☐ Officially submitted to a peer-reviewed journal

☐ Accepted by a peer-reviewed journal

☐ Published in a peer-reviewed journal

Publisher: American Geophysical Union

Anticipated date of submission: May 2020

Abstract

Large magnitude snow avalanches pose a hazard to humans and infrastructure worldwide. Analyzing the spatiotemporal behavior of avalanches and the contributory climate factors is important for interpreting climate and historical avalanche variability as well as improving avalanche forecasting. Here, we attempt to identify and examine trends in regional avalanche activity, and specific climate variables that contribute to years with large magnitude avalanche events across the U.S. northern Rocky Mountains of northwest Montana. Using established dendrochronological methods and signal to noise techniques, we developed a long-term (1867-2019) regional avalanche chronology using tree-rings from 647 trees exhibiting 2304 avalanche-related growth disturbances. We then used principal component analysis to examine avalanche-climate relationships that suggest large magnitude avalanche years are characterized by a deep snowpack represented by high seasonal maximum snow water equivalent. The major ocean-atmosphere teleconnections associated with these high snowpack and avalanche years were the Pacific Decadal Oscillation (PDO) and the Pacific North American (PNA) pattern. By using a generalized linear autoregressive moving average model that accounts for the past effect of avalanches on sample availability, we demonstrate that the first principal component is inversely proportional to avalanche probability suggesting a decrease in years with regional large magnitude avalanches as snowpack decreases. A decreasing trend in overall avalanche probability through time also exists which is coincident with snowpack losses across the region. Our results suggest potential future decreases in large magnitude avalanche frequency as climate warming drives snowpack losses across the study region which is consistent with similar avalanche climate regions in Canada and Switzerland.

1. Introduction

Snow avalanches affect transportation corridors and settlements throughout the world. For example, avalanches impact numerous roadways in the western United States (Armstrong, 1981; Blattenberger and Fowles, 1994; Hendrikx et al., 2014; Reardon et al., 2004; Wayand et al., 2015), and in Glacier National Park, Montana, they hamper road clearing operations and often delay the opening of a regionally important transportation corridor (Peitzsch et al., 2012; Reardon and Fagre, 2006). Understanding avalanche

processes and contributory climate and weather factors in northwest Montana will ultimately aid in local and regional avalanche forecasting operations.

Although weather directly influences avalanches on daily to seasonal timescales, climate works as a background influence on snowpack characteristics that can ultimately drive the avalanche climate (e.g. coastal, continental) (Armstrong and Armstrong, 1987; Mock and Birkeland, 2000; Mock et al., 2016) or prevalent avalanche problem type. For example, maritime influences on the Cascade Range in Washington and Oregon create a coastal avalanche climate dominated by direct action and wet snow avalanches (Mock and Birkeland, 2000). However, variability in synoptic-scale atmospheric circulation and persistent climate modes (i.e. ocean-atmosphere teleconnections such as the El Niño Southern Oscillation and Pacific Decadal Oscillation) can have substantial effects on snowpack processes (Abatzoglou, 2011; McCabe, 1994; McCabe and Dettinger, 2002; Mock, 1996; Pederson et al., 2013; Pederson et al., 2011a; Pederson et al., 2011b) as well as avalanche frequency and behavior (Birkeland and Mock, 1996; Birkeland et al., 2001; Fitzharris and Bakkehoi, 1986; Fitzharris and Schaerer, 1980).

Recent studies in North America investigating the association between avalanche activity and long-term climate drivers highlight a complex relationship that is challenging to disentangle from short-term synoptic-scale weather patterns. Mock and Birkeland (2000) used principal component analysis (PCA) in their investigation of atmospheric circulation and avalanche climate associations. Overall, they found the Pacific-North American (PNA) teleconnections (both phases) to be correlated with several avalanche-climate patterns. For example, in the central Rocky Mountains the first component in

their analysis explained 73% of the variance and was significantly correlated with positive December PNA anomalies. This suggests an increase in upper-level atmospheric ridging, which created warm conditions and a generally stable snowpack in the early 1980s. The third component negatively correlated with seasonal (December – March) PNA indices indicative of upper atmosphere troughs and, consequently, increased snowfall. The authors also suggest potential relationships of atmospheric circulation and avalanche activity with the Pacific-Decadal Oscillation (PDO) and the El-Niño Southern Oscillation (ENSO).

The effects of climate change and increasing winter air temperature on avalanche activity trends have only recently been examined in a few studies. Bellaire et al. (2016) analyzed weather, snow, and avalanche data from Glacier National Park, British Columbia, Canada between 1965 and 2014 and found several significant trends for weather and snowpack variables consistent with a warming climate, such as warmer temperatures and less snowfall over monthly and seasonal scales. In the Swiss Alps, Laternser and Schneebeli (2003) found a gradually increasing mean snow depth, persistence of continuous snow cover, and the number of snowfall days to increase until the 1980s. From that point forward they found a significant decrease in these same variables. However, though snow conditions had changed over a 50-year period, they were unable to discern an associated long-term change in avalanche activity (Laternser and Schneebeli, 2002), showing that these less specific variables may not capture the range of avalanche conditions. In the French Alps, Eckert et al. (2013) found a general decrease in dry snow avalanches since the mid-1970s as well as an increase in runout

altitude of low-frequency avalanches from 1980 to 2000 suggesting a potential change in avalanche character from dry snow to wet snow avalanches. Similarly, Pielmeier et al. (2013) found an increase in the proportion of wet snow avalanches in the Swiss Alps. Eckert et al. (2009), however, found no discernible change in overall avalanche occurrence processes that could be associated with climate change over the past 60 years in the northern French Alps.

In other regions more proximal to our study area, Fitzharris and Schaerer (1980) associated major avalanche winters at Rogers Pass, British Columbia, Canada, with either strong zonal flow that brought heavy snow and rising temperatures, or periods of sustained meridional flow resulting in extended cold and below average snowfall followed by wet storm systems from the Pacific. In Glacier National Park (GNP), Montana, Butler (1986) suggested these same patterns produce winters with extensive avalanching using historical local media reports, National Park Service ranger logs, and local accounts. Also in GNP, Dixon et al. (1999) reported a significant decrease in avalanche activity during El-Niño years, and suggested this was due to below-average snowfall and a shallow snowpack. However, they also used avalanche reports from a local media source, which is likely to only include large avalanches that affect transportation corridors or infrastructure. They also did not verify their assessment against available weather or snowpack data. The complexity of associating climate drivers or changes in climate and subsequent effects on large magnitude avalanching warrants careful analysis and cautious inference.

In regions with no data or a sparse observer network, large magnitude avalanches can be inferred from dendrochronological data (i.e. snow avalanche impacted tree-ring data). This technique not only provides a record large magnitude avalanche frequency with annual resolution, but also the ability to produce spatial reconstructions of events if sampled appropriately and strategically. Using a tree-ring-generated spatiotemporal avalanche data set for the U.S. northern Rocky Mountains of northwest Montana (Peitzsch et al., 2019), we address the following questions:

- 1) Are there specific seasonal climate or atmospheric circulation variables that contribute to years with common large magnitude avalanche events across the region?
- 2) Is there a discernable and statistically significant long-term temporal trend in annual regional avalanche activity?

We define large magnitude avalanches as avalanche events characterized by low and variable frequency with a high capacity for destruction (Germain, 2016). Given our sampling strategy and locations this would generally translate to a size three or greater on the destructive classification scale (Greene et al., 2016).

2. Methodology

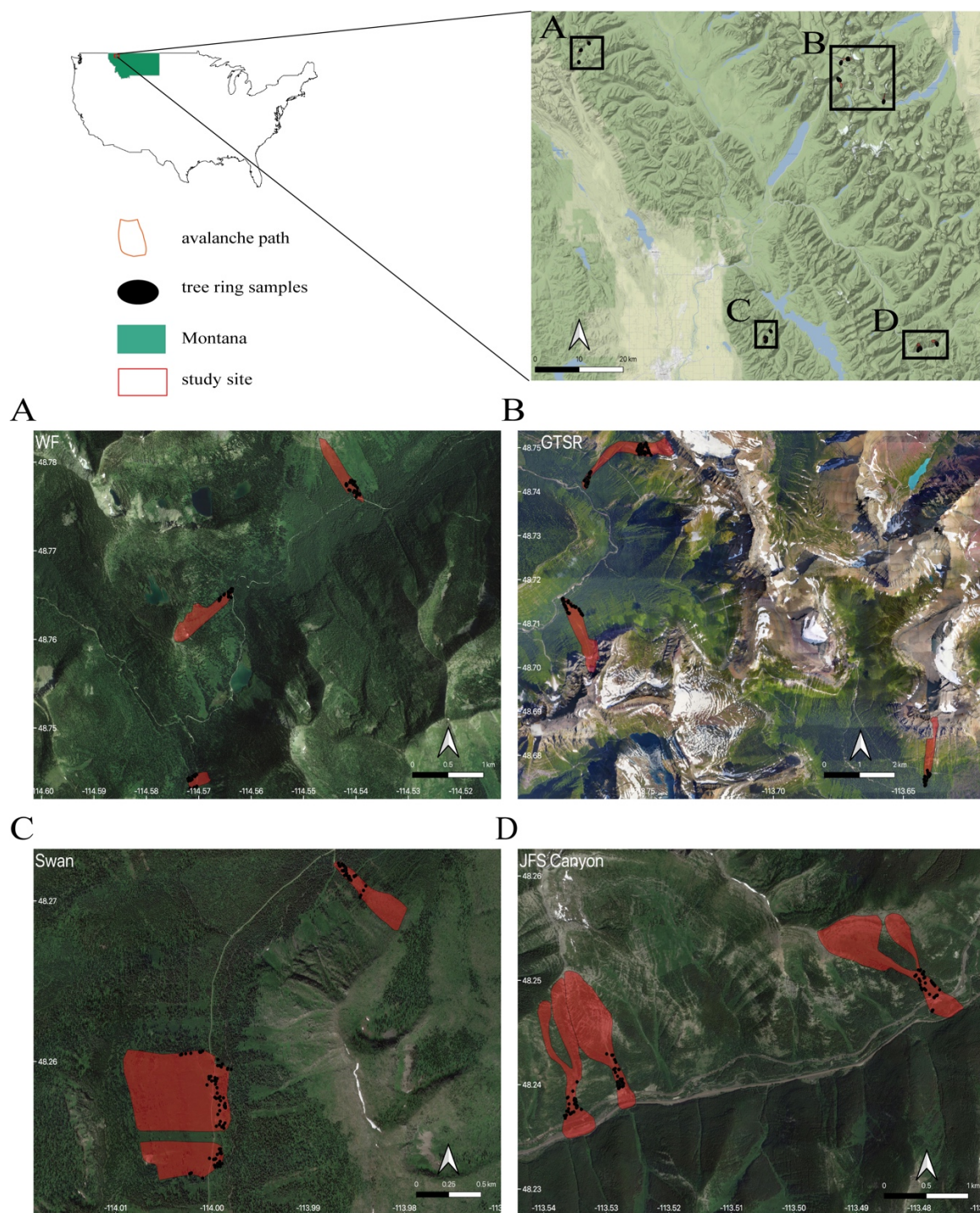
2.1 Study Site

Our regional network of avalanche paths consists of 12 paths located in the Rocky Mountains in northwest Montana, USA (Table 1, Figure 1). These sets of three paths in four distinct sub-regions are located within three mountain ranges: the Whitefish Range (WF, Red Meadow Creek) and Swan Range (Swan, Lost Johnny Creek) on the Flathead

National Forest, and two sub-regions within the Lewis Range in Glacier National Park (GNP) (Going-to-the-Sun Road (GTSR) and John F. Stevens Canyon (JFS)). The individual avalanche paths in each sub-region encompass a range of spatial extents from being located adjacent to one another up to locations as distant as ~10 km apart. The distance between any two sub-regions ranged from ~40 km to ~95 km, and the total regional extent of the study area encompassed ~3500 km² with an average per path area of 0.35 km².

Table 1: Descriptive statistics for 12 avalanche paths in the study site.

Subregion-Path	# samples collected	Full Path Elev. (mean) (m)	Full Path Elev. (range) (m)	Starting Zone Elev. (mean) (m)	Full Path Slope (mean) (°)	Starting Zone Slope (mean) (°)	Median Aspect (°)	Area (km ²)	Length (m)	Vertical (m)
WF-Red Meadow A (RMA)	41	1651	1462 - 1957	1774	26	32	155	0.32	1004.97	495.20
WF-Red Meadow B (RMB)	40	1870	1643 - 2164	1965	31	37	53	0.13	1041.98	521.27
WF-Red Meadow C (RMC)	42	1650	1582 - 1742	1692	28	33	257	0.08	326.14	160.46
GTSR - 54-3	56	1501	1080 - 2149	1708	31	40	327	0.44	2063.61	1068.49
GTSR-Little Granite (LGP)	109	1770	1109 - 2314	2170	24	34	250	0.78	2940.29	1205.07
GTSR-Jackson Glacier Overlook (JGO)	41	1863	1500 - 2660	2090	32	42	180	0.70	1793.13	1159.84
Swan-Lost Johnny A (LJA)	53	1619	1441 - 1896	1731	29	38	77	0.41	811.50	455.27
Swan-Lost Johnny B (LJB)	26	1633	1478 - 1879	1721	32	39	76	0.57	617.52	401.80
Swan-Lost Johnny C (LJC)	42	1550	1344 - 1750	1670	34	36	326	0.39	667.88	405.66
JFS-Shed 10-7 (S10.7)*	109	1644	1233 - 2193	1910 - 1964	31	35 - 39	176	0.13	1745.66	959.74
JFS-Shed 7 (S7)*	46	1712	1310 - 2078	1935 - 1837	29	34 - 36	152	0.57	1686.96	768.01
JFS-1163	50	1718	1250 - 2217	1861	38	42	158	0.17	1636.52	966.82
All Paths	655	1690	1080 - 2660	1869	31	37	Spatial extent = 3500 km ²			



Northwest Montana is classified as both coastal transition and intermountain avalanche climates (Mock and Birkeland, 2000), and thereby exhibits characteristics of both continental or coastal climates. Average annual precipitation is 2083 mm at Flattop SNOTEL (1810 m), and peak snow water equivalent (SWE) typically occurs mid- to late-April with a median value of ~1100 mm (1970–2018). Avalanche paths within the study site range from ~1100 m to 2700 m in elevation and cover all aspects except true north.

2.2 Sample collection and processing

Our sampling strategy targeted an even number of samples collected along the margins of each avalanche path at varying elevations as well as trees located in the main lower track and runout zone of the selected paths. We analyzed between 26-109 samples per avalanche path resulting in 673 total samples from 647 suitable trees. Of those 673 samples, we collected 614 cross sections (91%) and 59 cores (9%). See Peitzsch et al. (In Prep.) for processing methodology and tree-ring avalanche signal classification, and Peitzsch et al. (2019) for further details on cross dating methods and accuracy calculation for this dataset.

2.3 Chronology and Return Period Calculation

Data preparation and all analyses were completed in *R* (R, 2018). For tree-ring data, we used the package *slideRun*, an extension of the *burnR* library for forest fire history data (Malevich et al., 2018; R, 2018). We employed a multi-step process to generate a regional avalanche chronology and a regional avalanche activity index (RAAI). First, we implemented a double threshold approach (Corona et al., 2012; Favillier et al., 2018) using the number of growth disturbances (GD) per year and an

avalanche index I_t (Shroder, 1978) to distinguish between avalanche signals and noise (i.e. irregular growth, snow creep, non-avalanche disturbance). We then used the chronologies derived from the double threshold approach to calculate weighted index factor (W_{it} , adapted from (Kogelnig-Mayer et al., 2011)). We used a threshold of $W_{it} = 0.2$ to exclude years with low levels of confidence based on the quality of avalanche signals, as per Favillier et al. (2018), to provide us with a final avalanche chronology for four sub-regions and the overall region. We then calculated a regional avalanche activity index (RAAI) for the sub-regions and overall region (Germain et al., 2009).

2.4 Climate data

We used historical United States Department of Agriculture National Resource Conservation Service (NRCS) snow course data (NRCS, 2017) from seven middle to upper elevation sites nearest the sub-region sites and calculated mean seasonal maximum snow water equivalent ($SWE_{\max}$) and snow depth ($HS_{\max}$). These snow course sites are representative of the elevations of the starting zones and tracks of the avalanche paths in this study.

Table 2: NRCS snow course sites used in this study. Period of Record indicates the full record for each site. The analysis includes records from 1950-2017.

Snow Course Site	Period of Record	Elevation (m)	Relevant Sub-Region
Desert Mountain	1937- 2017	1707	Swan Range
Hell Roaring Divide	1942- 2017	1760	Whitefish Range
Marias Pass	1934- 2017	1600	JFS
Mount Allen No. 7	1922- 2017	1737	GTSR
Ptarmigan No. 8	1938-2017	1768	GTSR
Spotted Bear Mountain	1948- 2017	2134	JFS and Swan Range
Weasel Divide	1937-2017	1661	Whitefish Range

Upper elevation precipitation and temperature records are only available from the early 1980s to present, so are too temporally limited for our work. Therefore, we used temperature records from the Global Historical Climatology Network (GHCN) to derive a longer-term (1900-2017) high-resolution dataset (Menne et al., 2012). We applied winter (December through March) lapse rates to the Kalispell Glacier Airport site (elevation = 901 m, Figure 1) for upper elevation sites. Temperature lapse rates were derived using the existing upper elevation network values and the Kalispell site.

We used a gridded precipitation dataset (PRISM, Parameter-elevation Regressions on Independent Slope Model) that encompasses the study area with a 4-km resolution (PRISM, 2019). We then computed winter (December through March) mean precipitation values as well as monthly values for November through March.

We obtained monthly and winter mean values for atmospheric circulation and the common indices representing large-scale, ocean-atmosphere teleconnections that affect western North America climate from the United States National Oceanic and Atmospheric Administration National Centers for Environmental Information (NCDC, 2018). We included variables with potential effects on winter air temperature and

precipitation: 500-mb geopotential height anomalies, Arctic Oscillation (AO), El Niño/Southern Oscillation (ENSO, Niño 3.4 index), Pacific Decadal Oscillation (PDO), and the Pacific-North America Index (PNA). All data underwent quality control as per Zahumensky (2004).

Table 3: Climate, temperature, and snow property variables used in this study.

Climate Variable	Period of Record	Source
500-mb Height Anomalies	1948-2017	NCDC
Arctic Oscillation (AO)	1950-2017	NCDC
El Niño/Southern Oscillation (ENSO, Niño 3.4 index)	1900-2017	NCDC
Pacific Decadal Oscillation (PDO)	1900-2017	NCDC
Pacific North America Index (PNA)	1950-2017	NCDC
Temperature	1897-2017	GHCN
Precipitation (mm)	1899-2017	PRISM
Snow Height (HS)	varies (Table 2)	USDA-NRCS
Snow Water Equivalent (SWE)	varies (Table 2)	USDA-NRCS

2.5 Statistical analysis

We examined trends of annual winter (December through March) maximum snow water equivalent (SWE), maximum snow height (HS), temperature (minimum, mean, and maximum), and mean precipitation through time using the non-parametric Mann-Kendall test (Mann, 1945) or the modified Mann-Kendall test (Hamed and Rao, 1998) if the time series exhibited serial correlation. In the test for trend and all subsequent analyses, we use 0.05 as a significance level, but do not employ a strict cutoff of 0.05 (Amrhein et al., 2019).

Then, we compared all climate variables of avalanche years and non-avalanche avalanche years using the Wilcoxon rank-sum test (Wilcoxon, 1945). Climate variables

exhibiting a significant difference were then used in a principal component analysis (PCA) to reduce dimensionality. However, we included temperature and precipitation variables despite the lack of significant differences between avalanche year and non-avalanche years to provide representation in the PCA. All variables were scaled and centered by the mean. We then retained the number of principal components with eigenvalues greater than one or those that explained at least 80% percent of variance (Kanyongo, 2005). We completed the PCA and subsequent analysis steps using a period of record beginning in 1950 because this period provided the most complete record of climate variables. We also completed the PCA for 1990 to 2017 given the presence of large magnitude years below mean $SWE_{\max}$ level during this period in order to identify any shift in driving mechanisms.

We then examined the relationship of these first six axes of the PCA as orthogonal predictors of a binary response (avalanche year/non-avalanche year) by fitting a GLARMA (generalized autoregressive moving average) model. This technique has been used to examine avalanche activity on a smaller spatial extent in the western Himalaya (Ballesteros-Canovas et al., 2018). A GLARMA model is a state space model for a time series (Y_t) that consists of an observation variable (in this case avalanche years), and a state variable (i.e. climate variables), and is expressed as a conditional probability distribution for the observation and state variable (Dunsmuir and Scott, 2015). This class of model is suitable for examining avalanche occurrence as it accounts for the dependence on past observations ($Y_s, s < t$) as well as other covariates. We used the *glarma* package in *R* (Dunsmuir and Scott, 2015) to specify a binomial distribution with

estimation optimized using the Newton-Raphson iterative method. A likelihood ratio and Wald test allowed us to assess the goodness of fit. If the p-value was less than 0.05, we rejected the null hypothesis that the model is a generalized linear model with the same regression structure with the alternative hypothesis supporting the GLARMA model. Autoregressive (AR (ϕ)) and moving average (MA (θ)) order values were determined from examining autocorrelation and partial autocorrelation plots. We selected the final model with specific AR and MA terms based on the lowest Akaike Information Criterion (AIC) score.

Finally, we examined all years (avalanche and non-avalanche) associated with negative snowpack anomalies for a surface climatology signal to help explain the occurrence of large magnitudes during those years. We completed a Wilcoxon rank-sum test to compare avalanche and non-avalanche years for monthly temperature and precipitation values.

3. Results

3.1 Regional Avalanche Chronology

We analyzed 673 total samples from 647 trees. Of those 673 samples, we collected 614 cross sections and 59 cores. Within these samples we identified 2304 GD. The oldest tree we sampled is 367 years old and the mean age of the sampled trees is 73 years. The period of record of sampled trees extends from 1636 to 2017. The most common species in our dataset is *Abies lasiocarpa* (ABLA, sub-alpine fir) followed by *Pseudotsuga menziesii* (PSME, Douglas-fir) and *Picea engelmannii* (PIEN, Engelmann spruce). The oldest response was from 1655. Applying the double GD and I_t threshold

and subsequent W_{it} threshold (see Peitzsch et al. (In Prep.) for specific equations) to the sub-regions results in 12, 14, 13, and 18 avalanche years for the WF, GTSR, Swan, and JFS sub-regions, respectively, and 30 avalanche years for the overall region (Figure 2 and Table 4).

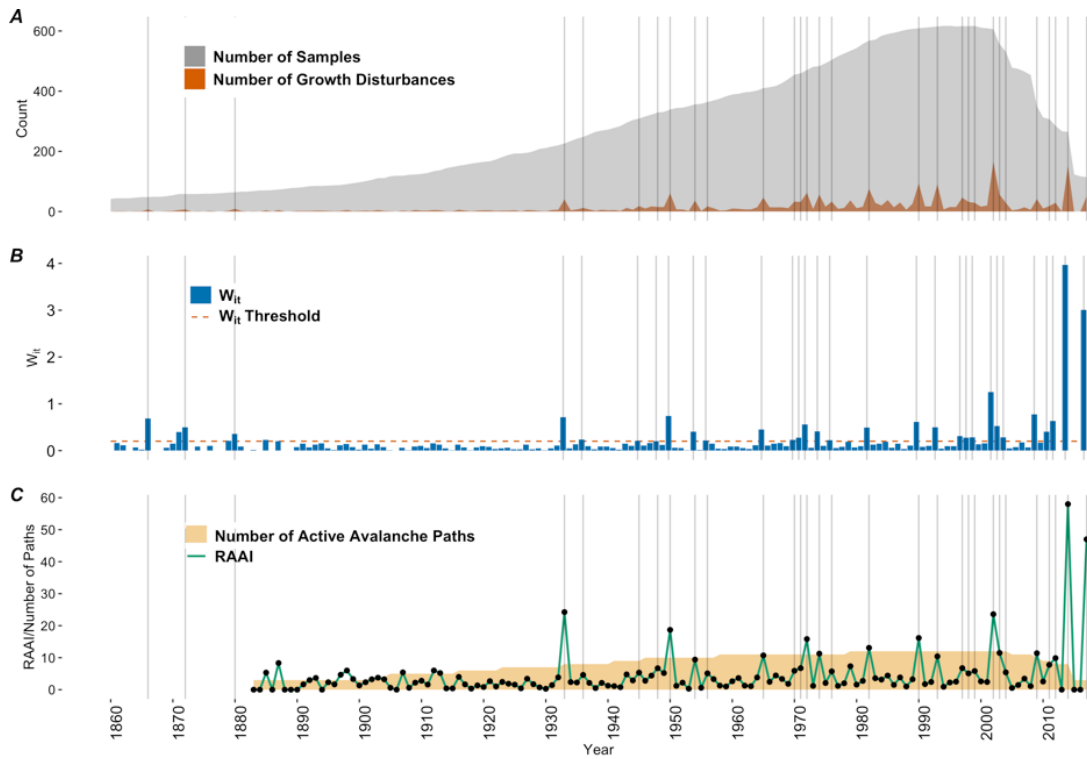


Figure 2: The regional avalanche activity index (RAAI) chronology and supporting double threshold analyses for avalanche event classification. (A) The number of samples (gray shaded area) shown alongside the number of growth responses (dark orange shaded area). (B) The W_{it} threshold (0.2, red dashed line) provides a means of discriminating against low confidence signals in the tree ring record. (C) The RAAI (green line, black points) is a measure of regional avalanche activity based on the I_t of each path and the number of active avalanche paths (yellow shaded area).

Table 4: Avalanche chronology characteristics for the various sub-regions and overall region. RI = return interval.

	WF	GTSR	Swan	JFS	Region
# of Avalanche Years	12	14	13	18	30
RI - median	7	8	4	3	3
RI - mean	6.27	11.35	11.25	4.94	5.21
RI – min.	2	1	1	1	1
RI – max.	13	53	54	16	53
1/RI	0.14	0.13	0.25	0.33	0.33
σ	3.69	13.48	15.70	4.60	9.53

3.2 Climate Conditions Characterizing Avalanche Years

Years characterized by large magnitude avalanches occur, on average, during years with greater SWE_{max} and HS_{max} (Figure 3A and B). However, large magnitude avalanches also occur during years of below average SWE_{max} and HS_{max} . SWE_{max} and HS_{max} exhibit negative trends during the period of record, and annual winter precipitation exhibits a slight positive trend in the region (Table S1). Significant differences between avalanche and non-avalanche years also exist for monthly total precipitation in January and March, as well as for annual precipitation totals (Figure 3C, Table S2). No significant differences in relationship to avalanche occurrence are observed for the other monthly precipitation and temperature variables. Significant differences exist between avalanche and non-avalanche years for 11 atmospheric variables (Figure 4, Table S2).

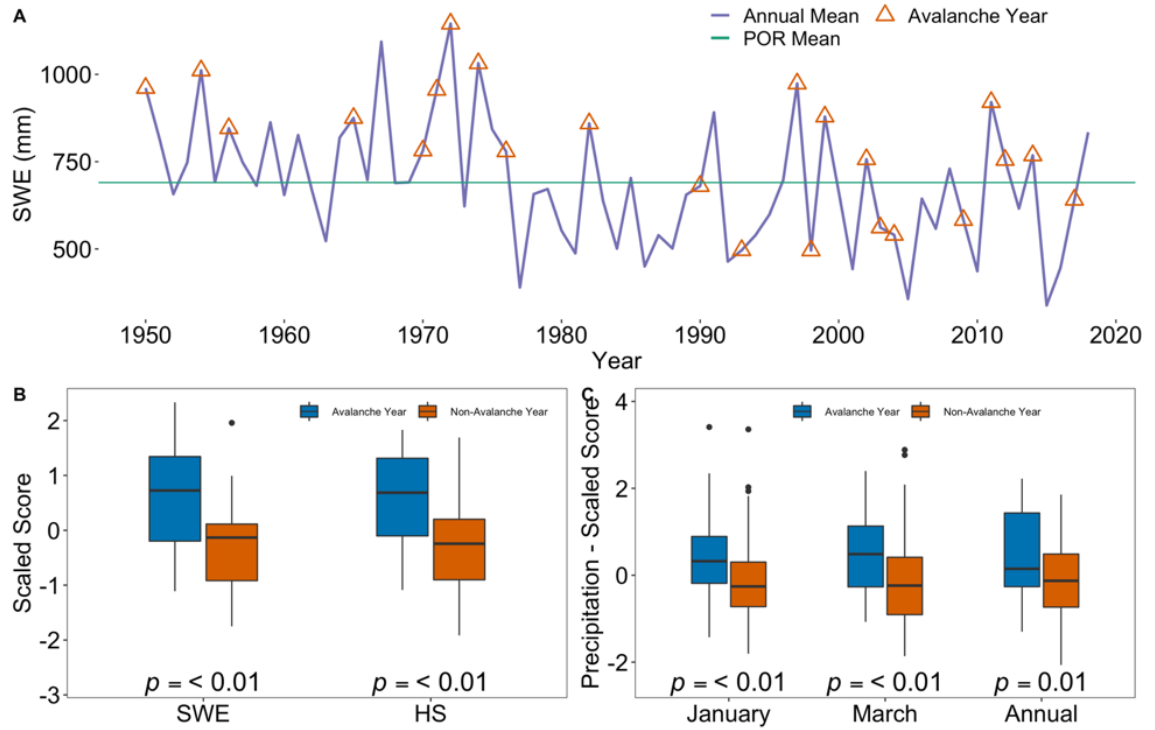


Figure 3: Time series and boxplots of snowpack and precipitation. Time Series of SWE (A) with avalanche years represented by red triangles and the annual mean SWE for the period of record (green horizontal line). SWE values between avalanche (blue box) and non-avalanche (red box) years for (B) regional SWE_{max} and HS_{max} , and (C) significant monthly and annual precipitation totals. Panel A displays only 23 out of 30 identified avalanche years because the analyzed period of record of SWE and HS begins in 1950 due to sparse data prior to 1950.

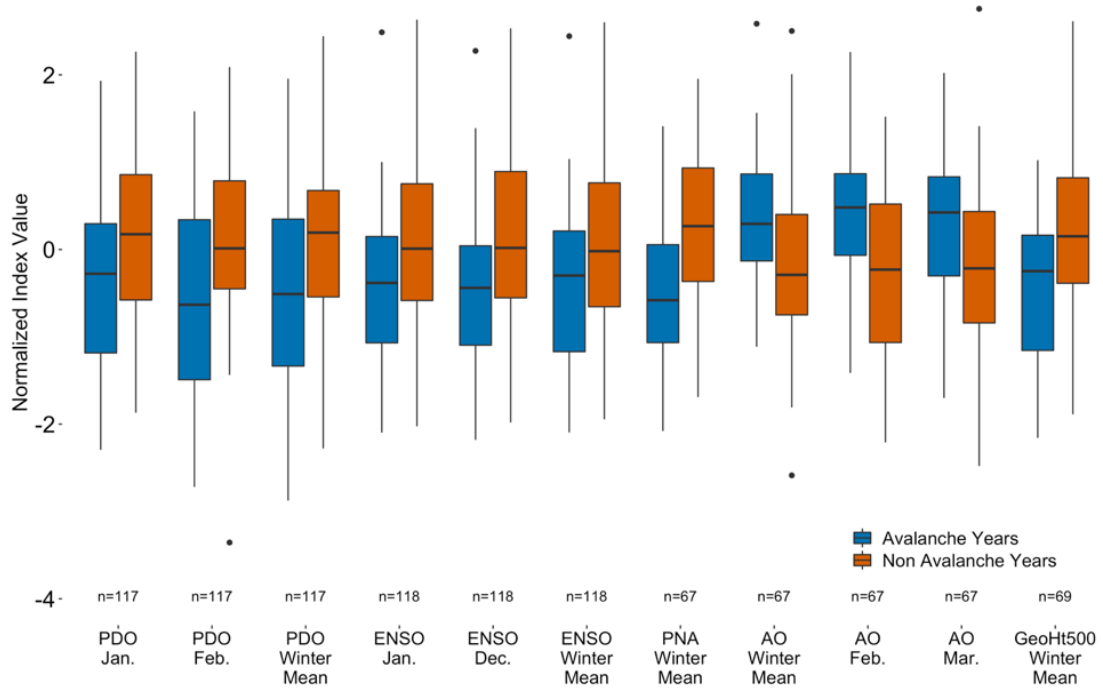


Figure 4: Boxplots of atmospheric variables and indices exhibiting a significant difference between conditions occurring in avalanche (blue) versus non-avalanche (red) years using the Wilcoxon rank-sum test. Sample size varies due to varying periods of record for each variable (Table 3). Y-axis is the normalized indices of all variables for direct comparison. Full descriptions of results of each atmospheric variable are shown in Table S2.

3.3 Multivariate Analysis of Large Magnitude Avalanche Years

Examining the period from 1950 to 2017, the PCA analysis results in 6 principal components (PC1 – PC6) with eigenvectors greater than one, capturing ~83% of the total variance in our dataset (Figure S1). The first two principal components alone account for more than half of the variance within the dataset (~54%). The largest five climate related variables contributing to PC1 ($r^2 \sim 94\%$) are $HS_{\max}$, February PDO, $SWE_{\max}$, PDO winter mean, and PNA winter mean, which are reflective of high snowpack years and the ocean-atmospheric teleconnections associated with those years (Figure 5A). Accordingly, ocean

to atmosphere teleconnected indices such as the PDO and PNA are highly correlated ($r = 0.78$) with each other, as is the associated linkage between atmospheric circulation (i.e. the PNA) and regional $HS_{\max}$ ($r = -0.62$) (Figure S3). PC1 is negatively correlated with $HS_{\max}$ and $SWE_{\max}$ ($r = -0.88$ and -0.85 , respectively) and positively correlated with February PDO, PDO winter mean, and PNA winter mean ($r = 0.87, 0.84$, and 0.82 , respectively) (Figures 5A and S1). Note that Figure 5A shows PC1 and PDO winter mean inverted (i.e. $x(-1)$) to highlight associated trends.

The largest five contributors ($r^2 \sim 90\%$) to PC2 are reflective of the importance of temperature in driving the variability within the second component and include $T_{\min}$ winter mean, February AO, mean winter AO, March AO, and $T_{\max}$ winter mean (Figure 5B). PC2 is negatively correlated with February, March, and winter mean AO ($r = -0.68$, -0.63 , and -0.66 , respectively) as well as $T_{\min}$ and $T_{\max}$ winter mean ($r = -0.69$ and -0.62 , respectively) (Figure 5B and S1). Note that Figure 5B shows PC2 inverted (i.e. $x(-1)$) to highlight associated trends with temperature and mean winter AO. The largest five contributors ($r^2 \sim 83\%$) to PC3 are reflective of higher-frequency (sub-decadal) variability in winter precipitation and include January ENSO, winter mean ENSO, December ENSO, January total precipitation, and total winter precipitation (Figure 5C). Winter mean ENSO is positively correlated with PC3 ($r = 0.54$).

While PC6 explained only 4.5% of the total variance in our dataset, it becomes important in subsequent analyses (see Section 3.4). The greatest five contributors to PC6 represent variability in winter precipitation, specifically late winter as March precipitation explains nearly half the variance ($r^2 \sim 41\%$). Other contributors to PC6

include monthly precipitation values from November, December, and February (total $r^2 \sim 89\%$). PC6 is negatively correlated with March precipitation ($r = -0.64$) (Figure 5D). Positive anomalies of March precipitation are associated with avalanche years in our dataset meaning large magnitude avalanches tend to occur as PC6 becomes negative. Note that Figure 5D shows PC6 inverted (i.e. $x(-1)$) to highlight associated trends with March precipitation. In a subset analysis of the period from 1977 to 2017, results exhibited similar patterns in both explained variance as well as contributions from all PCs.

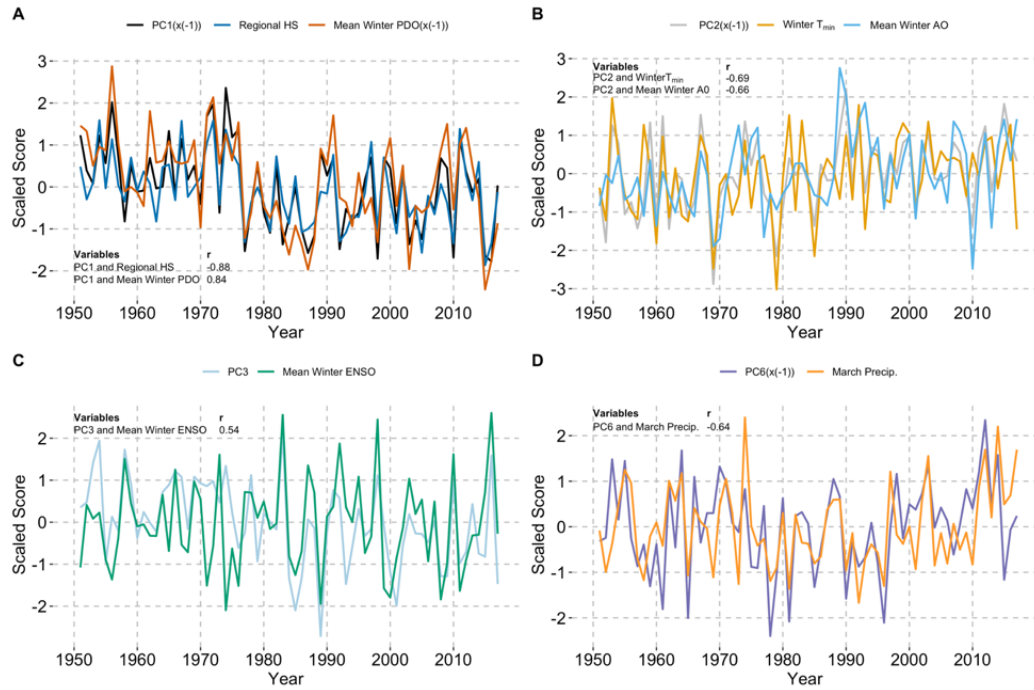


Figure 5: Time series plots of select PCs. (A) PC1 is negatively correlated with HS_{max} and positively correlated with mean winter PDO. PC1 and mean winter PDO are inverted (i.e. $x(-1)$) to show decreasing trend of HS_{max} . (B) PC2 is negatively correlated with February, March, and winter mean AO. PC2 is inverted (i.e. $x(-1)$) to show increasing temperature trend. (C) PC3 is positively correlated with ENSO mean winter ENSO index. (D) PC6 is negatively correlated with March precipitation. PC6 is inverted (i.e. $x(-1)$) to show correspondence with March precipitation patterns. These plots show only the greatest one or two contributors given the strong correlation of these variables to the rest of the top five contributors within each principal component (see Figure S1).

3.4 Analysis of Probability of Avalanche Years

The best fit GLARMA model (lowest AIC: 73.1) contains a moving average (MA) order of 6 with significant p-values from the Likelihood ratio and Wald tests ($p = 0.01$ and 0.01 , respectively) suggesting the model is suitable. The model also results in PC1 ($p < 0.01$), PC2 ($p = 0.07$), and PC6 ($p = 0.04$) as the most significant variables out of the six input principal components (Table S3). The probability of an avalanche year through time, as a result of applying the GLARMA model, exhibits a slight negative trend over the observed time period ($\tau = -0.16$, Sens slope = -0.002 , $p = 0.06$) (Figure 6A). The trend of $HS_{\max}$, the largest contributor to and function of the other contributors of PC1, decreases over time ($\tau = -0.25$, Sens slope = -0.73 , $p < 0.01$) (Figure 6B). Accordingly, the probability of an avalanche year decreases as PC1 become more positive ($r = -0.87$) (Figure 6C). As PC1 become more positive, $HS_{\max}$ and $SWE_{\max}$ both decrease, and the PDO and PNA indices become more positive. The probability of a large magnitude avalanche year and PC2 are weakly negatively correlated ($r = -0.43$) (Figure 6D).

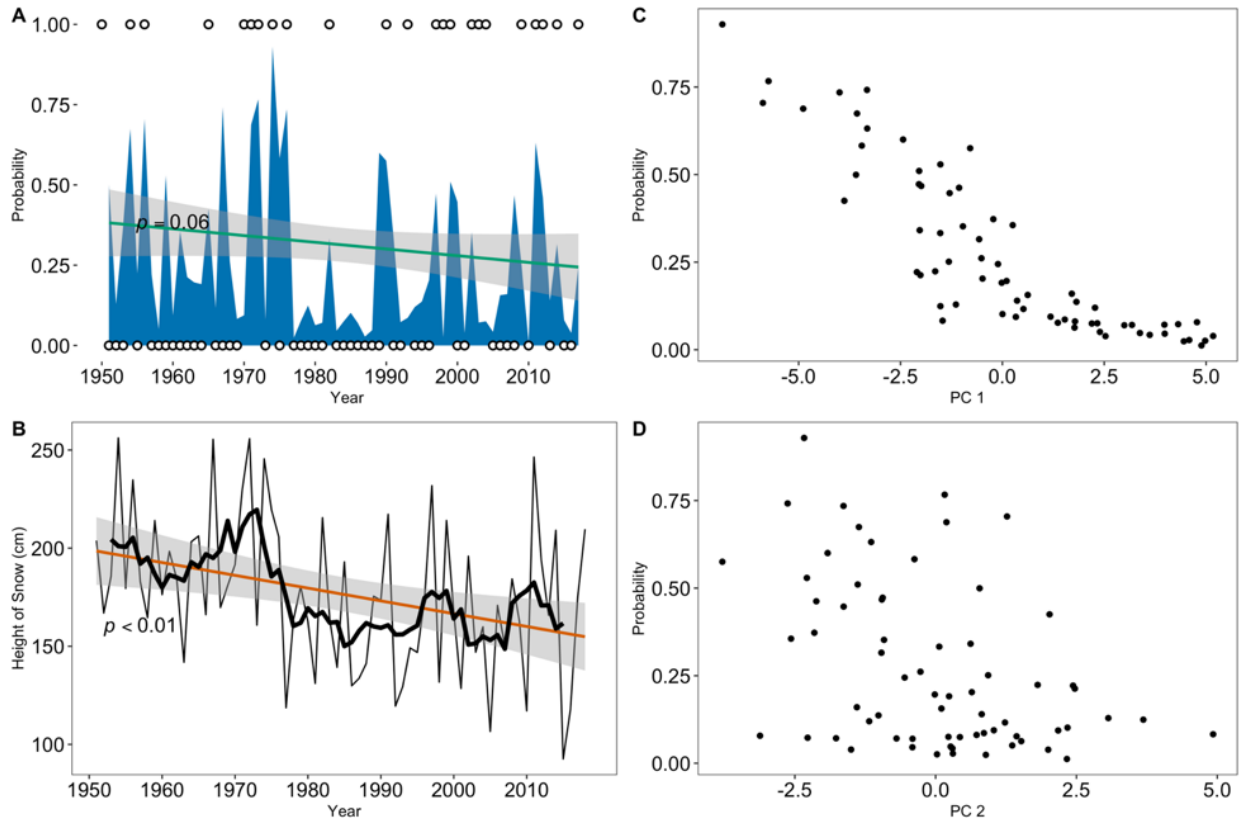


Figure 6: Regional avalanche probability and the major contributing variables. (A) Probability of an avalanche year in blue (white circles; 1 = observed avalanche year, 0 = observed non-avalanche year) using the GLARMA model. The green line represents a generalized linear model trend with 95% CIs shaded in gray. The p-value of 0.06 suggests a decreasing trend. (B) Time series of HS_{max} (cm) (a major contributor to and function of PC1) during the period of record. The red line represents a generalized linear model trend with 95% CIs shaded in gray. The p-value of < 0.01 suggests a decreasing trend. The black line denotes a 6-year moving average to the time series. (C) The probability of an avalanche year as a function of the values of PC1. D: The probability of an avalanche year as a function of the values of PC2.

Finally, our comparison of temperature and precipitation values of avalanche and non-avalanche years associated with negative snowpack anomalies resulted in no significant differences. We note the small sample size of avalanche years ($n = 7$) in this subset of our dataset.

4. Discussion

4.1 Regional Chronology and RAAI

We used avalanche signals in tree-ring samples from 12 avalanche paths to derive a regional avalanche chronology for the U.S. northern Rocky Mountains of northwest Montana. The avalanche paths cover a broad range of topographic characteristics (i.e. short vs. long vertical fall, convex vs. planar, all aspects except true north) and are roughly representative of avalanche paths throughout the region. Sampling adjacent or proximal avalanche paths as well as sub-regions distant from each other by nearly 100 km allows for a representative, regional avalanche chronology that includes local topographically related variability to be derived from tree-rings. When available, observational avalanche records offer a more complete avalanche record with finer time resolution than tree-ring derived avalanche chronologies. However, historical avalanche chronologies derived from tree rings extend avalanche records further back in time when observations are non-existent, inconsistent, or sparse, as is the case in our study area.

Using sub-regions as representative samples of the northern U.S. Rockies in northwest Montana, we identified 30 years of regional large magnitude avalanche activity from 1867 to 2017. This suggests that grouping smaller areas together throughout a larger region may provide a more accurate chronology representative of a larger spatial extent, therefore providing a more complete regional perspective on large magnitude avalanche variability. This is important when conducting a regional climate-avalanche analysis as the larger extent of the study area is more aligned with the effects of synoptic atmospheric and climate patterns (Mock et al., 2016). We also incorporated a regional

average SWE_{max} and HS_{max} record into the analysis to highlight the effects of some of these climate patterns on regional seasonal snowpack.

4.2 Climate – Avalanche Interactions

HS_{max} and SWE_{max} exhibit negative trends throughout the period of record in our region with large magnitude avalanches occurring, on average, during years with greater HS_{max} and SWE_{max} . However, over recent decades (and HS_{max} and SWE_{max} decreases), years characterized by large magnitude avalanches and negative snowpack anomalies become more frequent. This suggests that avalanches can and do occur during years with below average snowpack. Snow structure is an important factor in avalanche release, and with a prerequisite weak layer in the snowpack, one loading event (i.e. storm) can initiate an avalanche. If that weak layer is deep in the snowpack, even a below average snowpack can produce a large magnitude avalanche. In this study region, sufficient snowpack structure data are non-existent prior to the early 21st century.

In our PCA, PC1 and PC2 explain nearly 55% of the variance of the data. The largest contributors to PC1 associated with large magnitude avalanche years are positive anomalies of HS_{max} and SWE_{max} , and negative anomalies of the PDO and PNA. This suggests that PC1 represents increased snowfall and storminess. Years with a negative PDO index, a pattern of Pacific climate variability based on sea surface temperature anomalies in the North Pacific (Mantua and Hare, 2002), are characterized by relatively persistent low pressure anomalies centered over western North America, which is conducive to more frequent Arctic air outbreaks. More frequent cold air outbreaks in the region provide more opportunity for faceted snow crystal growth leading to the

development of weak layers in the snowpack and the preservation of snow cover later in the winter when accumulation is greatest (Bamzai, 2003). This, combined with positive snowpack anomalies ($HS_{\max}$ and $SWE_{\max}$) associated with PC1, provides the proper ingredients for large magnitude avalanches: deep snowpack, potential weak layer deep in the snowpack, and abundant snowfall (or at least one large storm/snow loading event).

Our results are consistent with earlier work that suggests the PDO as a potential driver of snowpack change in the northern Rockies on multi-decadal scales (Pederson et al., 2013). Winters associated with positive snowpack anomalies tend to be associated with negative PDO conditions in the northern U.S. Rocky Mountains (Pederson et al., 2011a). Reardon et al. (2008), using both an observational and tree-ring record in southern GNP, Montana, also found avalanche years associated with negative PDO values.

The PNA, a prominent mode of low-frequency variability in the Northern Hemisphere extra-tropics, is associated with strong changes in amplitude and location of the jet stream over the Pacific and North American sector. The positive phase is associated with positive height anomalies and above-average temperatures over western Canada and the western U.S. Negative PNA anomalies are associated with avalanche extremes and storminess across the western U.S. (Birkeland et al., 2001; Mock and Birkeland, 2000). This aligns with our results that suggest negative phases of PNA and associated positive snowpack anomalies contribute toward years with large magnitude avalanches.

Our results also align with previous avalanche-climate studies completed in the region and nearby. Reardon et al. (2008) found avalanche activity from the Shed 10-7 path (also used in this study) and historical records correlated with positive snowpack anomalies from a nearby snow course. This is also consistent with the results of Butler (1986) in GNP, Montana, and Fitzharris and Schaerer (1980) in the Canadian Selkirk Mountains, 400 km northwest of GNP.

PC2 contributes ~14% of the explained variance and represents winter warming temperatures on avalanche years in our dataset. The major contributors to PC2 are warmer temperatures and positive anomalies of the AO. The positive phase of the AO is often associated with fewer colder outbreaks in the mid-latitudes, while during the negative phase, the jet stream shifts toward the equator delivering more frequent outbreaks of colder air. The main avalanche years associated with PC2 are 1990, 2002, and 2003 (Figure S2B). Avalanche events in 1990 and 2003 occurred during winters with above average temperature, and all three years are associated with positive February, March, and winter mean AO indices. The contribution of temperature and AO indices to PC2 suggests that several of the avalanche years in our dataset are potentially driven by warming. Whether this principal component is associated with wet snow avalanches is difficult to determine. We are unable to distinguish between wet and dry snow avalanches from the tree-ring record. Though, the more recent observational record from JFS sub-region provides some insight. Both dry and wet slab avalanches occurred during the major March 2003 avalanche cycle in southern Glacier National Park that destroyed mature forests and closed a major transportation corridor (Reardon et al., 2004). Though

PC2 (positive temperature anomalies) explains a small proportion of overall variance of our data, it may become an increasingly important driver of large magnitude avalanche years. For example, our results highlight that large magnitude avalanches can occur during years with below average snowpack (e.g. after ~1989), and some of those years correspond to PC2. As winter and spring temperatures continue to increase in the region (Pederson et al., 2010), temperature may become a more influential driver of large magnitude avalanche years.

This study provided some insight into the complex climate drivers of large magnitude avalanche years but disentangling the climate signal from the more frequent and influential weather signal when analyzing avalanches remains difficult. Simply one large storm in a season combined with a snowpack with antecedent weak layers can cause a large magnitude avalanche. However, widespread large magnitude avalanching is only likely to be captured with a large enough sampling extent and intensity. Our regional sampling strategy allowed for a more scale appropriate assessment of regional avalanche activity and related climate drivers. The large spatial extent, sample size, and the nested sampling of sub-regions aligns with the synoptic influence of climate drivers.

We used a regional avalanche chronology that extends back to 1867, but the length of the climate records forced us to shorten the time series of the avalanche chronology from 1950 to 2017. While we attempt to reduce estimation errors in this study through a large sample size and a regional spatial extent, the climate and snowpack time series datasets are inherently influenced by the lack of stationarity – the concept that natural systems (e.g. snowpack and temperature) exhibit variability within a given range

– through time due to climate change (Milly et al., 2008). Therefore, the variability of a decreasing snowpack and increasing temperatures in northwest Montana (Pederson et al., 2013) is likely to become more influential on the stationarity of large magnitude avalanche frequency time series. Future work with longer avalanche datasets should consider elucidating the effect of non-stationarity of climate drivers on avalanche frequency.

4.3 Modeling Avalanche Years

The results of the Wald and Likelihood Ratio tests suggest a good GLARMA model fit to the data (Table S3). The quality of fit for logistic regression models with binary outcomes (e.g. avalanche years = 1, non-avalanche years=0) can be interpreted by a pseudo R^2 measure. However, these pseudo R^2 values should not be interpreted as the same as R^2 values of ordinary least squares regression since logistic regression models predict probability of response. The Nagelkerke pseudo $R^2 = 0.38$ for our generalized linear model. Low pseudo R^2 models do not necessarily indicate a poor fit, but rather the ability to compare against a null model.

The GLARMA model results suggest a moving average term of 6 years and that PC1, PC2, and PC6 are significant predictor variables. Though PC6 explains a small amount of variance in our dataset (4.5%), it suggests that precipitation, particularly spring precipitation, is a significant predictor. Ballesteros-Canovas (2018) first used a GLARMA model in modeling probability of avalanche years in the western Indian Himalayas and found increasing temperature to be a significant predictor of avalanche years. Our results suggest a more nuanced and complicated relationship than that simply

increasing air temperature will increase wet snow avalanche activity through time. In our dataset, increasing temperatures explain only a small portion of the variance and correspond to a subset of avalanche years. Positive snowpack anomalies and low-pressure persistence over the region are the dominant driver.

We also found a slight, but significant, decrease in the probability of large magnitude avalanche years through time. This is consistent with one study in the French Alps where the authors found a decrease in dry snow avalanches from the mid-1970s to the early 21st century (Eckert et al., 2013). However, this contrasts with other regional studies in western Canada and Europe using historical observational records that found no trend in avalanche activity (Bellaire et al., 2016; Eckert et al., 2009; Laternser and Schneebeli, 2002). These studies investigated all sizes of avalanches, not just large magnitude avalanches. Our results also contrast with a study using tree-ring records across a much smaller spatial extent in the western Himalaya in India that found increasing probability in avalanches (Ballesteros-Canovas et al., 2018).

The decrease in $HS_{\max}$ and $SWE_{\max}$ through time and the decrease in avalanche probability suggests snowpack depth plays a major role in large magnitude avalanche years and decreasing snow cover may have an effect in the future. Our results linking decreased probability of avalanche activity as snowpack decreases is similar to Dixon et al. (1999) who found decreased avalanche activity during El Niño years in GNP, which are typically characterized by negative snowpack anomalies.

Annual snowpack loss exists throughout the western U.S. except for the highest elevations (Klos et al., 2014; Mote et al., 2018). Our results suggest large magnitude

avalanches can occur during years of below average snowpack, but the probability of large magnitude avalanche years decreases through time as snowpack decreases. This can partially be explained by warmer temperatures (the largest contributor to PC2) causing wet storms, or rain-on-snow events, triggering large magnitude avalanches. In other words, though a decreasing probability of large magnitude avalanche years corresponds to snowpack decreases, increasing temperatures can contribute toward large magnitude avalanche years perhaps compensating for the effect of snowpack losses.

Lower elevation snowpacks are more susceptible to a warming climate and exhibit greater snowpack loss (Mote et al., 2018; Pederson et al., 2013; Wobus et al., 2017), but higher elevations may experience stable or increasing snowpack due to increased precipitation in the region (Gillan et al., 2010). The potential effect this has on large magnitude avalanche occurrence is that large avalanches may still initiate at upper elevations but may not be able to reach lower elevations due to lack of snow cover. Though we did not investigate changes in runout altitude of large magnitude avalanches, future work should examine the effects of low elevation snowpack loss in the region on avalanche runout. We also suggest that further analyses be completed when future records cover a longer time period that encompasses non-stationarity of current climate change effects on snow cover properties.

We examined all years (avalanche and non-avalanche) associated with negative snowpack anomalies for a surface climatology signal to help explain the occurrence of large magnitudes during those years. The small sample size of avalanche years is likely more influential than any surface climatology signal we were able to elucidate. Given the

lack of snow structure data we are limited in our interpretation of whether the seven avalanche years can be attributed to one large storm and antecedent weak snowpack during an otherwise low snow year or to a general change in avalanche character. Given that our results suggest temperature (as part of PC2) is a significant driver of large magnitude avalanche years, it is possible that large magnitude avalanche years associated with negative snowpack anomalies are due to a changing avalanche character. In other words, there may be a shift from large magnitude avalanche years influenced primarily by storminess and abundant snowfall to large magnitude years influenced by warmer temperatures and wet snow avalanches. This coincides with other studies in the French Alps where the proportion of powder snow avalanches decreased (Eckert et al., 2013), and Swiss Alps where wet snow avalanche activity increased since the mid-1900s (Pielmeier et al., 2013). A longer time series that encompasses the climate change signal and associated non-stationarity will help elucidate this signal in future studies. In addition, the PCA and subsequent GLARMA model reasonably explain climate drivers of large magnitude avalanche years in our dataset, but the model may be limited in predicting large magnitude avalanche years in the future due to non-stationarity and a potential change in avalanche character.

5. Conclusions

Identifying relationships between the climate and specific regional large magnitude avalanche activity is important for interpreting historical avalanche variability and improving avalanche forecasting. In this study, we reconstructed a long-term regional avalanche chronology using tree-rings in the U.S. northern Rocky Mountains of

northwest Montana. Using principal component analysis, we found that avalanche years are generally characterized by winters with large snowpack and persistence of low-pressure over the region as represented by the contribution of positive snowpack anomalies and negative PDO and PNA in the leading principal component. To examine the probability of an avalanche year based on the leading principal components, we used a generalized linear autoregressive moving average model that accounts for the past effect of avalanches to illustrate that the first principal component is inversely proportional to avalanche year probability meaning as snowpack decreases the probability of a large magnitude avalanche year decreases. We found an overall decreasing trend in the probability of large magnitude avalanches through time suggesting future reductions in large magnitude avalanche frequency are possible as climate warming continues to drive snowpack losses.

REFERENCES

- Abatzoglou, J.T., 2011. Influence of the PNA on declining mountain snowpack in the Western United States. *International Journal of Climatology*, 31(8): 1135-1142.
- Amrhein, V., Greenland, S. and McShane, B., 2019. Comment: Retire statistical significance. *Nature*, 567: 305-307.
- Armstrong, B.R., 1981. A quantitative analysis of avalanche hazard on U.S. Highway 550, southwestern Colorado, *Proceedings of the Western Snow Conference*, St. George, Utah, April 14-16, 2017, St. George, Utah, pp. 95-104.
- Armstrong, R.L. and Armstrong, B.R., 1987. Snow and avalanche climates of the western United States: a comparison of maritime, intermountain, and continental climates, the Davos symposium, September 1986 International Association of the Hydrological Sciences Publication. no. 162.
- Ballesteros-Canovas, J.A., Trappmann, D., Madrigal-Gonzalez, J., Eckert, N. and Stoffel, M., 2018. Climate warming enhances snow avalanche risk in the Western Himalayas. *Proc Natl Acad Sci U S A*, 115(13): 3410-3415.
- Bamzai, A.S., 2003. Relationship between snow cover variability and Arctic oscillation index on a hierarchy of time scales. *International Journal of Climatology*, 23(2): 131-142.
- Bellaire, S., Jamieson, B., Thumlert, S., Goodrich, J. and Statham, G., 2016. Analysis of long-term weather, snow and avalanche data at Glacier National Park, B.C., Canada. *Cold Regions Science and Technology*, 121: 118-125.
- Birkeland, K.W. and Mock, C.J., 1996. Atmospheric circulation patterns associated with heavy snowfall events, Bridger Bowl, Montana, USA. *Mountain Research and Development*, 16(3): 281-286.
- Birkeland, K.W., Mock, C.J. and Shinker, J.J., 2001. Avalanche extremes and atmospheric circulation patterns. *Annals of Glaciology*, 32: 135-140.
- Blattenberger, G. and Fowles, R., 1994. The Road Closure Decision in Little Cottonwood Canyon, *Proceedings of the 1994 International Snow Science Workshop*, October 30-November 3, 1994, Snowbird Utah, Snowbird, Utah, pp. 537-547.
- Butler, D.R., 1986. Snow-avalanche hazards in Glacier National Park, Montana: meteorological and climatological aspects. *Physical Geography*, 7(1): 72-87.

- Corona, C., Lopez Saez, J., Stoffel, M., Bonnefoy, M., Richard, D., Astrade, L. and Berger, F., 2012. How much of the real avalanche activity can be captured with tree rings? An evaluation of classic dendrogeomorphic approaches and comparison with historical archives. *Cold Regions Science and Technology*.
- Dixon, R.W., Butler, D.R., Dechano, L.M. and Henry, J.A., 1999. Avalanche Hazard in Glacier National Park: an El Nino Connection? *Physical Geography*, 20(6): 461-467.
- Dunsmuir, W.T.M. and Scott, D.J., 2015. The glarma Package for Observation-Driven Time Series Regression of Counts. *Journal of Statistical Software*, 67(7).
- Eckert, N., Keylock, C.J., Castebrunet, H., Lavigne, A. and Naaim, M., 2013. Temporal trends in avalanche activity in the French Alps and subregions: from occurrences and runout altitudes to unsteady return periods. *Journal of Glaciology*, 59(213): 93-114.
- Eckert, N., Parent, E., Kies, R. and Baya, H., 2009. A spatio-temporal modelling framework for assessing the fluctuations of avalanche occurrence resulting from climate change: application to 60 years of data in the northern French Alps. *Climatic Change*, 101(3-4): 515-553.
- Favillier, A., Guillet, S., Trappmann, D., Morel, P., Lopez-Saez, J., Eckert, N., Zenhäusern, G., Peiry, J.-L., Stoffel, M. and Corona, C., 2018. Spatio-temporal maps of past avalanche events derived from tree-ring analysis: A case study in the Zermatt valley (Valais, Switzerland). *Cold Regions Science and Technology*, 154: 9-22.
- Fitzharris, B.B. and Bakkehoi, S., 1986. A synoptic climatology of major avalanche winters in Norway. *Journal of Climatology*, 6: 431-446.
- Fitzharris, B.B. and Schaerer, P.A., 1980. Frequency of major avalanche winters. *Journal of Glaciology*, 26(94): 43-52.
- Germain, D., 2016. A Statistical Framework for Tree-Ring Reconstruction of High-Magnitude Mass Movements: Case Study of Snow Avalanches in Eastern Canada. *Geografiska Annaler: Series A, Physical Geography*, 98(4): 303-311.
- Germain, D., Filion, L. and Hétu, B., 2009. Snow avalanche regime and climatic conditions in the Chic-Choc Range, eastern Canada. *Climatic Change*, 92(1-2): 141-167.
- Gillan, B.J., Harper, J.T. and Moore, J.N., 2010. Timing of present and future snowmelt from high elevations in northwest Montana. *Water resources research*, 46(W01507).

- Greene, E., Birkeland, K.W., Elder, K., McCammon, I., Staples, M. and Sharaf, D., 2016. Snow, weather, and avalanches: Observation guidelines for avalanche programs in the United States (3rd ed). American Avalanche Association, Victor, ID, pp. 104.
- Hamed, K.H. and Rao, A.R., 1998. A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology*, 204(1-4): 182-196.
- Hendriks, J., Murphy, M. and Onslow, T., 2014. Classification trees as a tool for operational avalanche forecasting on the Seward Highway, Alaska. *Cold Regions Science and Technology*, 97: 113-120.
- Kanyongo, G.Y., 2005. The Influence of Reliability on Four Rules for Determining the Number of Components to Retain. *Journal of Modern Applied Statistical Methods*, 5(2): 332-343.
- Klos, P.Z., Link, T.E. and Abatzoglou, J.T., 2014. Extent of the rain-snow transition zone in the western U.S. under historic and projected climate. *Geophysical Research Letters*, 41: 4560-4568.
- Kogelnig-Mayer, B., Stoffel, M., Schneuwly-Bollschweiler, M., Hübl, J. and Rudolf-Miklau, F., 2011. Possibilities and Limitations of Dendrogeomorphic Time-Series Reconstructions on Sites Influenced by Debris Flows and Frequent Snow Avalanche Activity. *Arctic, Antarctic, and Alpine Research*, 43(4): 649-658.
- Laternser, M. and Schneebeli, M., 2002. Temporal trend and spatial distribution of avalanche activity during the last 50 years in Switzerland. *Natural Hazards*, 27: 201-230.
- Laternser, M. and Schneebeli, M., 2003. Long-term snow climate trends of the Swiss Alps (1931-99). *International journal of climatology*, 23: 733-750.
- Malevich, S.B., Guiterman, C.H. and Margolis, E.Q., 2018. burnr : Fire history analysis and graphics in R. *Dendrochronologia*, 49: 9-15.
- Mann, H.B., 1945. Nonparametric tests against trend. *Econometrica*, 13(3): 245-259.
- Mantua, N.J. and Hare, S.R., 2002. The Pacific Decadal Oscillation. *Journal of Oceanography*, 58: 10.
- McCabe, G.J., 1994. Relationships Between Atmospheric Circulation and Snowpack in the Gunnison River Basin, Colorado. *Journal of Hydrology*, 157(1-4): 157-175.
- McCabe, G.J. and Dettinger, M.D., 2002. Primary modes and predictability of year-to-year snowpack variations in the Western United States from teleconnections with Pacific ocean climate. *Hydrometeorology*, 3(13-25).

- Menne, M.J., Durre, I., Vose, R.S., Gleason, B.E. and Houston, T.G., 2012. An Overview of the Global Historical Climatology Network-Daily Database. *Journal of Atmospheric and Oceanic Technology*, 29(7): 897-910.
- Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W. and Lettenmaier, D.P.S., Ronald J., 2008. Stationarity is dead: whither water management? *Science*, 319: 573-574.
- Mock, C.J., 1996. Climatic controls and spatial variations of precipitation in the western United States. *Journal of Climate*, 9: 1111-1125.
- Mock, C.J. and Birkeland, K.W., 2000. Snow avalanche climatology of the western United States mountain ranges. *Bulletin of the American Meteorological Society*, 81(10): 2367-2392.
- Mock, C.J., Carter, K.C. and Birkeland, K.W., 2016. Some Perspectives on Avalanche Climatology. *Annals of the American Association of Geographers*: 1-10.
- Mote, P.W., Li, S., Lettenmaier, D.P., Xiao, M. and Engel, R., 2018. Dramatic declines in snowpack in the western US. *npj Climate and Atmospheric Science*, 1(1-5).
- NCDC, National Oceanic and Atmospheric Administration National Centers for Environmental Information <https://www.ncdc.noaa.gov/teleconnections/>.
- NRCS, United States Department of Agriculture National Resource Conservation Service Snow Course Data, <https://www.wcc.nrcs.usda.gov/snowcourse/>.
- Pederson, G.T., Betancourt, J.L. and McCabe, G.J., 2013. Regional patterns and proximal causes of the recent snowpack decline in the Rocky Mountains, U.S. *Geophysical Research Letters*: 1-6.
- Pederson, G.T., Graumlich, L.J., Fagre, D.B., Kipfer, T. and Muhlfield, C.C., 2010. A century of climate and ecosystem change in Western Montana: what do temperature trends portend? *Climatic Change*, 98(1-2): 133-154.
- Pederson, G.T., Gray, S.T., Ault, T., Marsh, W., Fagre, D.B., Bunn, A.G., Woodhouse, C.A. and Graumlich, L.J., 2011a. Climatic Controls on the Snowmelt Hydrology of the Northern Rocky Mountains. *Journal of Climate*, 24(6): 1666-1687.
- Pederson, G.T., Gray, S.T., Woodhouse, C.A., Betancourt, J.L., Fagre, D.B., Littell, J.S., Watson, E., Luckman, B.H. and Graumlich, L.J., 2011b. The unusual nature of recent snowpack declines in the North American Cordillera. *Science*.

- Peitzsch, E.H., Hendrikx, J., Fagre, D.B. and Reardon, B., 2012. Examining spring wet slab and glide avalanche occurrence along the Going-to-the-Sun Road corridor, Glacier National Park, Montana, USA. *Cold Regions Science and Technology*, 78: 73-81.
- Peitzsch, E.H., Stahle, D.K., Fagre, D.B., Clark, A.M., Pederson, G.T., Hendrikx, J. and Birkeland, K.W., 2019. Tree ring dataset for a regional avalanche chronology in northwest Montana, 1636-2017. U.S. Geological Survey. <https://doi.org/10.5066/P9TLHZAI>.
- Peitzsch, E.H., Hendrikx, J., Stahle, D.K., Pederson, G.T., Fagre, D.B. and Birkeland, K.W., In Prep. A regional spatio-temporal analysis for large magnitude avalanches using tree rings.
- Pielmeier, C., Techel, F., Marty, C. and Stucki, T., 2013. Wet snow avalanche activity in the Swiss Alps - trend analysis for mid-winter season. In F. Naaim-Bouvet, Y. Durand, & R. Lambert (Eds.), *Proceedings of the 2013 International snow science workshop proceedings 2013*. Grenoble, France. 7-11 October 2013.: 1240-1246.
- PRISM, 2019. Parameter-elevation Regressions on Independent Slope Model. PRISM Climate Group, Oregon State University. <http://prism.oregonstate.edu>, created 20 November 2019.
- R, 2018. R Core Team - R Foundation for Statistical Computing. 2018, R: A Language and Environment for Statistical Computing, <https://www.R-project.org>, Vienna, Austria.
- Reardon, B. and Fagre, D.B., 2006. Reassessing a troublesome fact of mountain life: avalanches in Glacier National Park. *Park Science*, 24(1): 37-39.
- Reardon, B.A., Fagre, D.B. and Steiner, R.W., 2004. Natural avalanches and transportation: a case study from Glacier National Park, Montana, USA, *Proceedings of the International Snow Science Workshop*, Sept. 19-24, 2004, Jackson, WY, U.S.A., pp. 582-597.
- Reardon, B.A., Pederson, G.T., Caruso, C.J. and Fagre, D.B., 2008. Spatial reconstructions and comparisons of historic snow avalanche frequency and extent using tree rings in Glacier National Park, Montana, U.S.A. *Arctic, Antarctic, and Alpine Research*, 40(1): 148-160.
- Shroder, J.F., 1978. Dendrogeomorphological analysis of mass movement on Table Cliffs Plateau, Utah. *Quaternary Research* 9, 168(18.5).

- Wayand, N.E., Massmann, A., Butler, C., Keenan, E., Stimberis, J. and Lendquist, J.D., 2015. A meteorological and snow observational data set from Snoqualmie Pass (921 m), Washington Cascades, USA. *Water Resources Research*, 51: 10092-10103.
- Wilcoxon, F., 1945. Individual comparisons by ranking methods. *Biometrics Bulletin*, 1(6): 80-83.
- Wobus, C., Small, E.E., Hosterman, H., Mills, D., Stein, J., Rissing, M., Jones, R., Duckworth, M., Hall, R., Kolian, M., Creason, J. and Martinich, J., 2017. Projected climate change impacts on skiing and snowmobiling: A case study of the United States. *Global Environmental Change*, 45: 1-14.
- Zahumensky, I., 2004. Guidelines on Quality Control Procedures for Data from Automatic Weather Stations, World Meteorological Organization.

APPENDIX

Table S1: Result of Mann Kendall test for monotonic trend.

Variable	<i>p</i> - value	τ	Sens slope
$T_{\max}$	0.08	0.13	0.13
$T_{\min}$	0.93	0.01	0.00
SWE	<0.01	-0.26	-3.55
HS	<0.01	-0.25	-0.73
Precip.	<0.01	0.16	3.56

Table S2: Table of climate variables tested in Wilcoxon rank-sum test between avalanche and non-avalanche years. See Figures 3-4 for median values.

Variable	<i>p</i> - value	Variable	<i>p</i> - value
PDO – January mean	0.03	$T_{\min}$ – Winter	0.33
PDO – February mean	0.01	$T_{\min}$ – January	0.75
PDO – March mean	0.19	$T_{\min}$ – February	0.28
PDO – December mean	0.20	$T_{\min}$ – March	0.20
PDO – Winter mean	0.04	$T_{\min}$ – November	0.65
ENSO – January mean	0.03	$T_{\min}$ – December	0.28
ENSO – February mean	0.13	$T_{\max}$ – Winter	0.42
ENSO – March mean	0.21	$T_{\max}$ – January	0.41
ENSO – December mean	0.03	$T_{\max}$ – February	0.16
ENSO – Winter mean	0.05	$T_{\max}$ – March	0.13
PNA – January mean	0.19	$T_{\max}$ – November	0.27
PNA – February mean	0.07	$T_{\max}$ – December	0.56
PNA – March mean	0.14	Precip. – January	<0.01
PNA – December mean	0.26	Precip. – February	0.16
PNA – Winter mean	0.03	Precip. – March	0.81
AO – January mean	0.76	Precip. – November	0.35
AO – February mean	0.03	Precip. – December	0.14
AO – March mean	0.05	Precip. – Winter	<0.01
AO – December mean	0.63	SWE – Winter	<0.01
AO – Winter mean	0.03	HS - Winter	<0.01
500 mb Height	0.04		

Table S3: Best fit GLARMA model results

GLARMA Coefficient				
	<i>Estimate</i>	<i>Std. Error</i>	<i>z-ratio</i>	<i>Pr (> z)</i>
$\theta = 6$	0.96	0.38	2.55	0.01
Linear Model Coefficients				
Intercept	-1.37	0.52	-2.64	<0.01
PC1	-0.46	0.14	-3.19	<0.01
PC2	-0.35	0.19	-1.78	0.07
PC3	0.05	0.25	0.20	0.84
PC4	-0.41	0.30	1.36	0.18
PC5	-0.42	0.27	-1.58	0.11
PC6	-0.68	0.33	-2.05	0.04
Goodness of fit tests				
Likelihood Test	<i>statistic</i> =6.64	$p = 0.01$		
Wald Test	<i>statistic</i> = 6.49	$p = 0.01$		

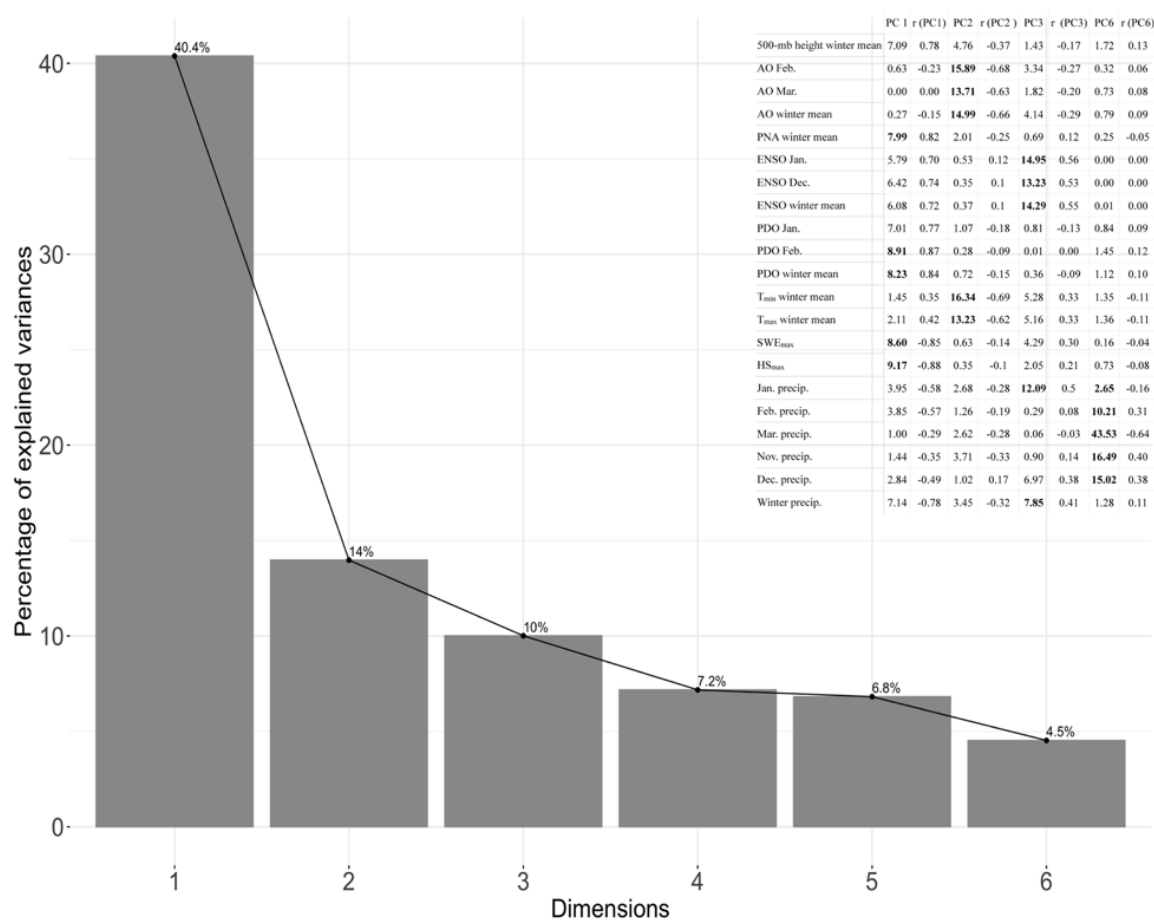


Figure S1: Scree plot of principal components (Dimensions – x-axis) and the percentage of explained variance of each (y-axis). Only the first six principal components are shown as they explain ~80% of the variance of the data. Inset table shows contributions (%) and r values of variables to principal components. Bold values indicate the five largest contributors in each principal component.

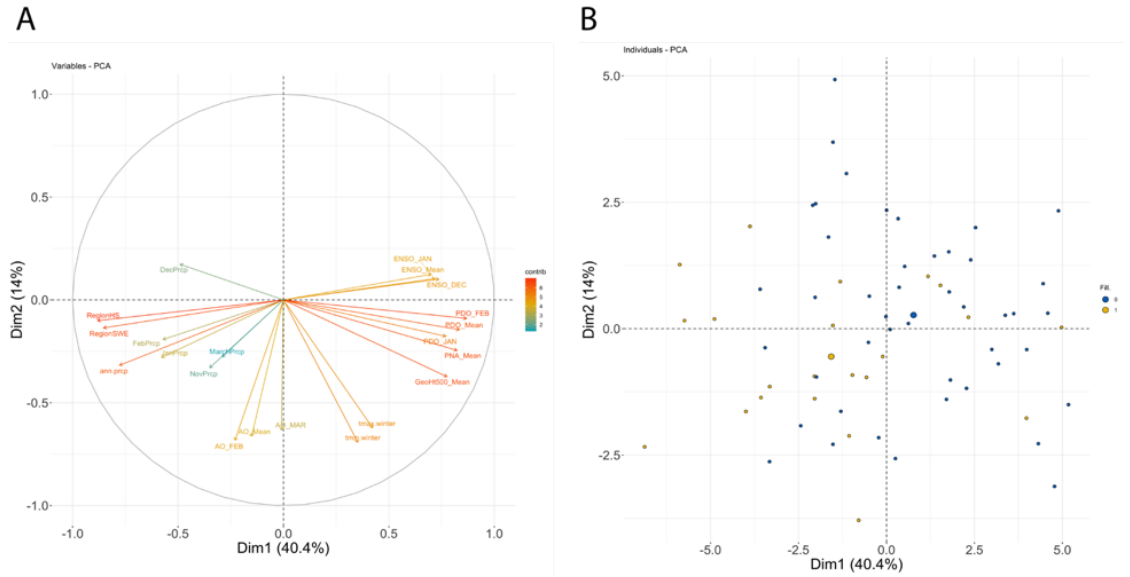


Figure S2: Plot of variables (A) in two dimensions with Dim1 (x-axis) representing the first principal component and Dim2 representing the second principal component, and plot of individual avalanche years (B) where blue points represent non-avalanche years (0) and yellow points represent avalanche years (1). The axes differ because they are scaled in the Plot A and normalized to Type (Avalanche vs. Non-Avalanche) in Plot B.

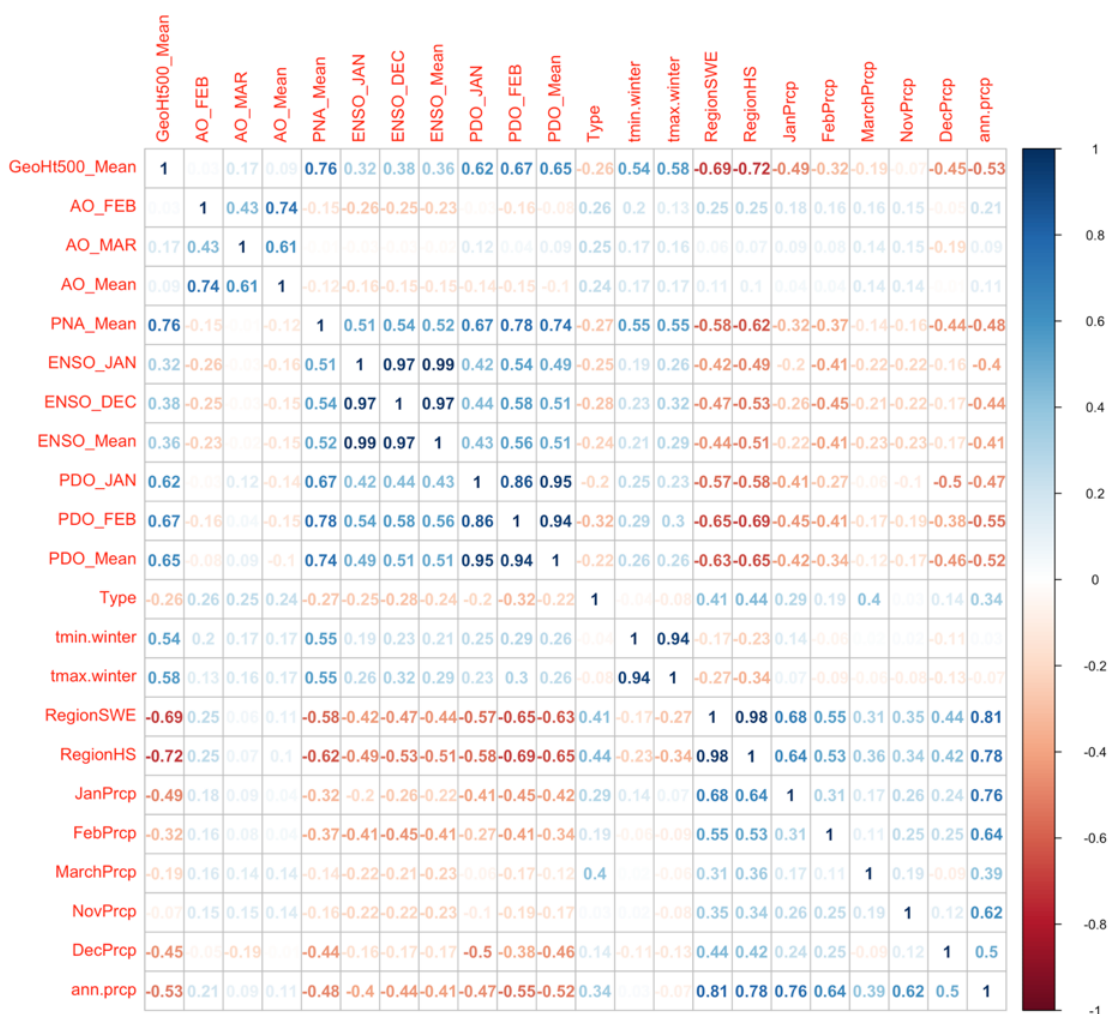


Figure S3: Correlation matrix of all variables used in the PCA.

CHAPTER FOUR

VEGETATION CHARACTERIZATION IN AVALANCHE PATHS USING LIDAR
AND SATELLITE IMAGERY

Contribution of Author and Co-Authors

Manuscript in Chapter 4

Author:	Erich H. Peitzsch
Contributions	Responsible for data acquisition, the development of analysis, the majority of the writing, and figure development.
Author:	Chelsea Martin-Mikle
Contributions	Assisted with field data collection, contributed toward data analysis, writing, and provided extensive discussion of the analysis procedures.
Author:	Jordy Hendrikx
Contributions	Provided extensive discussion of the development of methods used in the study and contributed to the editing of the manuscript throughout its development.
Author:	Gregory T. Pederson
Contributions	Contributed to the editing of the manuscript throughout its development.
Author:	Karl W. Birkeland
Contributions	Contributed to the editing of the manuscript throughout its development.
Author:	Daniel B. Fagre
Contributions	Contributed to the editing of the manuscript throughout its development.

Manuscript Information

Peitzsch, E.H.^{1,2}, Martin-Mikle C.J.¹, Hendrikx, J.², Birkeland, K.W.^{3,2}, Pederson, G.T.¹, and Fagre, D.B.¹. Vegetation characterization in avalanche paths using lidar and satellite imagery. Manuscript for submittal to Arctic, Antarctic, and Alpine Research.

¹ U.S. Geological Survey Northern Rocky Mountain Science Center, West Glacier, Montana, USA

² Snow and Avalanche Lab, Department of Earth Sciences, Montana State University, Bozeman, Montana, USA

³ U.S.D.A. Forest Service National Avalanche Center, Bozeman, Montana, USA

Journal: Arctic, Antarctic, and Alpine Research

Status of manuscript

- ☒ Prepared for submission to a peer-reviewed journal
- ☐ Officially submitted to a peer-reviewed journal
- ☐ Accepted by a peer-reviewed journal
- ☐ Published in a peer-reviewed journal

Publisher: Taylor and Francis

Anticipated date of submission: June 2020

Abstract

Snow avalanches are an ecological disturbance across mountain landscapes worldwide. Understanding how avalanche frequency affects forests and vegetation improves infrastructure planning and avalanche forecasting. We implemented a novel approach using lidar and aerial imagery and a Random Forest model to classify imagery-observed vegetation within avalanche paths in southern Glacier National Park, Montana, USA. We then used dendrochronological techniques combined with a thin plate spline interpolation procedure to calculate avalanche return periods and characterize the vegetation within those return period zones. The automated vegetation classification model differed slightly between avalanche paths, but the combination of lidar and spectral signature metrics provided the best accuracy (88-92%) for predicting vegetation classes within complex avalanche terrain rather than lidar or spectral signature metrics alone. The highest frequency return periods were broadly characterized by grassland and shrubland, but the influence of topography greatly influences the vegetation classes as well as the return periods. The ability to characterize vegetation within various avalanche return periods using remote sensing data provides land use planners and avalanche forecasters a tool for assessing large magnitude avalanche events. However, the optimal classification of vegetation is avalanche path specific and limits prediction to larger areas or to other paths.

1. Introduction

Snow avalanche (hereafter avalanche) disturbance across the landscape is an important ecological process in mountain locations throughout the world. Avalanches have the potential to affect alpine ecosystems, forests, and riparian zones, particularly in the case of large magnitude avalanches. Avalanches contribute to animal habitat, change the species of flora along an elevational gradient, and modify forest structure (Becker et al., 2007; Rixen et al., 2007; Waller and Mace, 1997). Avalanches also pose a substantial hazard to humans and infrastructure. Therefore, it is important to understand the interaction of avalanche frequency with forests and vegetation within avalanche paths.

Bebi et al. (2009) provides a thorough review of snow avalanche disturbance in forest ecosystems. Frequent avalanches sustain floristic communities while large, infrequent avalanches modify existing community structures (Patten and Knight, 1994).

A mutual relationship exists between avalanches and forest structure and function.

Avalanches shape vegetation patterns and forest structure, but forests can also influence the release and runout extent of avalanches.

1.1 Avalanche Effects on Vegetation Structure and Composition

The influence of avalanches at the scale of individual trees is important as it ultimately effects canopy size and distribution across the landscape (Johnson, 1987). More frequent avalanching in a given path can be a dominant control on vegetation size and structure within that path. When avalanches become less frequent, the vegetation changes from shrub-like communities to more mature forests (Butler, 1979; Johnson, 1987; Patten and Knight, 1994; Walsh et al., 1994). Ecosystems impacted more frequently by avalanches tend to be composed of smaller density, shade intolerant shrubs (Butler, 1979). Post-avalanche regeneration is typically due to reorganization of existing vegetation within the path as opposed to new recruitment (Bebi et al., 2009). Since most avalanches do not run to the ground, thereby creating new areas for colonization, new seedling recruitment is not often a method of regrowth. Both new and established shade-intolerant species flourish due to new light availability when canopies are thinned or removed by large magnitude avalanches (Burrows and Burrows, 1976; Kajimoto et al., 2004).

Avalanche disturbance also influences the structural and compositional vegetation diversity within ecosystems (Malanson and Butler, 1984; Veblen et al., 1994). Patten and Knight (1994) report moderate change in Granite Canyon, Wyoming, USA, but observed consistent vegetation fragmentation due to avalanche disturbance. Malanson and Butler (1984; 1986) examined the transverse vegetation patterns of avalanche paths in Glacier

National Park, Montana, USA. Their results showed three different lateral vegetation zones in an avalanche path. They found that the size and shape of these zones respond to external geomorphic controls, such as snow deposition by avalanches, and result in variable vegetation patterns across the slope. Erschbamer (1989) confirmed this with a similar study in the Austrian Alps. This vegetation mosaic across the landscape created by avalanche disturbance creates open areas used by a variety of animal species. Black and grizzly bears, elk, and wolverines use avalanche paths as “elevators” to travel from riparian zones to the alpine and in between (Krajick, 1998; Mace and Waller, 1997; Waller and Mace, 1997).

The structure and composition of vegetation within avalanche paths also depends largely on avalanche frequency. In Switzerland, the use of avalanche barriers affects vegetation characteristics below the barrier. Kulakowski (2006) reports a higher biodiversity in paths not impacted by avalanche berms, and thus having a greater avalanche frequency. This impact has been associated with cascading effects of vascular vegetation structural diversity in active avalanche paths (Rixen et al., 2007).

Additionally, Kajimoto et al. (2004) report avalanche disturbance enhanced growth in younger, surviving trees, but played a limited role in immediate seedling recruitment or growth release of advanced seedlings. Their results suggest post-avalanche forest regeneration depends upon smaller trees that were able to avoid mechanical damage and mortality. This implies that the rate of vegetation regeneration is site and event specific and dependent upon the vegetation that survives infrequent, large magnitude avalanches. Therefore, extrapolating vegetation characteristics from one

avalanche path to another, or a region, may not be appropriate depending on the timing and frequency of avalanche activity.

1.2 Effects of Vegetation Cover and Structure on Avalanches

The reciprocal effect of avalanches on vegetation structure and composition is the influence vegetation has on avalanche runout extent. Teich et al. (2012) demonstrated that forest structure has a significant effect on runout distance of small to medium avalanches in forest openings. The effect of forest structure on the runout extent of larger avalanches that initiate above tree-line is trivial with the caveat that some forests are still able to limit runout zone extent (Bartelt and Stockli, 2001; Feistl et al., 2014).

Ground cover and surface roughness also influence avalanche release and frequency. Areas of smooth and low vegetation (e.g. grasses) are more conducive to certain types of avalanches like glide snow avalanches and snow gliding, in general (Feistl et al., 2013; Newesely et al., 2000; Peitzsch et al., 2015). The roughness also influences avalanche release as long as the snow depth does not exceed the height of the vegetation (Leitinger et al., 2008).

Forests and vegetation also act to maintain or modify slope stability through interception of snowfall (Hesdstrom and Pomeroy, 1998; Veatch et al., 2009), influencing the energy balance (Molotch et al., 2007; Stähli et al., 2009), protecting from wind, and potential anchoring of the snowpack (McClung and Schaerer, 2006). These processes affect snow stability in forested terrain by influencing the formation of potential weak layers such as surface hoar or near surface facets, inhibiting wind loading, and anchoring areas within forested openings. Trees also tend to increase the heterogeneity of the snowpack structure (Musselmann et al., 2008) which influences avalanche release.

1.3 Characterizing Vegetation Using Remote Sensing

Walsh et al. (2004) estimated past avalanche vegetation structure and composition using Ikonos satellite data and interpreting Normalized Difference Vegetation Index (NDVI) greenness values (Walsh et al., 2004). Early remote sensing methods were limited by sensors that classified land cover into broad categories rather than the fine spatial resolution necessary for studying many ecological processes. Since then, laser altimetry, or light detection and ranging (lidar), has emerged as a valuable and widely used tool to help classify forest structure and vegetation composition. Lefsky et al. (2002) reports on one of the earliest uses of lidar for studying forest canopy studies. Lidar can also be used to calculate forest biomass and canopy height with high accuracy (Lim et al., 2003). McCollister and Comey (2009) also used lidar in a snow-off application to examine topographic characteristics of avalanche paths at Jackson Hole Mountain Resort in Wyoming, USA. Lidar has been used extensively to remotely sense snow cover and to detect change in snow depth (Deems et al., 2013) and other cryospheric processes (Telling et al., 2017). The proven widespread and effective use of lidar in modeling and characterizing various ecological and snow cover properties makes it suitable for characterizing vegetation structure and composition within avalanche paths.

In this study, we manually classified a sample of vegetation types within three avalanche paths using high-resolution imagery. We then tested the efficacy of an automated classification procedure using lidar and high-resolution aerial imagery trained on that sample to characterize and quantify the various types of vegetation throughout the three avalanche paths. We also utilized avalanche-dendrochronology records to accurately map avalanche return periods in two of those three avalanche paths and

subsequently characterized the vegetation composition within those reconstructed return periods. We hypothesize that vegetation characteristics will differ in various transverse zones of the avalanche path, and that varying return frequency bands will harbor substantially different vegetation types. This work uses a novel approach by using remote sensing products in combination with dendrochronological techniques to classify vegetation and characterize vegetation classes within various return periods across several avalanche paths.

2. Methods

2.1 Study Site

The three avalanche paths in this study are located along John F. Stevens (JFS) Canyon, a major transportation corridor traversing a portion of the southern boundary of Glacier National Park, Montana, USA, and containing U.S. Highway 2 and the Burlington Northern Santa Fe (BNSF) Railway (Figure 1). This canyon has also been the

site of previous dendrochronological avalanche research (Butler and Malanson, 1985a; Peitzsch et al., In Prep.; Reardon et al., 2008).

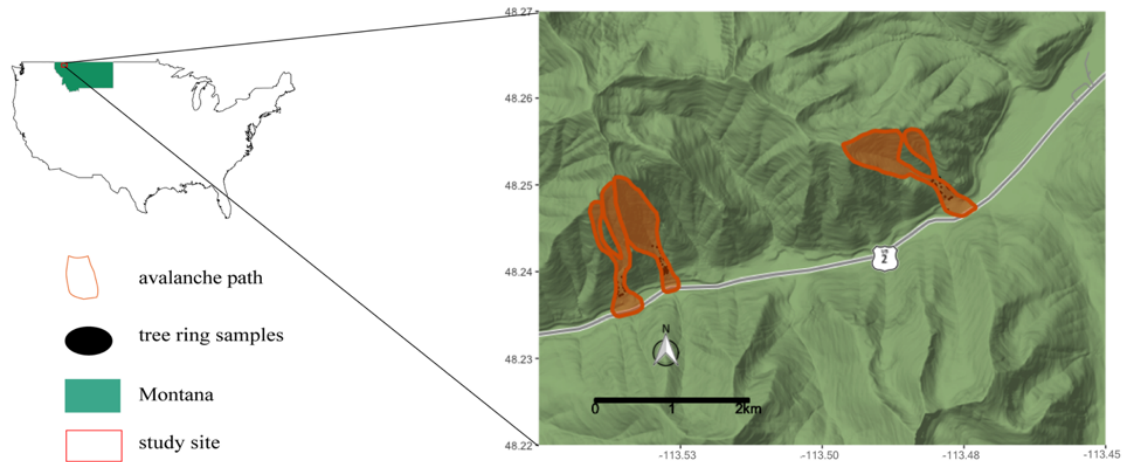


Figure 1: Study site. The red rectangle in the state of Montana designates the general area of the study site. From west to east (left to right on the map) the avalanche paths are: Shed 10-7, 1163, and Shed 7.

The U.S. northern Rocky Mountains of northwest Montana are classified as both coastal transition and intermountain avalanche climate (Mock and Birkeland, 2000), and therefore can exhibit characteristics of both continental or coastal climates. The contrasting precipitation and temperature regimes within the region are due to the study areas proximity to the Continental Divide, which allows both Pacific and continental air masses to influence the area's weather. Average annual precipitation is 2083 mm at Flattop SNOTEL (1810 m) and peak snow water equivalent (SWE) typically occurs mid-to late-April with a median value of approximately 1100 mm (1981-2010). The elevation

of avalanche paths within the study site range from approximately 1200 m to 2200 m and covers predominantly southeast to south aspects (Table 1).

Table 1: Topographic characteristics of all avalanche paths. * denotes two major starting zones for one runout.

Path	# tree ring samples collected	# GD	Full Path Elev. (range) (m)	Starting Zone Elev. (mean) (m)	Full Path Slope (mean) (°)	Starting Zone Slope (mean) (°)	Area (km ²)	Length (m)	Vertical (m)	Median Aspect (°)
Shed 10-7 (S10.7)*	109	NA	1233 - 2193	1910 1964	31	35 39	0.13	1745.66	959.74	176
1163	50	128	1250 - 2217	1861	38	42	0.17	1636.52	966.82	158
Shed 7 (S7)*	46	92	1310 - 2078	1935 1837	29	34 36	0.57	1686.96	768.01	152

The subalpine and montane forests are dominated by species of fir (*Abies lasiocarpa*, *Pseudotsuga menziesii*, *Abies grandis*), pine (*Pinus ponderosa*, *Pinus monticola*), and a mix of hemlock (*Tsuga heterophylla*), larch (*Larix occidentalis*), spruce (*Picea engelmannii*), cedar (*Thuja plicata*), birch (*Betula papyrifera*), and slide alder (*Alnus spp.*).

2.2 Lidar and Spectral Imagery Data Acquisition

High point density aerial lidar data were acquired for approximately 192 km² of JFS Canyon between July 20, 2016 and August 5, 2016 (USGS, 2016). The longer data collection period allowed for suitable flying and data collection during leaf-on conditions. The data were collected with a Dual-Head DragonEye system, mounted on a Leica PAV100 gyro-stabilized mount configured with a NovAtel SPAN GNSS and LCI-100C IMU. This sensor collects up to four returns per pulse, as well as intensity data for the first three returns. The data were collected and processed to meet a maximum nominal

post spacing of 0.35 m, with a mean point density of 16 points/m². The laser pulse wavelength and the pulse return frequency were 1064 nm and up to 1 MHz, respectively.

Using the approach outlined by Laes et al. (2011) we validated the lidar data by measuring tree height and diameter in July 2019 in Shed 7 using five circular field plots (plot area = 400 m²) and stratified random sampling along an elevation gradient. We did not sample vegetation types, but simply used this step to field validate canopy height values of the lidar data. However, we selected plots representative of homogenous vegetation cover in and adjacent to the avalanche path. We measured the height of the four tallest trees within each plot using a standard metric measuring tape and inclinometer. We also collected diameter and breast height measurements of all trees within the plots. We included all trees whose entire or partial canopy fell within the field plot in selection of the four tallest trees. We then mapped each plot and identified the four tallest trees within each plot in the lidar dataset. We then examined the relationship between field measurements and lidar data using the Pearson correlation coefficient.

Aerial imagery collected by the National Agricultural Imagery Program (NAIP) was acquired for JFS Canyon. The 4-band (red, green, blue and near infrared) NAIP imagery for the study site was collected in the fall of 2017 at 0.6 m spatial resolution (NRCS, 2017).

2.3 Imagery and Lidar Data Processing

Our workflow includes multiple steps from data processing to the final vegetation classification (Figure 2). First, we clipped the lidar point data to the study area. We generated a digital surface model (DSM) for the height of vegetation using a pit-free algorithm developed by Khosravipour et al. (2014). We also created a digital terrain

model (DTM) for the bare earth surface using a spatial interpolation algorithm based on nearest neighbor (KNN) approach with an inverse-distance weighting (IDW) method. We subtracted the DTM from the DSM to produce a canopy height model (CHM) data layer with 0.5 m vertical resolution.

We then clipped NAIP aerial imagery to the study area and georeferenced it to align with the CHM derived from the lidar point cloud. We segmented individual tree crowns from the CHM based on the marker-controlled watershed function developed by Meyer and Beucher (1990), a common segmentation methodology for data derived from an airborne laser scanner (ALS) (Holmgren et al., 2008; Hyyppä et al., 2001; Persson et al., 2002; Solberg et al., 2006). We clipped the resulting raster representing individual tree crowns by the extent of the three avalanche paths for this particular study: Shed 10-7, Path 1163, and Shed 7. We used a minimum canopy height of 0.5 m to include low-level vegetation that could provide useful information in avalanche path return period analysis. All analyses were performed using R statistical software (R, 2018) using the *lidR* (Roussel and Auty, 2019) and *rLiDAR* (Silva et al., 2017) packages.

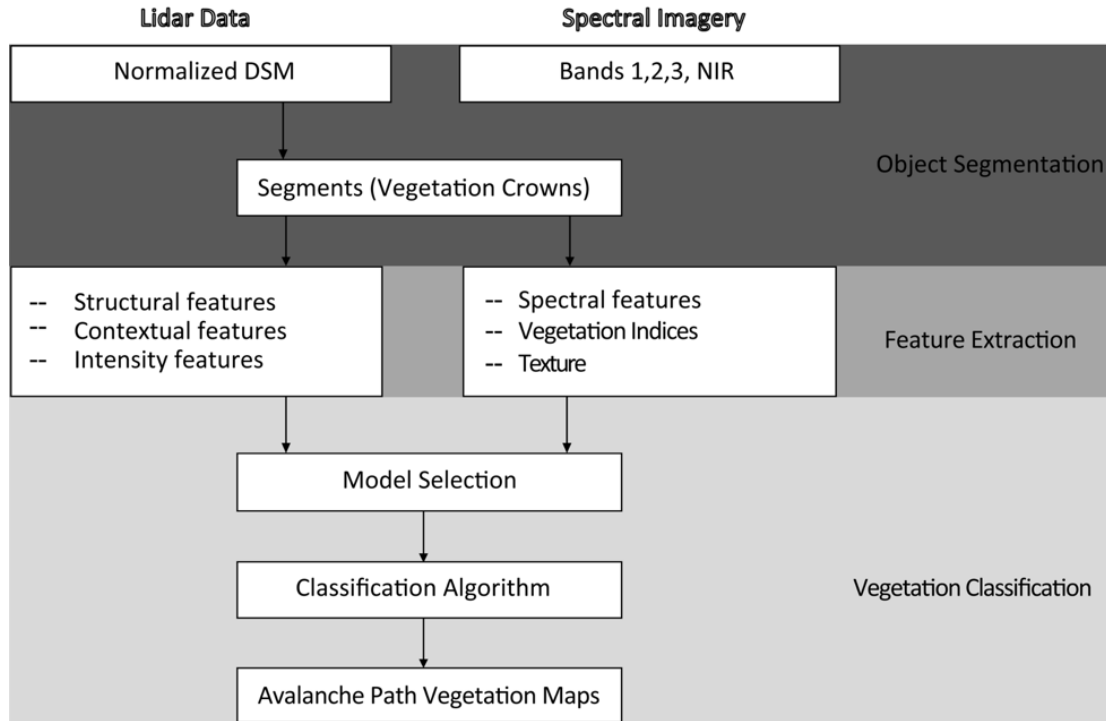


Figure 2: General workflow of classification procedure from data processing to final vegetation classification.

2.4 Manual Vegetation Classification

In order to create an automated vegetation classification procedure using remote sensing products, we first manually classified the vegetation of a sample of objects in the imagery to create a training dataset. To accomplish this, we selected 300 individual points from the segmented lidar (CHM) dataset for each avalanche path and manually classified each point to the Level 1 vegetation type based on the NAIP imagery (Table 2). Only objects that were clearly identifiable by vegetation type and had no confusion with other vegetation types were labeled. In object classes with low sample size, we included additional crown objects in those classes. The resultant total sample size for the crown objects increased from 300 to approximately 400 for each path. Originally, we manually identified between 15 and 19 classes in each avalanche path. We then aggregated the

classes from Level 1 (all classes) to Level 3 (coarse vegetation classes) to reflect broad classes applicable to the analysis of avalanche path vegetation composition (Table 2).

Table 2: Class aggregation for avalanche path return period analysis and detailed class descriptions.

Level 1 All classes used in original classification	Level 2 Aggregated classes to reflect vegetation type	Detailed class descriptions	Level 3 Further aggregated classes relevant to avalanche path return period analysis
Conifer no shadow Conifer with some shadow Conifer in shadow Subalpine Fir Dead Conifer	Coniferous forest	Subalpine Fir, Douglas Fir, Lodgepole Pine, White Spruce, Black Spruce	Mature forest
Deciduous forest Deciduous with some shadow	Deciduous forest	Cottonwood, Birch, Aspen, Larch	
Green shrub Green shrub in shadow Yellow shrub	Green shrub Yellow shrub	Alder, False Huckleberry Willow, Service berry, young Aspen, young Cottonwood, young Birch	Shrubland
Red shrub	Red shrub	Mountain Maple, Mountain Ash, Dogwood	
Huckleberry	Huckleberry	Huckleberry	
Brown grassland/shrubland Off-white grassland/shrubland Green grassland/shrubland	Grassland	Beargrass, Thimbleberry, Solomon Seal, grasses	Grassland
Grey rock outcrop White rock outcrop	Exposed rock	Exposed rock	Exposed rock
Snow Snow in shadow	Snow	Seasonal snow	Snow

We calculated metrics commonly used to distinguish differences between tree species for each delineated tree crown object (Brandtberg et al., 2003; Holmgren and Persson, 2004). These metrics can be grouped into three categories:

- (1) *Structural features*. The lidar measured maximum height and crown diameter for each tree object were extracted.
- (2) *Contextual features*. Z represents the lidar derived DTM + CHM. Maximum, mean, and standard deviation of Z were all calculated for each tree object as well as quantile metrics including 30th percentile, 50th percentile, 70th percentile, and 90th percentile.
- (3) *Intensity features*. Maximum, mean, and standard deviation of intensity were calculated for each tree object as well as intensity quantile metrics including 30th percentile, 50th percentile, 70th percentile, and 90th percentile.

Values from the spectral imagery were also extracted for each lidar-derived tree crown object and are grouped into the following three categories:

- (1) *Spectral features*. Mean value of all pixels within each tree crown object were extracted for bands 1, 2, 3, and 4 and used as features.
- (2) *Vegetation indices*. Mean normalized difference vegetation index (NDVI) was calculated for each tree crown object based on the equation:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (1)$$

where NIR is near infrared band and RED is the red band. We calculated mean Green-Red Vegetation Index (GRVI) for each tree crown object using the equation:

$$GRVI = \frac{(GREEN - RED)}{(GREEN + RED)} \quad (2)$$

- (3) *Texture*. NDVI variance and entropy were calculated for each tree crown object (Lillesand and Kiefer, 2000).

2.5 Model Selection and Image Classification

We grouped lidar-extracted metrics (e.g. descriptive statistics for intensity were grouped together, quantile statistics for intensity were grouped together, etc.) for inclusion in a model selection procedure. We used a Random Forest model (Breiman, 2001), an ensemble learning method for image classification that operates by developing several decision trees where each node is split based on the best of a subset of predictors, for our classification procedure. We calculated the kappa value for each random forest model of all possible combinations of lidar-derived metrics as well as all possible combinations of spectral signature-derived variables. We then used the metrics from the highest ranked model from both spectral signature-derived (Model 1-5) and lidar-derived metrics (Model 6-21) and combined them to produce a final best-fit model.

Each model was trained on a randomly chosen set of regions of interest (ROIs) within each avalanche path, representing approximately 50% of all ROIs ($n \approx 200$). The remaining 50% of the ROIs acted as a validation subset. We performed the model selection on each individual avalanche path and used the best performing model to predict vegetation across each avalanche path. The model was trained separately for each path due to different class prevalence between paths. All Random Forest modeling was performed in R using the caret package (Kuhn et al., 2019) with 100 resampling iterations for each model. Finally, we classified the segmented tree crown vector layer by vegetation type using the combined lidar and spectral signature best-fit model.

2.6 Dendrochronological Analysis and Return Period Reconstruction

This analysis utilizes the dendrochronology generated spatial-temporal avalanche data set by Peitzsch et al. (2019) and as presented in detail in Peitzsch et al. (In Prep.). Briefly, our sampling strategy targeted an even number of samples collected across the path where material was available and along the trimlines within each avalanche path at varying elevations. Location data were not available for all samples in the Shed 10-7 path, therefore we excluded it from the return period analysis. In Path 1163 and Shed 7 we collected a total of 96 cross sections. We sanded the samples to a fine polish to expose the anatomy of each growth ring, and cross-dated cores and cross sections with each other using the skeleton plot method to account for missing and false-rings (Stokes and Smiley, 1996). We developed a site composite chronology and cross-dated with preexisting regional chronologies to confirm the exact calendar dating of each tree-ring (ITRDB, 2018) using the dating quality control software COFECHA (Grissino-Mayer, 2001; Holmes, 1983). For further details on cross dating methods and accuracy calculation for this dataset see Peitzsch et al. (2019).

We used a combination thin plate spline and expert knowledge technique to reconstruct the return periods. Thin plate spline is a spatial interpolation method that minimizes the residual sum of squares subject to a constraint that the function has a certain level of smoothness. This technique has previously been used in estimating climate and rainfall (Hutchinson, 1995; Tait et al., 2006). The general partial thin plate spline observational model for n point values z_i at locations x_i is represented by

$$z_i = f(x_i) + \sum_{j=1}^p \beta_j \psi_j(x_i) + \varepsilon_i \quad (i = 1, \dots, n; j = 1, \dots, p), \quad (3)$$

where f is an estimated unknown smoothing function, ψ_j are a set of p known functions, β_j are a set of estimated unknown parameters, and ε_i are zero mean random errors. The smoothing parameter is estimated by minimizing the generalized cross-validation. See Hutchinson (1995) for further details using thin plate spline techniques for spatial interpolation. We converted the return period raster layers into vectors and grouped the return periods by 5-year intervals. The resultant return period polygons produced by using thin plate spline methods were manually smoothed using basic knowledge of avalanche flow as well as recent (within the past 10 years) spatial observations of avalanche flow and debris deposits in the two avalanche paths. Using expert knowledge in delineating minimum avalanche extent allows for more realistic values and scenarios when using interpolation techniques to derive return periods over space (Favillier et al., 2018; Meseşan et al., 2018). Lastly, we intersected the vegetation classification vector layers with the return period layers in order to calculate the proportion of each vegetation class for each return period.

3. Results

3.1 Lidar Field Validation

Comparing the mean in-situ canopy height measurements against the mean lidar canopy height measurements for each of the five plots yielded reasonably matched distributions and plot means that were strongly related ($R^2 = 0.85$) (Figure 3).

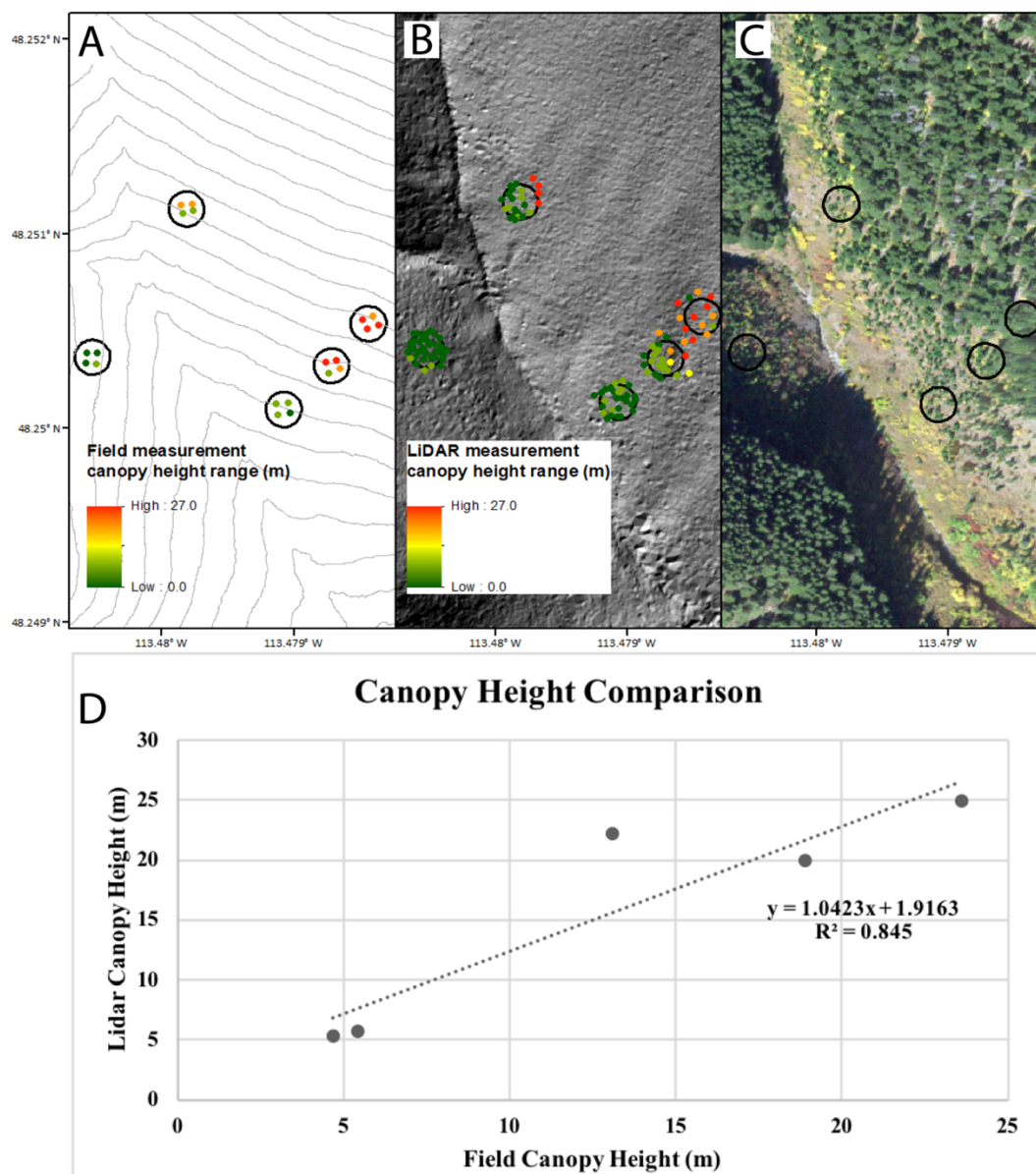


Figure 3: Canopy height measurements. (A) represents the in-situ height measurements of the four tallest trees in each plot. Contour lines represent 10 m elevation intervals. (B) represents the field plots with lidar measurements for each plot. Note that samples outside the plots were considered in the validation procedure because their canopy extended over the plot area. (C) represents the field measurement plots with the spectral imagery. (D) shows the relationship of measured mean height within each field plot (x-axis) against the lidar canopy height (y-axis).

3.2 Manually classified objects (ROI)

Each avalanche path contains a unique combination of specific avalanche vegetation classes. We attempted to manually identify similar amounts of each vegetation class within each path. Given the lack of some classes in each path the number of manually identified classes varies (Table 3).

Table 3: The number of objects (points) manually identified in each vegetation class within each avalanche path. n/a represents classes not present in corresponding classification.

ROIs in each vegetation class			
Level 1 Vegetation Class	Path 10.7	Path 1163	Shed 7
Conifer no shadow	27	31	15
Conifer with some shadow	55	50	20
Conifer in shadow	16	29	7
Subalpine fir	n/a	n/a	26
Dead conifer	8	8	17
Deciduous forest	34	31	49
Deciduous with some shadow	27	12	n/a
Green shrub	30	n/a	18
Green shrub in shadow	n/a	n/a	19
Yellow shrub	35	33	20
Red shrub	33	20	23
Huckleberry	n/a	n/a	18
Brown grassland/shrubland	29	28	11
Off-white grassland/shrubland	40	37	23
Green grassland/shrubland	n/a	21	n/a
Grey rock outcrop	n/a	19	n/a
White rock outcrop	40	34	19
Snow	26	27	6
Snow in shadow	10	10	29
TOTAL	410	390	320

3.3 Random Forest Model Classification

Accuracy results reflect the ability of the Random Forest model to automate vegetation classification against our manually identified vegetation classification. The

importance of each variable is different for each path (Figure 4). For Shed 7, models 4 and 18 had the highest-ranking kappa value based on the spectral and lidar datasets, respectively (Table 4). Vegetation predicted across Shed 10-7 based on these two combined models resulted in an overall accuracy of 88% (kappa value 0.86). For 1163, models 5 and 21 had the highest-ranking kappa values and when combined resulted in an overall accuracy of 91% (kappa value 0.89). For Shed 7, models 4 and 21 had the highest-ranking kappa value, and when combined resulted in an overall accuracy of 92% (kappa value 0.91). Accuracy statistics were calculated following aggregation to Level 2 vegetation classes (Table 2).

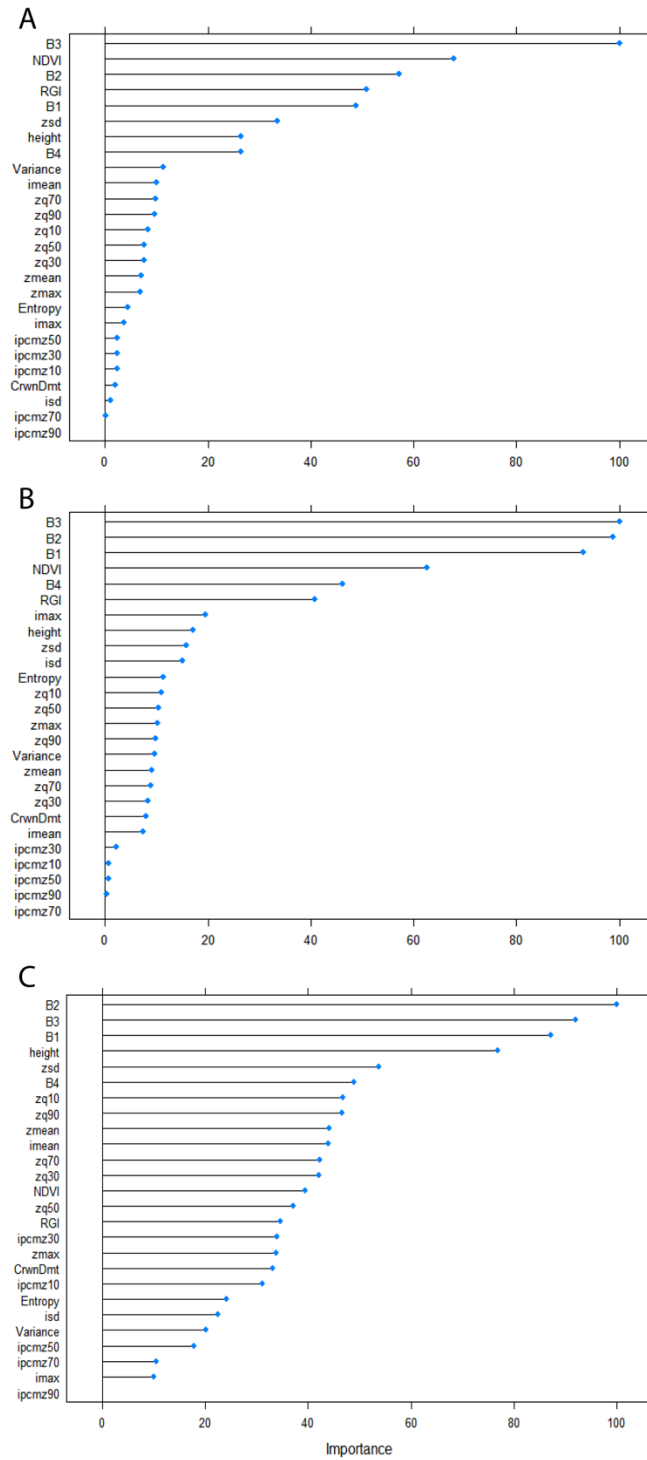


Figure 4: Variable importance plots. The relative importance of each variable in the random forest model for (A) Shed 10-7, (B) 1163, and (C) Shed 7.

Table 4: Overall accuracies and kappa values for random forest models of the combinations of spectral variables and lidar variables. Models in each category with highest kappa value were combined in best-fit model for each avalanche path. Best-fit models for each avalanche path are reported at the bottom of the table. I percentile statistics = the 10th, 30th, 50th, 70th and 90th percentiles of intensities; I descriptive statistics = the maximum, mean and standard deviation of intensities; z percentile statistics = the 10th, 30th, 50th, 70th and 90th percentiles of elevations; z descriptive statistics = the maximum, mean and standard deviation of the elevation. Bold indicates best-fit model.

Spectral imagery variables					Lidar data features						Shed 10-7		1163		Shed 7	
Model	B1-B4	NDVI	GRVI	Texture	Crown height	Crown diameter	I percentile statistics	I descriptive statistics	Z percentile statistics	Z descriptive statistics	Kappa Value	Overall Accuracy	Kappa Value	Overall Accuracy	Kappa Value	Overall Accuracy
1	X										0.80	83%	0.75	80%	0.69	74%
2	X	X									0.83	86%	0.76	81%	0.70	74%
3	X	X	X								0.85	87%	0.74	79%	0.71	75%
4	X	X	X	X							0.87	89%	0.82	86%	0.80	83%
5	X	X		X							0.80	83%	0.84	87%	0.80	83%
6					X						0.17	30%	0.26	41%	0.37	47%
7					X	X					0.25	36%	0.31	44%	0.37	46%
8					X	X	X				0.28	39%	0.27	41%	0.53	60%
9					X	X		X			0.47	54%	0.47	56%	0.60	66%
10					X	X	X	X			0.47	54%	0.46	56%	0.68	73%
11					X	X				X	0.65	70%	0.61	68%	0.77	80%
12					X	X			X		0.60	66%	0.61	69%	0.74	78%
13					X	X			X	X	0.62	67%	0.61	69%	0.74	78%
14					X	X	X		X		0.62	67%	0.64	71%	0.77	81%
15					X	X	X	X	X		0.58	64%	0.66	72%	0.83	86%
16					X	X		X		X	0.65	70%	0.63	71%	0.81	84%
17					X	X		X	X		0.62	68%	0.66	72%	0.81	84%
18					X	X		X	X	X	0.65	70%	0.68	74%	0.81	84%
19					X	X	X			X	0.63	69%	0.65	72%	0.78	81%
20					X	X	X	X		X	0.61	67%	0.65	72%	0.76	80%
21					X	X	X	X	X	X	0.60	66%	0.69	75%	0.84	87%
Best Spectral + Best Lidar																
Path 10-7	X	X	X	X	X	X		X	X	X	0.86	88%				
Path 1163	X	X		X	X	X	X	X	X	X			0.89	91%		
Shed 7	X	X	X	X	X	X	X	X	X	X					0.91	92%
All Variables																
Path 10-7	X	X	X	X	X	X	X	X	X	X	0.88	90%				
Path 1163	X	X	X	X	X	X	X	X	X	X			0.89	91%		
Shed 7	X	X	X	X	X	X	X	X	X	X					0.91	92%

All three classifications exhibited minor confusion between deciduous forest and coniferous forest classes (Table 5 and Figure 5). In Shed 10-7 and Shed 7, there was minor confusion amongst grassland, green shrub, yellow shrub and red shrub, as well as confusion between deciduous forest and yellow shrub. In Shed 10-7 there was minor confusion between coniferous forest and green shrub, and coniferous forest and snow. In 1163, rock outcrop was confused with snow.

Table 5: Confusion matrices associated with the best fit model for each individual avalanche path. Actual classifications are in the left column and predicted values are in the top row for each path. Confusion matrices for the best fit spectral and lidar can be found in Table S1.

<i>Shed 10-7</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	15	0	0	0	0		4	1	2
Coniferous forest	0	40	0	0	0		0	0	0
Deciduous forest	1	2	34	0	0		0	0	0
Snow	0	2	0	15	0		0	1	0
Green shrub	2	2	0	0	14		0	0	0
Huckleberry									
Red shrub	1	1	0	0	0		13	0	1
Exposed rock	0	0	0	0	0		0	20	0
Yellow shrub	0	0	2	0	0		0	0	10

<i>Path 1163</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	29	0	0	0			0	0	1
Coniferous forest	1	55	1	0			0	0	0
Deciduous forest	0	2	21	0			0	0	1
Snow	0	0	0	14			0	6	0
Green shrub									
Huckleberry									
Red shrub	1	0	0	0			8	0	0
Exposed rock	0	0	0	1			0	17	0
Yellow shrub	1	0	0	0			0	0	15

<i>Shed 7</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	19	0	0	0	0	0	0	0	2
Coniferous forest	0	67	0	0	1	0	0	0	0
Deciduous forest	0	5	39	0	0	0	0	0	0
Snow	0	0	0	13	0	0	0	0	0
Green shrub	0	0	0	0	34	1	0	0	0
Huckleberry	1	0	0	0	0	9	0	0	0
Red shrub	3	0	0	0	0	0	8	0	2
Exposed rock	0	0	0	0	0	0	0	28	0
Yellow shrub	2	0	2	0	0	0	0	1	17

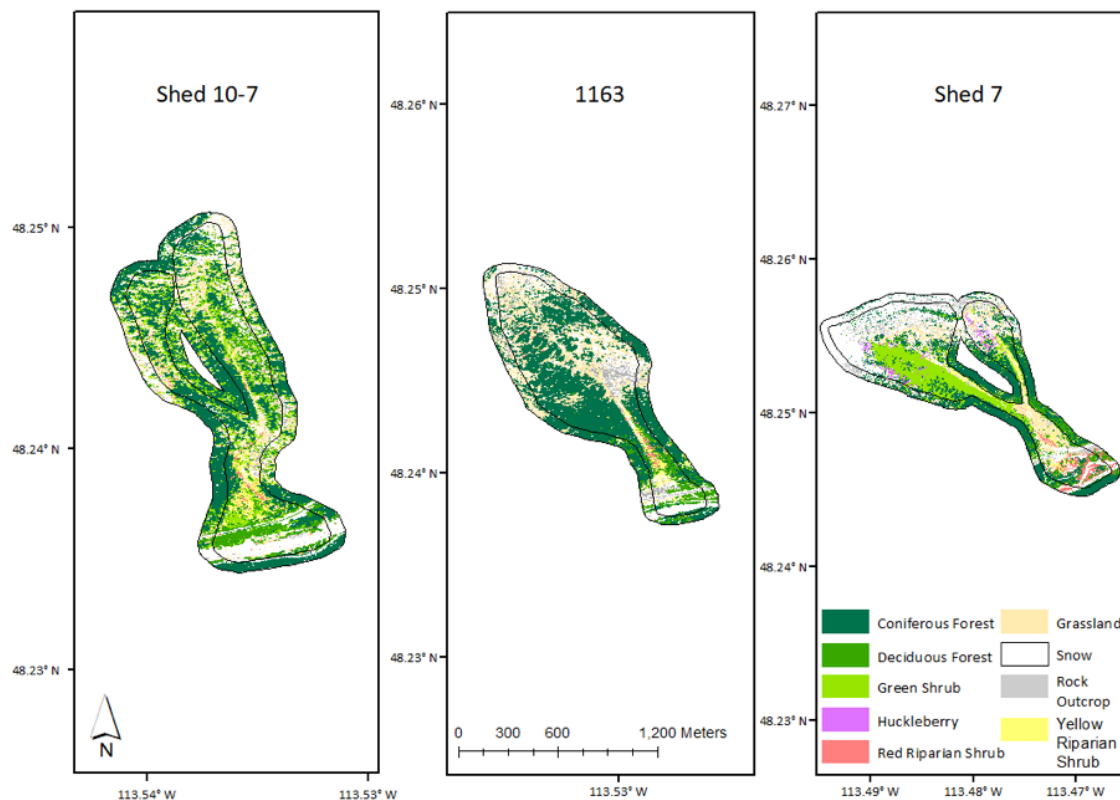


Figure 5: Labeled vegetation mapping results for Shed 10-7, 1163 and Shed 1163 using a combination of spectral and LiDAR data. The avalanche paths are outlined with a 50 m buffer (black polygons) for context of surrounding vegetation. Note these three paths are not all adjacent to each other.

Combining lidar and spectral imagery to automate species level vegetation classification yielded high overall accuracy for all three avalanche paths when compared to the manual classification of vegetation within avalanche paths using aerial imagery. In Path 1163 and Shed 7, combining spectral and lidar-derived variables represents a substantial improvement in overall accuracy from using spectral imagery alone, and from lidar data alone (+16% and +6% respectively) in the ability to map vegetation within avalanche paths (an improvement of +5% and +9% respectively) (Table 6). In Shed 10-7, combining spectral and lidar-derived variables resulted in a decrease in overall accuracy of -1% (within 95% CIs) when compared to overall accuracy obtained from spectral

imagery alone, and an increase of +17% compared to overall accuracy obtained from lidar-derived variables.

Table 6: Classification accuracies for each avalanche path using different data sets. See Table 3 for metrics included in each experiment. See Table S1 and S2 for confusion matrices on best-fit spectral and best-fit lidar models.

	1: Spectral		2: Lidar		3: Combined	
Path	Kappa value	Overall accuracy	Kappa value	Overall accuracy	Kappa value	Overall accuracy
Shed 10-7	0.87	89%	0.60	66%	0.88	90%
1163	0.82	86%	0.69	75%	0.89	91%
Shed 7	0.80	83%	0.84	87%	0.91	92%

3.4 Return Period Vegetation

The return period results from the thin plate spline and expert knowledge modification for Path 1163 and Shed 7 suggest minimum return periods of 5-10 years and 10-15 years for the locations sampled in Path 1163 and Shed 7, respectively (Figure 6). We were unable to reconstruct the 5-10-year return period intervals for S7 due to our strategic sampling for large magnitude avalanche events. Had we sampled higher in the path we likely would have captured this return period. However, the purpose of sampling was to capture relatively infrequent large magnitude events. In addition, we were unable to reconstruct return period intervals beyond 35-40 years in Path 1163 because we did not sample below the railway. We refrained from sampling below the railroad due to the potential for disturbance from railway and highway operations in the tree-ring signal. The number of trees available for sampling below the railway was also very limited.

The RMSE for Path 1163 is 6.43, and 15.65 for Shed 7. The mapped return periods generally follow the slope morphology with higher frequency return periods

centered around the incised channel along the vertical extent of the slope for both avalanche paths. However, for Shed 7, return periods for a corner of the southwest portion of the path are high frequency where the highest frequency interval is no longer associated with the incised channel.

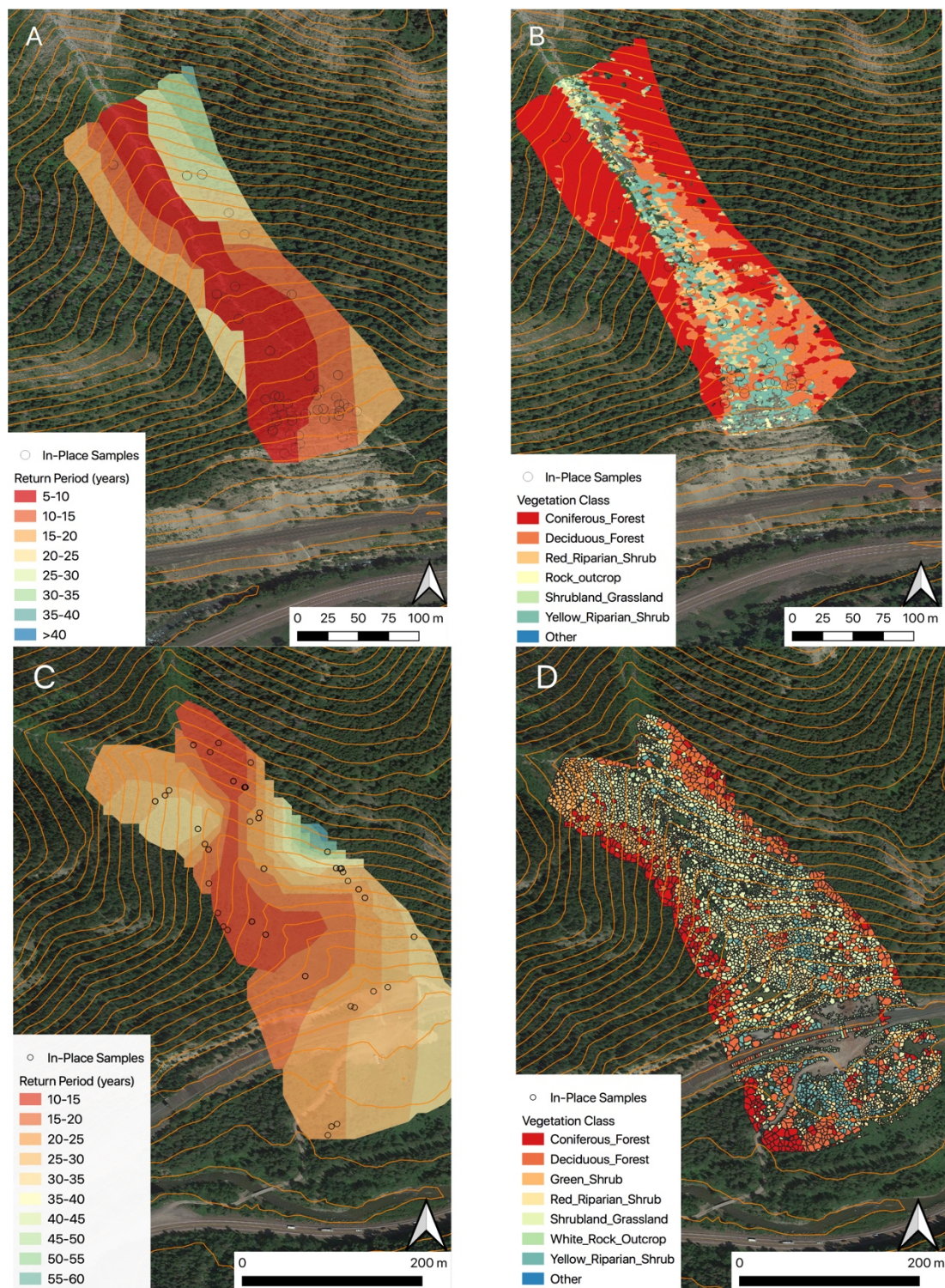


Figure 6: Return periods (A,C) and Random Forest model generated vegetation classes for return interval zones (B,D) for Path 1163 (A,B) and Shed 7 (C,D). The orange lines represent contour lines spaced at 10 m intervals to illustrate topography changes.

The proportion of vegetation classes within the return period intervals for both avalanche paths generally follows a similar pattern. The proportion of shrubland and grassland is greater in areas of higher frequency avalanche activity and the proportion of forest is greater in areas of lower frequency (Figure 7). However, in Path 1163, the high frequency interval locations are comprised of substantial amounts of forest and a greater amount than Shed 7 when comparing similar return intervals. Shed 7 also contains substantially more grassland than Path 1163 throughout all of the return period zones except the 60-65 year return period zone.

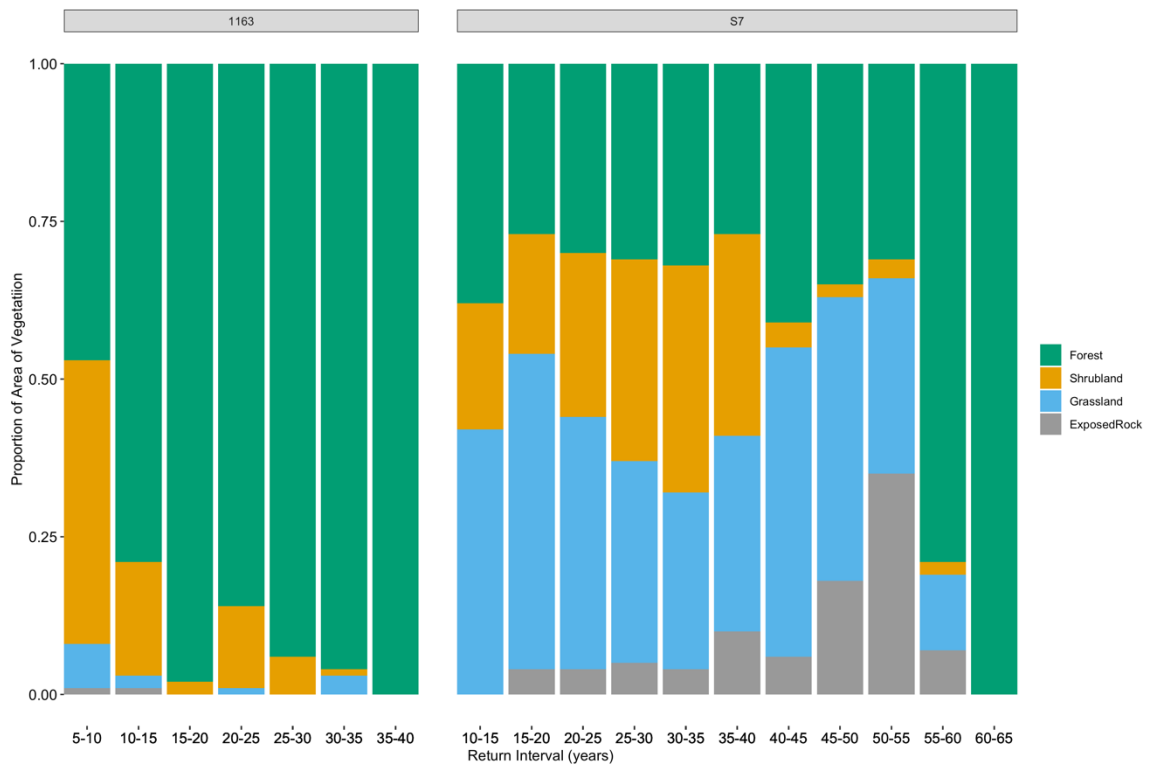


Figure 7: Proportions of each vegetation class for Path 1163 (left) and Shed 7 (right). Return Interval years are represented on the x-axis. Vegetation classes are represented by color (legend on right).

4. Discussion

4.1 Vegetation Classification

Using lidar and spectral imagery products to estimate avalanche path vegetation classes appears promising. The strong correlation between lidar canopy height and field-measured canopy height suggests lidar estimates are suitable for vegetation class modeling. Slight differences between the measured and lidar height datasets can be attributed to using plot mean height values instead of comparing individual tree heights from one dataset to another. Comparing individual tree heights between datasets would require cm-level resolution for each dataset, and the lidar data have a resolution of 0.5 m. Field measurement error could also be a source of error given the steep terrain associated with the plots.

For all paths, we used the best fit Random Forest model that combined the best spectral with the best lidar Random Forest models. However, in the interest of experimenting with a less complex model, for Shed 7 we manually omitted elevation and intensity quantile statistics and maximum values resulting in a decrease of approximately -2% overall accuracy for Shed 7 when compared to the full best-fit Random Forest model. This suggests that the full suite of metrics used for the best-fit model is necessary to obtain higher accuracy for vegetation modeling in avalanche paths. Accordingly, we did not run a Random Forest model for all permutations of variables because of the increase in accuracy as variables were added to each model.

A large-magnitude avalanche in Path 1163, and medium-sized avalanches in Shed 10-7 and Shed 7 occurred in March 2017, falling between the lidar and NAIP data

collection dates. This could impact the labeling of training and validation tree crowns, since we delineated crowns from the lidar data but manually classified vegetation based on NAIP imagery. For example, it is possible that a tree crown that existed in 2016 no longer existed in 2017, resulting in a polygon manually classified with spectral attributes with physical variables related to the previous landcover (i.e. an ROI labeled grassland in 2017 imagery was a coniferous tree in 2016 with associated canopy variables). This could be one source of confusion between classes and could have negatively impacted overall accuracy values.

The starting zones of each avalanche path are characterized by predominantly grassland and rock outcrop except for Shed 10-7 which is characterized by grassland and coniferous forest. The coniferous forest in Shed 10-7 is comprised of generally small trees characteristic of tree-line forests. One possible explanation for this is that Shed 10-7 is dominated by vegetation classes easily distinguishable by spectral variables (e.g. coniferous forest and senesced grassland) and as a result does not rely as heavily on variables such as canopy height, or that in some classes (e.g. coniferous forest) the age of vegetation varies greatly and was not completely captured when we developed our regions of interest. Using Ikonos satellite imagery in the same study area as ours, Walsh et al. (2004) found higher greenness levels at higher elevations suggesting the presence of mixed shrubs and herbaceous material, and lower greenness levels at lower elevations where the accumulation of debris piles and other downed and scoured materials may exist. Our results suggest vegetation patterns along an elevational gradient within an

avalanche path are more complex than a simple pattern with smaller, herbaceous vegetation near the starting zones and larger trees near the runout zones.

Vegetation patterns across a lateral transect indicate shrub or grasslands associated with incised stream channels in all three avalanche paths. Similarly, Walsh et al. (2004) found a decrease in greenness away from the center of the avalanche track indicating more herbaceous shrubs in the center of the paths and larger trees toward the trimlines of the avalanche paths. However, the lateral composition of vegetation also varies along an elevational gradient despite the strong signal of grassland in the incised channel. In other words, the vegetation along the flanks adjacent to the incised channel zone is not consistent up and down the avalanche paths. This coincides with earlier work by Malanson and Butler (1986) and Erschbamer (1989).

4.2 Return Period Intervals and Vegetation Classification

The return periods derived for the runout zones using only the thin plate spline procedure without manual smoothing exhibited substantial error. However, implementing slight modifications of the return period polygons based on expert knowledge of avalanche flow allowed for more realistic return period scenarios. The return periods depicted here are likely underestimations given the limitation of dendrochronological techniques in developing an avalanche chronology (Corona et al., 2012), particularly in locations where few samples exist (e.g. the incised channel on the avalanche paths). Therefore, the absolute values of the return periods should be used with caution, and the patterns of return periods are the more critical component to this analysis.

The location in Shed 7 where the highest frequency band continues into the southwest sector of the path and no longer follows the incised channel is likely due to a substantial decrease in slope angle and more uniform planar slope. The stream channel is not as deep at this location potentially allowing avalanche debris to disperse laterally. This is also the point where a decrease in avalanche velocity occurs as it nears the theoretical alpha angle (Mears, 1989).

For Shed 7, locations with higher frequency avalanche activity within the mapped area are characterized predominantly by grassland and shrubland, which are mostly shade intolerant species, and this is consistent with previous work (Butler, 1979). However, for Path 1163, the zone with the highest frequency return period consists of nearly half shrubland and half forest. This avalanche path is steep and narrow with a constriction approximately two-thirds down the avalanche path from the top. Thus, very frequent avalanches are likely to follow the incised channel, but avalanches at the upper limit of the 5 to 10-year frequency zone or lower limit of the 10 to 15-year frequency zone appear to spread more laterally across the lower track and runout zone. In Path 1163, the relatively large proportion of forest in the two most frequent return periods zones is likely attributable to the influence of the incised channel constraining avalanche flow to a certain level within the path or the ability of small to moderately sized trees to withstand avalanche impact. These trees may be young, but large enough to be characterized as coniferous forest in the vegetation classification (Kajimoto et al., 2004).

Differences in vegetation within the specific return periods for Path 1163 and Shed 7 are due to the geomorphology of each slope. Path 1163 has a smaller and

narrower starting zone and is further constrained by the narrow, incised channel of the track. This causes all of the return periods within the path to be laterally narrower when compared to Shed 7 with potentially more overlap. Shed 7, on the other hand, has a wide starting zone and track and is, overall, less steep than Path 1163. This allows avalanches to disperse more easily thereby causing a greater proportion of each return period to harbor grassland and shrubland vegetation classes.

It would be useful to train a vegetation model on one or several avalanche paths to be able to predict across other avalanche paths where return period data are nonexistent. However, our results suggest doing so would be potentially inaccurate because of the variable vegetation classes and patterns across any given path. The best-fit model in each path is highly dependent upon the vegetation class prevalence within the given path. Therefore, to extrapolate return period intervals across a large area using a lidar and spectrally derived vegetation model would require a larger training dataset from a wide variety of avalanche paths and a very large tree-ring reconstructed return period interval dataset.

Future work should consider classifying the return period zones based solely on canopy height of the coniferous forest alone to identify if any nuances in adjacent return period zones exist. The low frequency return period zones in both avalanche paths are characterized by predominantly forest, which is expected, but are still prone to impact from larger avalanches (Teich et al., 2012). Therefore, investigating patterns in canopy height alone may provide some basic insight into broad vegetation classes. However,

inferring return periods from lidar data requires observational or tree-ring return period data.

4.3 Limitations

We recognize that the vegetation composition of the avalanche paths is only representative of the time when data were collected. Timing of data acquisition, often a factor of data availability, can impact classification accuracy in the event of disturbances such as avalanches around the time of data collection. In this study, lidar data were collected in July to August 2016. In the absence of NAIP imagery collected in 2016, we chose to work with 2017 NAIP imagery due to its unusually late collection date (September/October) and therefore unique ability to aid in differentiating between species groups that at other times of the year would have similar spectral signatures. The coarse resolution (30 m) of Landsat data (while available semi-monthly) would negate the utility of the high-resolution (crown-level) lidar. Another limitation is the underestimation that using dendrochronological techniques can yield in terms of avalanche frequency. The proportions of vegetation classes within return period zones would potentially change if avalanche return periods were more frequent.

5. Conclusions

In this study, we implemented a novel approach using lidar and aerial imagery and a Random Forest model to classify vegetation within avalanche paths. We then used dendrochronological techniques combined with spatial interpolation to calculate avalanche return periods and characterize the vegetation within those return period zones.

By synchronizing the timing of dendrochronological data collection with vegetation mapping we were able to generally classify vegetation in return period zones. Our results suggest the combination of lidar and spectral signature metrics provide the best accuracy for predicting vegetation classes within complex avalanche terrain rather than lidar or spectral signatures alone. The zones with highest frequency return periods were broadly characterized by grassland and shrubland, but topography greatly influences the vegetation classes as well as the return periods. The ability to characterize vegetation within various avalanche return period zones using remote sensing data provides land use planners and avalanche forecasters a tool for assessing the ecological effects of large magnitude avalanche events.

REFERENCES

- Allen, T.R., Walsh, S.J., Cairns, D.M., Messina, J.B., D. R. and Malanson, G.P., 2004. Geostatistics and spatial analysis: characterizing form and pattern at the alpine treeline. In: M. Bishop and J. Shroder (Editors), *Geographic Information Science and Mountain Geomorphology*. Springer Verlag-Praxis Scientific.
- Bartelt, P. and Stockli, V., 2001. The influence of tree and branch fracture, overturning and debris entrainment on snow avalanche flow. *Annals of Glaciology*, 32: 209-216.
- Bebi, P., Kulakowski, D. and Rixen, C., 2009. Snow avalanche disturbances in forest ecosystems-State of research and implications for management. Elsevier Science Bv, pp. 1883-1892.
- Becker, A., Körner, C., Gurung, A.B. and Haeberli, W., 2007. Selected Issues from the Samedan GLOCHAMORE Workshop on Altitudinal Gradient Studies. *Mountain Research and Development*, 27(1): 82-86.
- Brandtberg, T., Warner, T.A., Landenberger, R.E. and McGraw, J.B., 2003. Detection and analysis of individual leaf-off tree crowns in small footprint, high sampling density lidar data from the eastern deciduous forest in North America. *Remote Sensing of Environment*, 85(3): 290-303.
- Breiman, L., 2001. Random Forests. *Machine Learning*, 45: 5-32.
- Burrows, C.J. and Burrows, V.L., 1976. Procedures for the study of snow avalanche chronology using growth layers of woody plants, Institute of Arctic and Alpine Research, University of Colorado, Boulder, CO.
- Butler, D.R., 1979. Snow avalanche path terrain and vegetation, Glacier National Park, Montana. *Arctic and Alpine Research*, 11(1): 17-32.
- Butler, D.R. and Malanson, G., P., 1985. A history of high-magnitude snow avalanches, southern Glacier National Park, Montana, U.S.A. *Mountain Research and Development*, 5(2): 175-182.
- Corona, C., Lopez Saez, J., Stoffel, M., Bonnefoy, M., Richard, D., Astrade, L. and Berger, F., 2012. How much of the real avalanche activity can be captured with tree rings? An evaluation of classic dendrogeomorphic approaches and comparison with historical archives. *Cold Regions Science and Technology*.
- Deems, J.S., Painter, T.H. and Finnegan, D.C., 2013. Lidar measurement of snow depth: a review. *Journal of Glaciology*, 59(215): 467-479.

- Erschbamer, B., 1989. Vegetation on avalanche paths in the Alps. *Vegetatio*, 80: 139-146.
- Favillier, A., Guillet, S., Trappmann, D., Morel, P., Lopez-Saez, J., Eckert, N., Zenhäusern, G., Peiry, J.-L., Stoffel, M. and Corona, C., 2018. Spatio-temporal maps of past avalanche events derived from tree-ring analysis: A case study in the Zermatt valley (Valais, Switzerland). *Cold Regions Science and Technology*, 154: 9-22.
- Feistl, T., Bebi, P. and Bartelt, P., 2013. The role of slope angle, ground roughness and stauchwall strength in the formation of glide-snow avalanches in forest gaps. In: F. Naaim-Bouvet, Y. Durand and R. Lambert (Editors), *Proceedings of the 2013 International Snow Science Workshop*, Grenoble, France, pp. 760-765.
- Feistl, T., Bebi, P., Teich, M., Buhler, Y., Christen, M., Thuro, K. and Bartelt, P., 2014. Observations and modeling of the braking effect of forests on small and medium avalanches. *Journal of Glaciology*, 60(219): 124-138.
- Grissino-Mayer, H., 2001. Evaluating crossdating accuracy: A manual and tutorial for the computer program COFECHA. *Tree-Ring Research*, 57(2): 205-221.
- Hesdstrom, N.R. and Pomeroy, J.W., 1998. Measurements and modelling of snow interception in the boreal forest. *Hydrological Processes*, 12: 1611-1625.
- Holmes, R.L., 1983. Analysis of tree rings and fire scars to establish fire history. *Tree-Ring Bulletin*, 43: 51-67.
- Holmgren, J. and Persson, A., 2004. Identifying species of individual trees using airborne laser scanner. *Remote Sensing of Environment*, 90(4): 415-423.
- Holmgren, J., Persson, A. and Soderman, U., 2008. Species identification of individual trees by combining high resolution LIDAR data with multi-spectral images. *International Journal of Remote Sensing*, 29(5): 1537-1552.
- Hutchinson, M.F., 1995. Interpolating mean rainfall using thin plate smoothing splines. *International journal of geographical information systems*, 9(4): 385-403.
- Hyypä, J., Kelle, O., Lehikoinen, M. and Inkinen, M.A., 2001. A segmentation-based method to retrieve stem volume estimates from 3-D tree height models produced by laser scanners. *IEEE Transactions on Geoscience and Remote Sensing*, 39: 969-975.
- ITRDB, 2018. International Tree Ring Data Bank (ITRDB).
- Johnson, E.A., 1987. The relative importance of snow avalanche disturbance and thinning on canopy plant populations. *Ecology*, 68(1): 43-53.

- Kajimoto, T., Daimaru, H., Okamoto, T., Otani, T. and Onodera, H., 2004. Effects of snow avalanche disturbance on regeneration of subalpine *Abies mariesii* forest, Northern Japan. *Arctic, Antarctic, and Alpine Research*, 36(4): 436-554.
- Khosravipour, A., Skidmore, A.K., Isenburg, M., Wang, T.J. and Hussin, Y.A., 2014. Generating Pit-free Canopy Height Models from Airborne Lidar. *Photogrammetric Engineering and Remote Sensing*, 80(9): 863-872.
- Krajick, K., 1998. Animals thrive in an avalanche's wake. *Science*, 279(5358): 11853.
- Kuhn, M., Wing, J., Weston, S., Williams, A., Keefer, C., Engelhardt, A., Cooper, T., Mayer, Z., Kenkel, B., Benesty, M., Lescarbeau, R., Ziem, A., Scrucça, L., Tang, Y., Candan, C. and Hunt, T., 2019. caret: Classification and Regression Training. R package version 6.0-84. <https://CRAN.R-project.org/package=caret>.
- Kulakowski, D., Rixen, C. and Bebi, P., 2006. Changes in forest structure and in the relative importance of climatic stress as a result of suppression of avalanche disturbances. *Forest Ecology and Management*, 223(1-3): 66-74.
- Laes, D., Reutebuch, S.E., McGaughey, R.J. and Metchell, B., 2011. Guidelines to estimate forest inventory parameters from lidar and field plot data, U.S. Forest Service.
- Lefsky, M.A., Cohen, W.B., Parker, G.G. and Harding, D.J., 2002. Lidar Remote Sensing for Ecosystem Studies. *BioScience*, 52(1): 19.
- Leitinger, G., Höller, P., Tasser, E., Walde, J. and Tappeiner, U., 2008. Development and validation of a spatial snow-glide model. *Ecological Modelling*, 211(3-4): 363-374.
- Lillesand, T.M. and Kiefer, R.W., 2000. *Remote Sensing and Image Interpretation*, 4. Wiley & Sons, New York, New York, USA.
- Lim, K., Treitz, P., Wulder, M., St-Onge, B. and Flood, M., 2003. LiDAR remote sensing of forest structure. *Progress in Physical Geography*, 27(1): 88-106.
- Mace, R.D. and Waller, J.S., 1997. Spatial and temporal interaction of male and female grizzly bears in Northwestern Montana. *Journal of Wildlife Management*, 61(1): 39-52.
- Malanson, G.P. and Butler, D.R., 1984. Transverse pattern of vegetation on avalanche paths in the northern Rocky Mountains, Montana. *Great Basin Naturalist*, 44(3): 453-457.
- Malanson, G.P. and Butler, D.R., 1986. Floristic patterns on avalanche paths in the Northern Rocky Mountains, USA. *Physical Geography*, 7(3): 231-238.

- McClung, D. and Schaerer, P., 2006. The avalanche handbook. Mountaineers Books, Seattle, Wash.
- McCollister, C.M. and Comey, R.H., 2009. Using LiDAR (Light Distancing and Ranging) data to more accurately describe avalanche terrain, In: J. Schweizer and A. van Herwijnen (Editors), Proceedings of the 2009 International Snow Science Workshop, Davos, Switzerland, September 27-October 2, 2009., pp. 463-467.
- Mears, A.I., 1989. Regional comparisons of avalanche-profile and runout data. *Arctic and Alpine Research*, 21(3): 283-287.
- Meseşan, F., Gavrilă, I.G. and Pop, O.T., 2018. Calculating snow-avalanche return period from tree-ring data. *Natural Hazards*, 94(3): 1081-1098.
- Meyer, F. and Beucher, S., 1990. Morphological Segmentation. *Journal of Visual Communication and Image Representation*, 1(1): 21-46.
- Mock, C.J. and Birkeland, K.W., 2000. Snow avalanche climatology of the western United States mountain ranges. *Bulletin of the American Meteorological Society*, 81(10): 2367-2392.
- Molotch, N., Blanken, P., Williams, M., Turnipseed, A., Monson, R. and Margulis, S., 2007. Estimating sublimation of intercepted and sub-canopy snow using eddy covariance systems. *Hydrological Processes*, 21: 1567-1575.
- Musselmann, K.N., Molotch, N.P. and Brooks, P.D., 2008. Effects of vegetation on snow accumulation and ablation in a mid-latitude sub-alpine forest. *Hydrological processes*, 22: 2767-2776.
- Newesely, C., Tasser, E., Spadinger, P. and Cernusca, A., 2000. Effects of land-use changes on snow gliding processes in alpine ecosystems. *Basic and Applied Ecology*, 1(1): 61-67.
- NRCS, 2017. USDA Natural Resource Conservation Service, National Agricultural Imagery Program. Last Accessed: September 2019.
- Patten, R.S. and Knight, D.H., 1994. Snow avalanches and vegetation pattern in Cascade Canyon, Grand Teton National Park, Wyoming, USA. *Arctic and Alpine Research*, 26(1): 35-41.
- Peitzsch, E.H., Hendrikx, J. and Fagre, D.B., 2015. Terrain parameters of glide snow avalanches and a simple spatial glide snow avalanche model. *Cold Regions Science and Technology*, 120: 237-250.

- Peitzsch, E.H., Stahle, D.K., Fagre, D.B., Clark, A.M., Pederson, G.T., Hendrikx, J. and Birkeland, K.W., 2019. Tree ring dataset for a regional avalanche chronology in northwest Montana, 1636-2017. U.S. Geological Survey. <https://doi.org/10.5066/P9TLHZAI>.
- Peitzsch, E.H., Hendrikx, J., Stahle, D.K., Pederson, G.T., Fagre, D.B. and Birkeland, K.W., In Prep. A regional spatio-temporal analysis for large magnitude avalanches using tree rings. *Natural Hazards and Earth Systems Sciences*.
- Persson, A., Holmgren, J. and Soderman, U., 2002. Detecting and measuring individual trees using an airborne laser scanner. *Photogrammetric Engineering and Remote Sensing*, 68(9): 925-932.
- R, 2018. R Core Team - R Foundation for Statistical Computing. 2018, R: A Language and Environment for Statistical Computing, <https://www.R-project.org>, Vienna, Austria.
- Reardon, B.A., Pederson, G.T., Caruso, C.J. and Fagre, D.B., 2008. Spatial reconstructions and comparisons of historic snow avalanche frequency and extent using tree rings in Glacier National Park, Montana, U.S.A. *Arctic, Antarctic, and Alpine Research*, 40(1): 148-160.
- Rixen, C., Haag, S., Kulakowski, D. and Bebi, P., 2007. Natural avalanche disturbance shapes plant diversity and species composition in subalpine forest belt. *Journal of Vegetation Science*, 18: 735-A7.
- Roussel, J.-R. and Auty, D., 2019. lidR: Airborne LiDAR Data Manipulation and Visualization for Forestry Applications. R package version 2.1.4. <https://CRAN.R-project.org/package=lidR>.
- Silva, C.A., Crookston, N.L., Hudak, A.T., Vierling, L.A., Klauberg, C. and Cardil, A., 2017. rLiDAR: LiDAR Data Processing and Visualization. R package version 0.1.1. <https://CRAN.R-project.org/package=rLiDAR>
- Solberg, S., Naesset, E. and Bollandsas, O.M., 2006. Single tree segmentation using airborne laser scanner data in a structurally heterogeneous spruce forest. *Photogrammetric Engineering and Remote Sensing*, 72(12): 1369-1378.
- Stähli, M., Jonas, T. and Gustafsson, D., 2009. The role of snow interception in winter-time radiation processes of a coniferous sub-alpine forest. *Hydrological Processes*, 23(17): 2498-2512.
- Stokes, M.A. and Smiley, T.L., 1996. *An Introduction to Tree-Ring Dating*. The University of Arizona Press, Tucson.

- Tait, A., Henderson, R., Turner, R. and Zheng, X., 2006. Thin plate smoothing spline interpolation of daily rainfall for New Zealand using a climatological rainfall surface. *International Journal of Climatology*, 26(14): 2097-2115.
- Teich, M., Bartelt, P., Grêt-Regamey, A. and Bebi, P., 2012. Snow Avalanches in Forested Terrain: Influence of Forest Parameters, Topography, and Avalanche Characteristics on Runout Distance. *Arctic, Antarctic, and Alpine Research*, 44(4): 509-519.
- Telling, J., Glennie, C., Fountain, A. and Finnegan, D., 2017. Analyzing Glacier Surface Motion Using LiDAR Data. *Remote Sensing*, 9(3): 283.
- USGS, 2016. U.S. Geological Survey 20171122, USGS Lidar Point Cloud MT GlacierNP 2016 12UUU135475 LAS 2017: U.S. Geological Survey.
- Veatch, W., Brooks, P.D., Gustafson, J.R. and Molotch, N.P., 2009. Quantifying the effects of forest canopy cover on net snow accumulation at a continental, mid-latitude site. *Ecohydrology*, 2: 115-128.
- Veblen, T.T., Hadley, K.S., Nel, E.M., Kitzberger, T., Reid, M. and Villalba, R., 1994. Disturbance regime and disturbance interactions in a Rocky Mountain subalpine forest. *Journal of Ecology*, 82: 125-135.
- Waller, J.S. and Mace, R.D., 1997. Grizzly bear habitat selection in the Swan Mountains, Montana. *Journal of Wildlife Management*, 61(4): 1032-1039.
- Walsh, S.J., Butler, D.R., Allen, T.R. and Malanson, G.P., 1994. Influence of snow patterns and snow avalanches on the alpine treeline ecotone. *Journal of Vegetation Science*, 5: 657-672.
- Walsh, S.J., Weiss, D.J., Butler, D.R. and Malanson, G.P., 2004. An assessment of snow avalanche paths and forest dynamics using Ikonos satellite data. *Geocarto International*, 19(2).

APPENDIX

Table S1: Confusion matrices associated with the best fit spectral model for each individual avalanche path.

<i>Shed 10-7</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	14	1	0	0	0		0	0	1
Coniferous forest	0	41	0	0	1		0	0	0
Deciduous forest	0	2	31	0	0		0	0	0
Snow	0	0	0	15	0		0	2	0
Green shrub	2	2	0	0	13		0	0	0
Huckleberry									
Red shrub	1	1	1	0	0		17	0	1
Exposed rock	1	0	0	0	0		0	20	0
Yellow shrub	1	0	4	0	0		0	0	11
<i>Path 1163</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green Shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	29	1	5	0			0	0	1
Coniferous forest	1	55	1	0			0	0	0
Deciduous forest	1	1	13	0			0	0	2
Snow	0	0	0	14			0	5	0
Green Shrub									
Huckleberry									
Red shrub	1	0	0	0			8	0	0
Exposed rock	0	0	0	1			0	18	0
Yellow shrub	0	0	3	0			0	0	14
<i>Shed 7</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	23	0	0	0	0	0	0	0	3
Coniferous forest	0	51	5	0	1	0	0	0	0
Deciduous forest	0	15	36	0	1	0	1	0	1
Snow	0	2	0	10	0	0	0	0	0
Green shrub	0	3	0	2	32	1	0	0	0
Huckleberry	1	0	0	0	0	8	1	0	0
Red shrub	0	1	0	0	1	1	6	0	0
Exposed rock	0	0	0	1	0	0	0	29	0
Yellow shrub	1	0	0	0	0	0	0	0	17

Table S2: Confusion matrices associated with the best fit lidar model for each individual avalanche path.

<i>Shed 10-7</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	13	2	1	1	0		5	4	1
Coniferous forest	1	31	3	0	0		0	0	0
Deciduous forest	1	2	31	0	0		1	1	0
Snow	1	10	0	13	0		0	0	1
Green shrub	0	0	1	0	14		0	0	0
Huckleberry									
Red shrub	1	1	0	0	0		4	2	1
Exposed rock	2	1	0	1	0		4	14	1
Yellow shrub	0	0	0	0	0		3	1	9
<i>Path 1163</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	22	4	0	1			0	6	0
Coniferous forest	2	50	3	0			1	2	1
Deciduous forest	0	0	17	0			0	0	0
Snow	1	1	0	12			0	4	1
Green Shrub									
Huckleberry									
Red shrub	3	1	0	0			6	0	1
Exposed rock	4	1	0	2			0	10	0
Yellow shrub	0	0	2	0			1	1	14
<i>Shed 7</i>	Grassland	Coniferous forest	Deciduous forest	Snow	Green shrub	Huckleberry	Red shrub	Exposed rock	Yellow shrub
Grassland	20	0	0	0	0	2	0	0	3
Coniferous forest	0	64	6	0	0	0	0	0	0
Deciduous forest	0	7	34	0	0	0	0	0	0
Snow	0	0	0	12	0	0	0	0	0
Green shrub	0	0	0	0	35	0	0	0	0
Huckleberry	1	0	0	0	0	8	0	0	0
Red shrub	3	0	0	0	0	0	7	2	2
Exposed rock	0	0	1	1	0	0	0	26	2
Yellow shrub	1	1	0	0	0	0	1	1	14

CHAPTER FIVE

CONCLUSION

Summary

The work undertaken in this dissertation reflects an effort to understand the frequency, climate associations, and vegetation characteristics of large magnitude avalanches on a regional scale. The broad focus of this dissertation was to use a tree-ring derived avalanche chronology to understand spatial and temporal patterns of avalanche frequency, and associated atmospheric indices and synoptic climate drivers, across a region consisting of three mountain ranges. We accomplished this by collecting a unique and large dataset over a large spatial extent and through a series of analyses that examined the influence of spatial extent on developing a regional avalanche chronology, the climate and atmospheric drivers commonly associated with large magnitude avalanche events, and vegetation patterns of avalanche return periods.

In Chapter 2, we developed a large magnitude avalanche chronology using dendrochronological techniques for a region in the northern U.S. Rocky Mountains. We implemented a strategic sampling design that allowed us to examine avalanche activity through time in single avalanche paths, four sub-regions, and throughout the region. By analyzing over 650 tree cross sections from 12 avalanche paths, we identified 30 years with large magnitude events across the region. Throughout the sub-regions, the large magnitude avalanche return interval and number of avalanche years vary suggesting the importance of local terrain and weather factors. Our work emphasizes the importance of

sample size, spacing, and spatial extent when attempting to derive a regional large magnitude avalanche chronology from tree-ring records. It also highlights the importance of collecting a sufficient number of avalanche paths to reconstruct a regional large magnitude avalanche chronology.

Chapter 3 highlighted the influence of specific climate and atmospheric patterns associated with years when large magnitude avalanches occurred. Identifying relationships between the climate and specific regional large magnitude avalanche activity is important for interpreting historical avalanche variability and improving avalanche forecasting. In this study, we used the long-term regional avalanche chronology reconstructed from tree-rings in Chapter 2. Using principal component analysis, we found that avalanche years are generally characterized by winters with large snowpack and persistence of low-pressure over the region as represented by the contribution of negative PDO and PNA in the leading principal component. To examine the probability of avalanching based on the leading principal components, we used a generalized linear autoregressive moving average model that accounted for the past effect of avalanches to illustrate that the first principal component is inversely proportional to avalanche probability. We also found a decreasing trend in avalanche probability through time, suggesting a decrease in large magnitude avalanche frequency as climate warming drives snowpack losses.

Finally, in Chapter 4, we implemented a novel approach using lidar and aerial imagery and a Random Forest model to classify vegetation within avalanche paths. We then used dendrochronological techniques combined with spatial interpolation to

calculate return periods and characterize the vegetation within those return period zones. By synchronizing the timing of dendrogeomorphic data collection with vegetation mapping we were able to generally classify vegetation in return periods. Our results suggest the combination of lidar and spectral signature metrics provide the best accuracy for predicting vegetation classes within complex avalanche terrain rather than lidar or spectral signatures alone. The highest frequency return periods were broadly characterized by grassland and shrubland, but topography greatly influences the vegetation classes as well as the return periods. The ability to characterize vegetation within various avalanche return periods using remote sensing data provides land use planners and avalanche forecasters a tool for assessing large magnitude avalanche events.

Limitations and Recommendations for Future Work

Examining avalanche frequency through time across a large spatial extent is challenging due to sparse observational records. The use of dendrochronological techniques allows us to develop an avalanche record in areas without consistent avalanche records and to extend the chronology beyond historical records further back in time. We highlight the use of these methods in this dissertation. However, there are limitations to these techniques. First and foremost, tree-ring derived avalanche chronologies can underestimate avalanche frequency. We attempted to highlight this and place our record in context by comparing the historical record in one sub-region (JFS Canyon) to the tree-ring record. However, this record is incomplete and inconsistent. Therefore, it was difficult to assess how well our tree-ring derived avalanche record compared to a complete historical record. As such, the record we presented here provides

the maximum frequency of large magnitude avalanches throughout the region and should not be used as the only tool for infrastructure planning purposes. The use of other complementary tools including more recent and complete historical records as well as vegetation patterns within specific avalanche paths will allow for a more complete assessment of avalanche frequency in any one given path. The methods and results of Chapter 4 are an example of such a tool using vegetation clues for avalanche frequency.

Secondly, collecting cross-sections allows for a more robust and complete picture of various signals within the tree rings of any given tree. However, this comes at a time-intensive cost, particularly in processing a large number of samples. Therefore, the cost-benefit ratio of processing time to more robust data using cross-sections should be considered when planning such a study.

Another limitation relates to the interaction of avalanches and climate. Avalanches depend on weather, and any one given storm can potentially trigger a large magnitude avalanche with a snowpack structure conducive for avalanching. While climate drives weather, it is a secondary influence on avalanche activity. Therefore, we can only consider climate drivers on a seasonal scale as we have done here. Attempting to associate climate drivers to any one given large magnitude event is difficult and potentially misleading. However, as with other extreme event attribution studies (Trenberth et al., 2015), future research should examine the probability of a widespread large magnitude avalanche cycle (i.e. Colorado, March 2019 (Lazar, 2019)) in the context of climate change. With enough extreme avalanche events in a dataset, one could begin to

discriminate the signal from noise or examine drivers of these extreme events and any climate change linkages.

Future work should quantify the uncertainty of using cores versus cross sections for tree-ring sampling to assess the benefit of sampling cross sections versus the limitations of using cores. This would fill a research gap in the field of avalanche dendrochronology and address the issue of how much time and effort is necessary to develop a representative regional avalanche chronology using either cross sections or cores.

We demonstrated that there is considerable variability of the number of avalanche years between individual avalanche paths and sub-regions. With observations from regional avalanche forecasting operations, it would be feasible to associate the spatial distribution and timing of large-magnitude avalanches with snowpack structure on a regional scale. Snowpack structure distribution could help explain the variability across paths and sub-regions. Currently, tree-ring studies that associate large magnitude avalanches with climate or weather data lack proper snowpack structure data. These additional snowpack data would allow for a more robust assessment of weather, climate, and snowpack influences on regional large magnitude avalanche frequency. The limitation, of course, is that snow structure data for many regions is limited in time.

Finally, assessing vegetation patterns within an avalanche path can help identify areas with more frequent avalanche activity. Future work should consider mapping vegetation changes over time using remote sensing products. This would help identify avalanche frequency on a very large scale over at least several decades given these

products only extend that far back in time. These are simply several recommendations that would help advance the field of avalanche research by examining large magnitude avalanches on numerous spatio-temporal scales.

In this dissertation the three broad topics of large spatial patterns of large magnitude avalanches, associations with climate drivers, and vegetation characteristics of avalanche paths were considered. Accordingly, the research presented here addressed a variety of aspects with the intent to better understand large magnitude avalanche frequency and improve our ability to forecast such infrequent but destructive and impactful events.

CUMULATIVE REFERENCES CITED

- Abatzoglou, J.T., 2011. Influence of the PNA on declining mountain snowpack in the Western United States. *International Journal of Climatology*, 31(8): 1135-1142.
- Allen, T.R., Walsh, S.J., Cairns, D.M., Messina, J.B., D. R. and Malanson, G.P., 2004. Geostatistics and spatial analysis: characterizing form and pattern at the alpine treeline. In: M. Bishop and J. Shroder (Editors), *Geographic Information Science and Mountain Geomorphology*. Springer Verlag-Praxis Scientific.
- Amrhein, V., Greenland, S. and McShane, B., 2019. Comment: Retire statistical significance. *Nature*, 567: 305-307.
- Armstrong, B.R., 1981. A quantitative analysis of avalanche hazard on U.S. Highway 550, southwestern Colorado, *Proceedings of the Western Snow Conference*, St. George, Utah, April 14-16, 2017, St. George, Utah, pp. 95-104.
- Armstrong, R.L. and Armstrong, B.R., 1987. Snow and avalanche climates of the western United States: a comparison of maritime, intermountain, and continental climates, the Davos symposium, September 1986 *International Association of the Hydrological Sciences Publication*. no. 162.
- Ballesteros-Canovas, J.A., Trappmann, D., Madrigal-Gonzalez, J., Eckert, N. and Stoffel, M., 2018. Climate warming enhances snow avalanche risk in the Western Himalayas. *Proc Natl Acad Sci U S A*, 115(13): 3410-3415.
- Bamzai, A.S., 2003. Relationship between snow cover variability and Arctic oscillation index on a hierarchy of time scales. *International Journal of Climatology*, 23(2): 131-142.
- Bartelt, P. and Stockli, V., 2001. The influence of tree and branch fracture, overturning and debris entrainment on snow avalanche flow. *Annals of Glaciology*, 32: 209-216.
- Bebi, P., Kulakowski, D. and Rixen, C., 2009. Snow avalanche disturbances in forest ecosystems-State of research and implications for management. Elsevier Science Bv, pp. 1883-1892.
- Becker, A., Körner, C., Gurung, A.B. and Haeberli, W., 2007. Selected Issues from the Samedan GLOCHAMORE Workshop on Altitudinal Gradient Studies. *Mountain Research and Development*, 27(1): 82-86.
- Bellaire, S., Jamieson, B., Thumlert, S., Goodrich, J. and Statham, G., 2016. Analysis of long-term weather, snow and avalanche data at Glacier National Park, B.C., Canada. *Cold Regions Science and Technology*, 121: 118-125.

- Birkeland, K.W., 2001. Spatial patterns of snow stability throughout a small mountain range. *Journal of Glaciology*, 47(157): 176-186.
- Birkeland, K.W. and Mock, C.J., 1996. Atmospheric circulation patterns associated with heavy snowfall events, Bridger Bowl, Montana, USA. *Mountain Research and Development*, 16(3): 281-286.
- Birkeland, K.W., Mock, C.J. and Shinker, J.J., 2001. Avalanche extremes and atmospheric circulation patterns. *Annals of Glaciology*, 32: 135-140.
- Blattenberger, G. and Fowles, R., 1994. The Road Closure Decision in Little Cottonwood Canyon, Proceedings of the 1994 International Snow Science Workshop, October 30-November 3, 1994, Snowbird Utah, Snowbird, Utah, pp. 537-547.
- Blöschl, G., 1999. Scaling issues in snow hydrology. *Hydrological Processes*, 13: 2149-2175.
- Blöschl, G. and Sivapalan, M., 1995. Scale issues in hydrological modelling: A review. *Hydrological Processes*, 9: 251-290.
- Brandtberg, T., Warner, T.A., Landenberger, R.E. and McGraw, J.B., 2003. Detection and analysis of individual leaf-off tree crowns in small footprint, high sampling density lidar data from the eastern deciduous forest in North America. *Remote Sensing of Environment*, 85(3): 290-303.
- Breiman, L., 2001. Random Forests. *Machine Learning*, 45: 5-32.
- Bryant, C.L., Butler, D.R. and Vitek, J.D., 1989. A Statistical-Analysis of Tree-Ring Dating in Conjunction With Snow Avalanches - Comparison of on-Path Versus Off-Path Responses. *Environmental Geology and Water Sciences*, 14(1): 53-59.
- Burrows, C.J. and Burrows, V.L., 1976. Procedures for the study of snow avalanche chronology using growth layers of woody plants, Institute of Arctic and Alpine Research, University of Colorado, Boulder, CO.
- Butler, D.R., 1979. Snow avalanche path terrain and vegetation, Glacier National Park, Montana. *Arctic and Alpine Research*, 11(1): 17-32.
- Butler, D.R., 1986. Snow-avalanche hazards in Glacier National Park, Montana: meteorological and climatological aspects. *Physical Geography*, 7(1): 72-87.
- Butler, D.R. and Malanson, G., P., 1985a. A history of high-magnitude snow avalanches, southern Glacier National Park, Montana, U.S.A. *Mountain Research and Development*, 5(2): 175-182.

- Butler, D.R. and Malanson, G.P., 1985b. A reconstruction of snow-avalanche characteristics in Montana, U.S.A., using vegetative indicators. *Journal of Glaciology*, 31(108): 185-187.
- Butler, D.R., Malanson, G.P. and Oelfke, J.G., 1987. Tree-ring analysis and natural hazard chronologies: minimum sample sizes and index values. *Professional Geographer*, 39(1): 41-47.
- Butler, D.R., Malanson, G.P. and Walsh, S.J., 1992. Snow-avalanche paths: conduits from the periglacial-alpine to the subalpine depositional zone. In: J.C. Dixon and A.D. Abrahams (Editors), *Periglacial Geomorphology*. John Wiley and Sons Ltd., pp. 185-202.
- Butler, D.R. and Sawyer, C.F., 2008. Dendrogeomorphology and high-magnitude snow avalanches: a review and case study. *Natural Hazards and Earth System Sciences*, 8(2): 303-309.
- CAIC, 2018. Colorado Avalanche Information Center Statistics and Reporting. <http://avalanche.state.co.us/accidents/statistics-and-reporting/>.
- Carrara, P.E., 1979. The determination of snow avalanche frequency through tree-ring analysis and historical records. *Geological Society of America Bulletin*, 90: 773-780.
- Casteller, A., Stoeckli, V., Villalba, R. and Mayer, A.C., 2007. An evaluation of dendroecological indicators of snow avalanches in the Swiss Alps. *Arctic Antarctic and Alpine Research*, 39(2): 218-228.
- Chiroui, P., Stoffel, M., Onaca, A. and Urdea, P., 2015. Testing dendrogeomorphic approaches and thresholds to reconstruct snow avalanche activity in the Făgăraș Mountains (Romanian Carpathians). *Quaternary Geochronology*, 27: 1-10.
- Choulakian, V. and Stephens, M.A., 2001. Goodness-of-fit tests for the Generalized Pareto distribution. *Technometrics*, 43(4): 478-484.
- Corona, C., Lopez Saez, J., Stoffel, M., Bonnefoy, M., Richard, D., Astrade, L. and Berger, F., 2012. How much of the real avalanche activity can be captured with tree rings? An evaluation of classic dendrogeomorphic approaches and comparison with historical archives. *Cold Regions Science and Technology*.
- de Bouchard d'Aubeterre, G., Favillier, A., Mainieri, R., Lopez Saez, J., Eckert, N., Saulnier, M., Peiry, J.L., Stoffel, M. and Corona, C., 2019. Tree-ring reconstruction of snow avalanche activity: Does avalanche path selection matter? *Science of The Total Environment*, 684: 496-508.

- Deems, J.S., Painter, T.H. and Finnegan, D.C., 2013. Lidar measurement of snow depth: a review. *Journal of Glaciology*, 59(215): 467-479.
- Dixon, R.W., Butler, D.R., Dechano, L.M. and Henry, J.A., 1999. Avalanche Hazard in Glacier National Park: an El Nino Connection? *Physical Geography*, 20(6): 461-467.
- Dube, S., Filion, L. and Hetu, B., 2004. Tree-Ring Reconstruction of High-Magnitude Snow Avalanches in the Northern Gaspé Peninsula, Quebec, Canada. *Arctic, Antarctic, and Alpine Research*, Vol. 36(No. 4): 555-564.
- Dunsmuir, W.T.M. and Scott, D.J., 2015. The glarma Package for Observation-Driven Time Series Regression of Counts. *Journal of Statistical Software*, 67(7).
- Eckert, N., Keylock, C.J., Castebrunet, H., Lavigne, A. and Naaim, M., 2013. Temporal trends in avalanche activity in the French Alps and subregions: from occurrences and runout altitudes to unsteady return periods. *Journal of Glaciology*, 59(213): 93-114.
- Eckert, N., Parent, E., Kies, R. and Baya, H., 2009. A spatio-temporal modelling framework for assessing the fluctuations of avalanche occurrence resulting from climate change: application to 60 years of data in the northern French Alps. *Climatic Change*, 101(3-4): 515-553.
- Erschbamer, B., 1989. Vegetation on avalanche paths in the Alps. *Vegetatio*, 80: 139-146.
- Favillier, A., Guillet, S., Morel, P., Corona, C., Lopez Saez, J., Eckert, N., Ballesteros Cánovas, J.A., Peiry, J.-L. and Stoffel, M., 2017. Disentangling the impacts of exogenous disturbances on forest stands to assess multi-centennial tree-ring reconstructions of avalanche activity in the upper Goms Valley (Canton of Valais, Switzerland). *Quaternary Geochronology*, 42: 89-104.
- Favillier, A., Guillet, S., Trappmann, D., Morel, P., Lopez-Saez, J., Eckert, N., Zenhäusern, G., Peiry, J.-L., Stoffel, M. and Corona, C., 2018. Spatio-temporal maps of past avalanche events derived from tree-ring analysis: A case study in the Zermatt valley (Valais, Switzerland). *Cold Regions Science and Technology*, 154: 9-22.
- Feistl, T., Bebi, P. and Bartelt, P., 2013. The role of slope angle, ground roughness and stauchwall strength in the formation of glide-snow avalanches in forest gaps. In: F. Naaim-Bouvet, Y. Durand and R. Lambert (Editors), *Proceedings of the 2013 International Snow Science Workshop*, Grenoble, France, pp. 760-765.
- Feistl, T., Bebi, P., Teich, M., Buhler, Y., Christen, M., Thuro, K. and Bartelt, P., 2014. Observations and modeling of the braking effect of forests on small and medium avalanches. *Journal of Glaciology*, 60(219): 124-138.

- Finklin, A.I., 1986. A Climatic Handbook for Glacier National Park - with Data for Waterton Lakes National Park. INT-204, U.S.D.A. Forest Service Intermountain Research Station, Ogden.
- Fitzharris, B.B. and Bakkehoi, S., 1986. A synoptic climatology of major avalanche winters in Norway. *Journal of Climatology*, 6: 431-446.
- Fitzharris, B.B. and Schaerer, P.A., 1980. Frequency of major avalanche winters. *Journal of Glaciology*, 26(94): 43-52.
- Germain, D., 2016. A Statistical Framework for Tree-Ring Reconstruction of High-Magnitude Mass Movements: Case Study of Snow Avalanches in Eastern Canada. *Geografiska Annaler: Series A, Physical Geography*, 98(4): 303-311.
- Germain, D., Filion, L. and Hétu, B., 2005. Snow avalanche activity after fire and logging disturbances, northern Gaspé Peninsula, Quebec, Canada. *Can. J. Earth Sci.*, 42: 2103-2116.
- Germain, D., Filion, L. and Hétu, B., 2009. Snow avalanche regime and climatic conditions in the Chic-Choc Range, eastern Canada. *Climatic Change*, 92(1-2): 141-167.
- Germain, D., Hétu, B. and Filion, L., 2010. Tree-ring based reconstruction of past snow avalanche events and risk assessment in Northern Gaspé Peninsula (Québec, Canada). In: M. Stoffel, M. Bollschweiler, D.R. Butler and B.H. Luckman (Editors), *Tree Rings and Natural Hazards - A State-of-the-Art. Advances in Global Change Research*. Springer, London.
- Gillan, B.J., Harper, J.T. and Moore, J.N., 2010. Timing of present and future snowmelt from high elevations in northwest Montana. *Water resources research*, 46(W01507).
- Gratton, M., Germain, D. and Boucher, É., 2019. Meteorological triggering scenarios of tree-ring-based snow avalanche occurrence on scree slopes in a maritime climate, Eastern Canada. *Physical Geography*: 1-18.
- Greene, E., Atkins, D., Birkeland, K., Elder, K., Landry, C., Lazar, B., McCammon, I., Moore, M., Sharaf, D., Sternenz, C., Tremper, B. and Williams, K., 2010. Snow, weather and avalanches: observation guidelines for avalanche programs in the United States, Pagosa Springs, CO.
- Greene, E., Birkeland, K.W., Elder, K., McCammon, I., Staples, M. and Sharaf, D., 2016. Snow, weather, and avalanches: Observation guidelines for avalanche programs in the United States (3rd ed). American Avalanche Association, Victor, ID, pp. 104.
- Grissino-Mayer, H., 2001. Evaluating crossdating accuracy: A manual and tutorial for the computer program COFECHA. *Tree-Ring Research*, 57(2): 205-221.

- Hamed, K.H. and Rao, A.R., 1998. A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology*, 204(1-4): 182-196.
- Hebertson, E.G. and Jenkins, M.J., 2003. Historic climate factors associated with major avalanche years on the Wasatch Plateau, Utah. *Cold Regions Science and Technology*, 37(3): 315-332.
- Hendrikx, J., Murphy, M. and Onslow, T., 2014. Classification trees as a tool for operational avalanche forecasting on the Seward Highway, Alaska. *Cold Regions Science and Technology*, 97: 113-120.
- Hesdstrom, N.R. and Pomeroy, J.W., 1998. Measurements and modelling of snow interception in the boreal forest. *Hydrological Processes*, 12: 1611-1625.
- Holmes, R.L., 1983. Analysis of tree rings and fire scars to establish fire history. *Tree-Ring Bulletin*, 43: 51-67.
- Holmgren, J. and Persson, A., 2004. Identifying species of individual trees using airborne laser scanner. *Remote Sensing of Environment*, 90(4): 415-423.
- Holmgren, J., Persson, A. and Soderman, U., 2008. Species identification of individual trees by combining high resolution LIDAR data with multi-spectral images. *International Journal of Remote Sensing*, 29(5): 1537-1552.
- Hutchinson, M.F., 1995. Interpolating mean rainfall using thin plate smoothing splines. *International journal of geographical information systems*, 9(4): 385-403.
- Hyypä, J., Kelle, O., Lehtikainen, M. and Inkinen, M.A., 2001. A segmentation-based method to retrieve stem volume estimates from 3-D tree height models produced by laser scanners. *IEEE Transactions on Geoscience and Remote Sensing*, 39: 969-975.
- ITRDB, 2018. International Tree Ring Data Bank (ITRDB).
- Johnson, E.A., 1987. The relative importance of snow avalanche disturbance and thinning on canopy plant populations. *Ecology*, 68(1): 43-53.
- Kajimoto, T., Daimaru, H., Okamoto, T., Otani, T. and Onodera, H., 2004. Effects of snow avalanche disturbance on regeneration of subalpine *Abies mariesii* forest, Northern Japan. *Arctic, Antarctic, and Alpine Research*, 36(4): 436-554.
- Kanyongo, G.Y., 2005. The Influence of Reliability on Four Rules for Determining the Number of Components to Retain. *Journal of Modern Applied Statistical Methods*, 5(2): 332-343.

- Khosravipour, A., Skidmore, A.K., Isenburg, M., Wang, T.J. and Hussin, Y.A., 2014. Generating Pit-free Canopy Height Models from Airborne Lidar. *Photogrammetric Engineering and Remote Sensing*, 80(9): 863-872.
- Klos, P.Z., Link, T.E. and Abatzoglou, J.T., 2014. Extent of the rain-snow transition zone in the western U.S. under historic and projected climate. *Geophysical Research Letters*, 41: 4560-4568.
- Kogelnig-Mayer, B., Stoffel, M., Schneuwly-Bollschweiler, M., Hübl, J. and Rudolf-Miklau, F., 2011. Possibilities and Limitations of Dendrogeomorphic Time-Series Reconstructions on Sites Influenced by Debris Flows and Frequent Snow Avalanche Activity. *Arctic, Antarctic, and Alpine Research*, 43(4): 649-658.
- Köse, N., Aydın, A., Akkemik, Ü., Yurtseven, H. and Güner, T., 2010. Using tree-ring signals and numerical model to identify the snow avalanche tracks in Kastamonu, Turkey. *Natural Hazards*, 54(2): 435-449.
- Krajick, K., 1998. Animals thrive in an avalanche's wake. *Science*, 279(5358): 11853.
- Kuhn, M., Wing, J., Weston, S., Williams, A., Keefer, C., Engelhardt, A., Cooper, T., Mayer, Z., Kenkel, B., Benesty, M., Lescarbeau, R., Ziem, A., Scrucça, L., Tang, Y., Candan, C. and Hunt, T., 2019. caret: Classification and Regression Training. R package version 6.0-84. <https://CRAN.R-project.org/package=caret>.
- Kulakowski, D., Rixen, C. and Bebi, P., 2006. Changes in forest structure and in the relative importance of climatic stress as a result of suppression of avalanche disturbances. *Forest Ecology and Management*, 223(1-3): 66-74.
- Laes, D., Reutebuch, S.E., McGaughey, R.J. and Metchell, B., 2011. Guidelines to estimate forest inventory parameters from lidar and field plot data, U.S. Forest Service.
- Latenser, M. and Schneebeli, M., 2002. Temporal trend and spatial distribution of avalanche activity during the last 50 years in Switzerland. *Natural Hazards*, 27: 201-230.
- Latenser, M. and Schneebeli, M., 2003. Long-term snow climate trends of the Swiss Alps (1931-99). *International journal of climatology*, 23: 733-750.
- Lazar, B., 2019. March Avalanches in Colorado. Presentation - 18th Annual Colorado Snow and Avalanche Workshop, Breckenridge, Colorado, USA. October 4, 2019.
- Lefsky, M.A., Cohen, W.B., Parker, G.G. and Harding, D.J., 2002. Lidar Remote Sensing for Ecosystem Studies. *BioScience*, 52(1): 19.
- Leitinger, G., Höller, P., Tasser, E., Walde, J. and Tappeiner, U., 2008. Development and validation of a spatial snow-glide model. *Ecological Modelling*, 211(3-4): 363-374.

- Lillesand, T.M. and Kiefer, R.W., 2000. Remote Sensing and Image Interpretation, 4. Wiley & Sons, New York, New York, USA.
- Lim, K., Treitz, P., Wulder, M., St-Onge, B. and Flood, M., 2003. LiDAR remote sensing of forest structure. *Progress in Physical Geography*, 27(1): 88-106.
- Mace, R.D. and Waller, J.S., 1997. Spatial and temporal interaction of male and female grizzly bears in Northwestern Montana. *Journal of Wildlife Management*, 61(1): 39-52.
- Malanson, G.P. and Butler, D.R., 1984. Transverse pattern of vegetation on avalanche paths in the northern Rocky Mountains, Montana. *Great Basin Naturalist*, 44(3): 453-457.
- Malanson, G.P. and Butler, D.R., 1986. Floristic patterns on avalanche paths in the Northern Rocky Mountains, USA. *Physical Geography*, 7(3): 231-238.
- Malevich, S.B., Guiterman, C.H. and Margolis, E.Q., 2018. burnr : Fire history analysis and graphics in R. *Dendrochronologia*, 49: 9-15.
- Mann, H.B., 1945. Nonparametric tests against trend. *Econometrica*, 13(3): 245-259.
- Mantua, N.J. and Hare, S.R., 2002. The Pacific Decadal Oscillation. *Journal of Oceanography*, 58: 10.
- Martin, J.P. and Germain, D., 2016. Dendrogeomorphic reconstruction of snow avalanche regime and triggering weather conditions: A classification tree model approach. *Progress in Physical Geography*.
- McCabe, G.J., 1994. Relationships Between Atmospheric Circulation and Snowpack in the Gunnison River Basin, Colorado. *Journal of Hydrology*, 157(1-4): 157-175.
- McCabe, G.J. and Dettinger, M.D., 2002. Primary modes and predictability of year-to-year snowpack variations in the Western United States from teleconnections with Pacific ocean climate. *Hydrometeorology*, 3(13-25).
- McClung, D. and Schaerer, P., 2006. The avalanche handbook. Mountaineers Books, Seattle, Wash.
- McCollister, C.M. and Comey, R.H., 2009. Using LiDAR (Light Distancing and Ranging) data to more accurately describe avalanche terrain, In: J. Schweizer and A. van Herwijnen (Editors), *Proceedings of the 2009 International Snow Science Workshop*, Davos, Switzerland, September 27-October 2, 2009., pp. 463-467.
- Mears, A.I., 1989. Regional comparisons of avalanche-profile and runout data. *Arctic and Alpine Research*, 21(3): 283-287.

- Mears, A.I., 1992. Snow-Avalanche Hazard Analysis for Land-use Planning and Engineering. Colorado Geological Survey Bulletin, 49.
- Menne, M.J., Durre, I., Vose, R.S., Gleason, B.E. and Houston, T.G., 2012. An Overview of the Global Historical Climatology Network-Daily Database. *Journal of Atmospheric and Oceanic Technology*, 29(7): 897-910.
- Meseşan, F., Gavrilă, I.G. and Pop, O.T., 2018. Calculating snow-avalanche return period from tree-ring data. *Natural Hazards*, 94(3): 1081-1098.
- Meyer, F. and Beucher, S., 1990. Morphological Segmentation. *Journal of Visual Communication and Image Representation*, 1(1): 21-46.
- Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W. and Lettenmaier, D.P.S., Ronald J., 2008. Stationarity is dead: whither water management? *Science*, 319: 573-574.
- Mock, C.J., 1996. Climatic controls and spatial variations of precipitation in the western United States. *Journal of Climate*, 9: 1111-1125.
- Mock, C.J. and Birkeland, K.W., 2000. Snow avalanche climatology of the western United States mountain ranges. *Bulletin of the American Meteorological Society*, 81(10): 2367-2392.
- Mock, C.J., Carter, K.C. and Birkeland, K.W., 2016. Some Perspectives on Avalanche Climatology. *Annals of the American Association of Geographers*: 1-10.
- Molotch, N., Blanken, P., Williams, M., Turnipseed, A., Monson, R. and Margulis, S., 2007. Estimating sublimation of intercepted and sub-canopy snow using eddy covariance systems. *Hydrological Processes*, 21: 1567-1575.
- Mote, P.W., Li, S., Lettenmaier, D.P., Xiao, M. and Engel, R., 2018. Dramatic declines in snowpack in the western US. *npj Climate and Atmospheric Science*, 1(1-5).
- Muntan, E., Garcia, C., Oller, P., Marti, G., Garcia, A. and Gutierrez, E., 2009. Reconstructing-snow-avalanches-in-the-Southeastern-Pyrenees. *Natural-Hazards-and-Earth-System-Science*, 9: 1599-1612.
- Musselmann, K.N., Molotch, N.P. and Brooks, P.D., 2008. Effects of vegetation on snow accumulation and ablation in a mid-latitude sub-alpine forest. *Hydrological processes*, 22: 2767-2776.
- NCDC, National Oceanic and Atmospheric Administration National Centers for Environmental Information <https://www.ncdc.noaa.gov/teleconnections/>.

- Newesely, C., Tasser, E., Spadinger, P. and Cernusca, A., 2000. Effects of land-use changes on snow gliding processes in alpine ecosystems. *Basic and Applied Ecology*, 1(1): 61-67.
- NRCS, United States Department of Agriculture National Resource Conservation Service Snow Course Data, <https://www.wcc.nrcs.usda.gov/snowcourse/>.
- NRCS, 2017. USDA Natural Resource Conservation Service, National Agricultural Imagery Program. Last Accessed: September 2019.
- Ott, R.L. and Longnecker, M.T., 2016. *An Introduction to Statistical Methods and Data Analysis*. Cengage Learning, Boston, MA.
- Patten, R.S. and Knight, D.H., 1994. Snow avalanches and vegetation pattern in Cascade Canyon, Grand Teton National Park, Wyoming, USA. *Arctic and Alpine Research*, 26(1): 35-41.
- Pederson, G.T., Betancourt, J.L. and McCabe, G.J., 2013. Regional patterns and proximal causes of the recent snowpack decline in the Rocky Mountains, U.S. *Geophysical Research Letters*: 1-6.
- Pederson, G.T., Graumlich, L.J., Fagre, D.B., Kipfer, T. and Muhlfeld, C.C., 2010. A century of climate and ecosystem change in Western Montana: what do temperature trends portend? *Climatic Change*, 98(1-2): 133-154.
- Pederson, G.T., Gray, S.T., Ault, T., Marsh, W., Fagre, D.B., Bunn, A.G., Woodhouse, C.A. and Graumlich, L.J., 2011a. Climatic Controls on the Snowmelt Hydrology of the Northern Rocky Mountains. *Journal of Climate*, 24(6): 1666-1687.
- Pederson, G.T., Gray, S.T., Woodhouse, C.A., Betancourt, J.L., Fagre, D.B., Littell, J.S., Watson, E., Luckman, B.H. and Graumlich, L.J., 2011b. The unusual nature of recent snowpack declines in the North American Cordillera. *Science*, 333(6040): 332-335.
- Peitzsch, E.H., Hendrikx, J. and Fagre, D.B., 2015. Terrain parameters of glide snow avalanches and a simple spatial glide snow avalanche model. *Cold Regions Science and Technology*, 120: 237-250.
- Peitzsch, E.H., Hendrikx, J., Fagre, D.B. and Reardon, B., 2012. Examining spring wet slab and glide avalanche occurrence along the Going-to-the-Sun Road corridor, Glacier National Park, Montana, USA. *Cold Regions Science and Technology*, 78: 73-81.
- Peitzsch, E.H., Hendrikx, J., Stahle, D.K., Pederson, G.T., Fagre, D.B. and Birkeland, K.W., In Prep. A regional spatio-temporal analysis for large magnitude avalanches using tree rings. *Natural Hazards and Earth Systems Sciences*.

- Peitzsch, E.H., Stahle, D.K., Fagre, D.B., Clark, A.M., Pederson, G.T., Hendrikx, J. and Birkeland, K.W., 2019. Tree ring dataset for a regional avalanche chronology in northwest Montana, 1636-2017. U.S. Geological Survey. <https://doi.org/10.5066/P9TLHZAI>.
- Persson, A., Holmgren, J. and Soderman, U., 2002. Detecting and measuring individual trees using an airborne laser scanner. *Photogrammetric Engineering and Remote Sensing*, 68(9): 925-932.
- Pielmeier, C., Techel, F., Marty, C. and Stucki, T., 2013. Wet snow avalanche activity in the Swiss Alps - trend analysis for mid-winter season. In F. Naaim-Bouvet, Y. Durand, & R. Lambert (Eds.), *Proceedings of the 2013 International snow science workshop proceedings 2013*. Grenoble, France. 7-11 October 2013.: 1240-1246.
- Pop, O.T., Munteanu, A., Flaviu, M., Gavrilă, I.-G., Timofte, C. and Holobacă, I.-H., 2018. Tree-ring-based reconstruction of high-magnitude snow avalanches in Piatra Craiului Mountains (Southern Carpathians, Romania). *Geografiska Annaler: Series A, Physical Geography*, 100(2): 99-115.
- Potter, N., 1969. Tree-ring dating of snow avalanche tracks and the geomorphic activity of avalanches, Northern Absaroka Mountains, Wyoming. *Geological Society of America Special Papers*(123): 141-165.
- PRISM, 2019. Parameter-elevation Regressions on Independent Slope Model. PRISM Climate Group, Oregon State University. <http://prism.oregonstate.edu>, created 20 November 2019.
- R, 2018. R Core Team - R Foundation for Statistical Computing. 2018, R: A Language and Environment for Statistical Computing, <https://www.R-project.org>, Vienna, Austria.
- Rayback, S.A., 1998. A dendrogeomorphological analysis of snow avalanches in the Colorado Front Range, USA. *Physical Geography*, 19(6): 502-515.
- Reardon, B. and Fagre, D.B., 2006. Reassessing a troublesome fact of mountain life: avalanches in Glacier National Park. *Park Science*, 24(1): 37-39.
- Reardon, B.A., Fagre, D.B. and Steiner, R.W., 2004. Natural avalanches and transportation: a case study from Glacier National Park, Montana, USA, *Proceedings of the International Snow Science Workshop*, Sept. 19-24, 2004, Jackson, WY, U.S.A., pp. 582-597.
- Reardon, B.A., Pederson, G.T., Caruso, C.J. and Fagre, D.B., 2008. Spatial reconstructions and comparisons of historic snow avalanche frequency and extent using tree rings in Glacier National Park, Montana, U.S.A. *Arctic, Antarctic, and Alpine Research*, 40(1): 148-160.

- Rixen, C., Haag, S., Kulakowski, D. and Bebi, P., 2007. Natural avalanche disturbance shapes plant diversity and species composition in subalpine forest belt. *Journal of Vegetation Science*, 18: 735-A7.
- Roussel, J.-R. and Auty, D., 2019. lidR: Airborne LiDAR Data Manipulation and Visualization for Forestry Applications. R package version 2.1.4. <https://CRAN.R-project.org/package=lidR>.
- Schläppy, R., Eckert, N., Jomelli, V., Stoffel, M., Grancher, D., Brunstein, D., Naaim, M. and Deschatres, M., 2014. Validation of extreme snow avalanches and related return periods derived from a statistical-dynamical model using tree-ring techniques. *Cold Regions Science and Technology*, 99: 12-26.
- Schläppy, R., Jomelli, V., Eckert, N., Stoffel, M., Grancher, D., Brunstein, D., Corona, C. and Deschatres, M., 2015. Can we infer avalanche–climate relations using tree-ring data? Case studies in the French Alps. *Regional Environmental Change*, 16(3): 629-642.
- Schläppy, R., Jomelli, V., Grancher, D., Stoffel, M., Corona, C., Brunstein, D., Eckert, N. and Deschatres, M., 2013. A New Tree-Ring-Based, Semi-Quantitative Approach for the Determination of Snow Avalanche Events: use of Classification Trees for Validation. *Arctic, Antarctic, and Alpine Research*, 45(3): 383-395.
- Schweizer, J., 2003. Snow avalanche formation. *Reviews of Geophysics*, 41(4).
- Schweizer, J., Kronholm, K., Jamieson, J.B. and Birkeland, K.W., 2008. Review of spatial variability of snowpack properties and its importance for avalanche formation. *Cold Regions Science and Technology*, 51(2-3): 253-272.
- Schweizer, J., Kronholm, K. and Wiesinger, T., 2003. Verification of regional snowpack stability and avalanche danger. *Cold Regions Science and Technology*, 37(3): 277-288.
- Schweizer, J., Mitterer, C. and Stoffel, L., 2009. On forecasting large and infrequent snow avalanches. *Cold Regions Science and Technology*, 59(2-3): 234-241.
- Selkowitz, D.J., Fagre, D.B. and Reardon, B.A., 2002. Interannual variations in snowpack in the Crown of the Continent Ecosystem. *Hydrological Processes*, 16(18): 3651-3665.
- Shroder, J.F., 1978. Dendrogeomorphological analysis of mass movement on Table Cliffs Plateau, Utah. *Quaternary Research* 9, 168(18.5).
- Shroder, J.F., 1980. Dendrogeomorphology: review and new techniques of tree-ring dating. *Progress in Physical Geography*, 4(2): 161-188.

- Šilhán, K. and Tichavský, R., 2017. Snow avalanche and debris flow activity in the High Tatras Mountains: New data from using dendrogeomorphic survey. *Cold Regions Science and Technology*, 134: 45-53.
- Silva, C.A., Crookston, N.L., Hudak, A.T., Vierling, L.A., Klauberg, C. and Cardil, A., 2017. rLiDAR: LiDAR Data Processing and Visualization. R package version 0.1.1. <https://CRAN.R-project.org/package=rLiDAR>
- Skoien, J.O. and Blochl, G., 2006. Sampling scale effects in random fields and implications for environmental monitoring. *Environ Monit Assess*, 114(1-3): 521-52.
- Smith, L., 1973. Indication of snow avalanche periodicity through interpretation of vegetation patterns in the North Cascades, Washington. , *Methods of Avalanche Control on Washington Mountain Highways: Third Annual Report*. Washington State Highway Commission Department of Highways, Olympia, Washington, USA.
- Smith, M.J. and McClung, D.M., 1997. Avalanche frequency and terrain characteristics at Rogers' pass, British Columbia, Canada. *Journal of Glaciology*, 43(143): 165-171.
- Solberg, S., Naesset, E. and Bollandsas, O.M., 2006. Single tree segmentation using airborne laser scanner data in a structurally heterogeneous spruce forest. *Photogrammetric Engineering and Remote Sensing*, 72(12): 1369-1378.
- Stähli, M., Jonas, T. and Gustafsson, D., 2009. The role of snow interception in winter-time radiation processes of a coniferous sub-alpine forest. *Hydrological Processes*, 23(17): 2498-2512.
- Stoffel, M. and Bollschweiler, M., 2008. Tree-ring analysis in natural hazards research - an overview. *Natural Hazards and Earth System Science*, 8: 15.
- Stoffel, M., Bollschweiler, M., Butler, D.R. and Luckman, B.H. (Editors), 2010. *Tree Rings and Natural Hazards - A State of the Art*. Springer Science and Business Media, 505 pp.
- Stokes, M.A. and Smiley, T.L., 1996. *An Introduction to Tree-Ring Dating*. The University of Arizona Press, Tucson.
- Tait, A., Henderson, R., Turner, R. and Zheng, X., 2006. Thin plate smoothing spline interpolation of daily rainfall for New Zealand using a climatological rainfall surface. *International Journal of Climatology*, 26(14): 2097-2115.
- Teich, M., Bartelt, P., Grêt-Regamey, A. and Bebi, P., 2012. Snow Avalanches in Forested Terrain: Influence of Forest Parameters, Topography, and Avalanche

- Characteristics on Runout Distance. *Arctic, Antarctic, and Alpine Research*, 44(4): 509-519.
- Telling, J., Glennie, C., Fountain, A. and Finnegan, D., 2017. Analyzing Glacier Surface Motion Using LiDAR Data. *Remote Sensing*, 9(3): 283.
- Trenberth, K.E., Fasullo, J.T. and Shepherd, T.G., 2015. Attribution of climate extreme events. *Nature Climate Change*, 5(8): 725-730.
- USGS, 2016. U.S. Geological Survey 20171122, USGS Lidar Point Cloud MT GlacierNP 2016 12UUU135475 LAS 2017: U.S. Geological Survey.
- Veatch, W., Brooks, P.D., Gustafson, J.R. and Molotch, N.P., 2009. Quantifying the effects of forest canopy cover on net snow accumulation at a continental, mid-latitude site. *Ecohydrology*, 2: 115-128.
- Veblen, T.T., Hadley, K.S., Nel, E.M., Kitzberger, T., Reid, M. and Villalba, R., 1994. Disturbance regime and disturbance interactions in a Rocky Mountain subalpine forest. *Journal of Ecology*, 82: 125-135.
- Voiculescu, M., Onaca, A. and Chiroiu, P., 2016. Dendrogeomorphic reconstruction of past snow avalanche events in Bâlea glacial valley–Făgăraș massif (Southern Carpathians), Romanian Carpathians. *Quaternary International*, 415: 286-302.
- Voight, B., Armstrong, R.R., Armstrong, R.L., Bachman, D., Bowles, D., Brown, R.L., Faisant, R.D., Ferguson, S.A., Fedston, J.A., Kennedy, J.L., Kiusalaas, J., LaChapelle, E., McFarlane, R.C., Newcomb, R., Penniman, R. and Perla, R., 1990. *Snow Avalanche Hazards and Mitigation in the United States*. National Academy Press, Washington, D.C.
- Waller, J.S. and Mace, R.D., 1997. Grizzly bear habitat selection in the Swan Mountains, Montana. *Journal of Wildlife Management*, 61(4): 1032-1039.
- Walsh, S.J., Butler, D.R., Allen, T.R. and Malanson, G.P., 1994. Influence of snow patterns and snow avalanches on the alpine treeline ecotone. *Journal of Vegetation Science*, 5: 657-672.
- Walsh, S.J., Weiss, D.J., Butler, D.R. and Malanson, G.P., 2004. An assessment of snow avalanche paths and forest dynamics using Ikonos satellite data. *Geocarto International*, 19(2).
- Wayand, N.E., Massmann, A., Butler, C., Keenan, E., Stemberis, J. and Lendquist, J.D., 2015. A meteorological and snow observational data set from Snoqualmie Pass (921 m), Washington Cascades, USA. *Water Resources Research*, 51: 10092-10103.

- Wilcoxon, F., 1945. Individual comparisons by ranking methods. *Biometrics Bulletin*, 1(6): 80-83.
- Wobus, C., Small, E.E., Hosterman, H., Mills, D., Stein, J., Rissing, M., Jones, R., Duckworth, M., Hall, R., Kolian, M., Creason, J. and Martinich, J., 2017. Projected climate change impacts on skiing and snowmobiling: A case study of the United States. *Global Environmental Change*, 45: 1-14.
- Zahumensky, I., 2004. Guidelines on Quality Control Procedures for Data from Automatic Weather Stations, World Meteorological Organization.