TRAVEL BEHAVIOR AND DECISION-MAKING BIASES OF LIFT ACCESS BACKCOUNTRY SKIERS ON SADDLE PEAK, BRIDGER MOUNTAINS, MONTANA, USA.

by

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ABSTRACT

Backcountry skiers recreate in a complex environment, with the goal of minimizing the risk of avalanche hazard and maximizing recreational opportunities. Traditional backcountry outings start and end in uncontrolled backcountry settings, with responsibility for avalanche safety and rescue falling in the hands of each group of skiers. Lift access backcountry skiing (LABC) is a particular genre of the sport in which ski resort lifts are utilized to access backcountry recreation sites. By shifting skiers mentality from the traditional backcountry setting to a LABC setting, the line between whether the ski resort provides avalanche mitigation and rescue services or not, becomes less clearly defined in the minds of skiers.

We observe the travel behavior and evaluate the decision-making biases of LABC skiers via GPS tracking and survey responses. Participants were recruited in the field, at the boundary between the relative safety of the ski resort and the uncontrolled backcountry terrain beyond. A geographic information system (GIS) is implemented to analyze the travel behavior of participants, with the aim to detect changes in behavior, as indexed via terrain used under different levels of avalanche hazard. Logistic regression and multiple linear regression are used to model travel behavior and decision-making biases as a function of observed terrain metrics.

Data was collected over 19 days from February 2017 to February 2018 at Saddle Peak backcountry area, a prime LABC location at the southern boundary of Bridger Bowl Ski Area, Montana, USA. Avalanche hazard during data collection was either moderate (119 tracks) or considerable (20 tracks). Regression models indicate subtle changes in the terrain preferences of participants under elevated avalanche hazard, with increased travel on ridge features and decreased use of convex features. These indicate a positive response, minimizing the risk of an avalanche involvement by managing slope shape. Survey responses indicate that female participants and those with greater backcountry experience have a significantly lower percentage of their total GPS track in complex avalanche terrain as defined using the avalanche terrain exposure scale. Participants who perceived the ski patrol as providing avalanche mitigation in the backcountry area adjacent to the resort had a significantly higher percentage of GPS track in complex avalanche terrain.

INTRODUCTION

Snow avalanches are the primary hazard for winter backcountry recreationists in mountainous terrain. Most avalanche fatalities are not random. On the contrary, in 90% of fatal accidents the victim or someone in the victims party trigger the avalanche (Schweizer & Lutsc, 2001). There is a bright side to this statistic; backcountry parties have control over when and where they enter terrain capable of producing avalanches. However, over the past ten seasons an average of 140 people per year were killed by avalanches worldwide (Shandro & Haegeli, 2018). In many cases it is not the complexity of the avalanche hazard evaluation that leads to accidents, but rather the failure to recognize obvious signs of unstable conditions due to decision-making biases. Over the last ten years researchers have drawn on the fields of psychology and decision-making to attempt to reduce avalanche fatalities by learning about effective decision-making in complex environments.

Background

In the United States, most avalanche fatalities occur in four populations of backcountry recreationists; backcountry skiers, snowmobilers, climbers, and lift access backcountry skiers (Colorado Avalanche Information Center, 2018). Individuals who participate in these activities all share the desire to recreate in snowy mountainous terrain and therefore expose themselves to higher risk of avalanche involvement. The recreational goals and terrain use are different between these populations. This thesis will focus on backcountry and lift access backcountry skiers. For reference, the term backcountry skier will be used to describe any recreational user travelling in backcountry avalanche terrain, whether they travel on skis, snowboard, or any other form of human powered snow sliding device. Our research goals are to evaluate the travel behavior and decision-making biases of lift access backcountry skiers.

Human Factors in Avalanche Terrain

The complexity of managing group expectation and goals with the ever-changing avalanche hazard has been recognized as a potential source of accidents in avalanche terrain since the 1980s. Using avalanche fatality data from the 1970's, Doug Fesler characterized avalanche accidents based on user group, trigger mechanism, and burial time to develop a profile for targeted avalanche education (Fesler, 1980). This early research revolved around the idea that backcountry skiers did not make decisions based on risk evaluation and data collection, but rather on preconceived assumptions that are not verified with field data collection.

Human factors were coined as a term for identifying decision-making biases and group dynamics that negatively impact the safety of backcountry ski groups by Doug Fesler and Jill Fredston of the Alaska Mountain Safety Center. Their knowledge of human factors was based on their personal experience in avalanche terrain and their role as avalanche education and rescue professionals. Specific decision-making biases identified in this research include: attitude, ego, incorrect assumptions, peer pressure, denial, tunnel vision, complacency, money considerations, poor planning, poor communication, the "sheep syndrome", barn yard syndrome, and lion syndrome

(Fredston & Fesler, 1994). While this list of biases is not a based on empirical research, all experienced backcountry travelers can identify with their influence on decision-making in backcountry skiing. These concepts are included in one of the first widespread published books for avalanche education, *Snow Sense, A Guide to Evaluating Snow Avalanche Hazard* (Fredston & Fesler, 1984), and became integrated in US avalanche education curriculum .

Empirical Decision-Making Research

Ian McCammon conducted the first empirically based research on decision-making biases in 2004, focusing on heuristic traps in avalanche fatality data. He approached this issue using avalanche fatality case studies to estimate the risk taken by backcountry groups with varying levels of avalanche education and experience. Based on the accident reports, groups were categorized by their susceptibility to heuristic traps in their decision-making process. Six specific heuristics were highlighted in this research, familiarity, acceptance, consistency, expert halo, social facilitation, and scarcity (McCammon, 2004). Despite the limited scope of inference from research based exclusively on avalanche fatality data, his findings continue to be widely utilized in avalanche education in the US.

Building off the formative work of McCammon (2004), many researchers have extended his methods to encompass non-accident based data. Survey data is the most widely used research method to evaluate decision-making biases and the influence of heuristics on hypothetical decisions. Using the heuristic traps identified by McCammon

(2004), Furman et al. (2010) used vignette style surveys to analyze hypothetical decisions of students prior to taking a level one avalanche course with American Institute on Avalanche Research and Education (AIARE). The Simulated Risk Inventory (SRI) was used to evaluate participants overall tendency for risk taking. Results showed that avalanche forecast, untracked slope, familiarity with slope, having a leader in the group, other ski parties in the area, and commitment to the ski run were significant contributors to self-rated likelihood of skiing a slope (Furman et al., 2010). Of the six heuristic identified by McCammon (2004), the only one that did not show significant influence is acceptance. In addition to building the body of literature of empirical research on decision-making in avalanche terrain, Furman et al. (2010) presented a robust summary of decision theory from cognitive psychology as it applies to the backcountry skiing environment.

Additional support for the influence of McCammon’s (2004) heuristics is presented in Marengo et al. (2017), using an online survey sample. Their research added the availability of safety equipment, slope angle, and previous avalanche involvement as variables in survey vignettes. Results indicate the avalanche forecast, availability of safety equipment, and slope angle have the highest contribution to likelihood of skiing the slope (Marengo et al., 2017). The heuristics of familiarity and tracks on the slope also had positive correlations with likelihood of skiing. A slight positive correlation between direct avalanche involvement and likelihood of skiing was described as a function of unrealistic comparative optimism and self-efficacy.

As a counter point, DiGiacomo (2006) called into question the statistical methodology used by McCammon (2004) to analyze decision-making in avalanche terrain via accident reports. He specifically cites selection bias and base rate neglect as confounding elements of the methods used to identify heuristic traps (DiGiacomo, 2006). Selection bias addresses the subjective nature of accident reporting and conclusions drawn by accident investigators. Base rate neglect references the tendency to ignore the overall frequency of avalanche accidents as a function of the whole population of backcountry ski tours, and focus only on the population of accidents. Ignoring the fact that the vast majority of ski tours do not result in avalanche involvement underrepresents the effectiveness of avalanche education. These critiques call into question the validity of the results from McCammon (2004) and highlight the importance of further research of decision-making in avalanche terrain than did not result in an accident.

Field Based Intercept Surveys

Decision-making research using online survey methodology allows researchers to control for every input variable in their scenarios; however, there is a fundamental difference between measuring participant's hypothetical choices and their actual choices. One approach to measuring backcountry skier's behavior in the field is by intercept survey at trailheads or ski area boundaries. Group size, knowledge of avalanche forecast, rescue preparedness, and perception of avalanche hazard have all been measured via intercept survey (Fitzgerald et al., 2016; Procter et al., 2014; Zweifel et al., 2016).

Results of this research have shown that, generally, backcountry skiers are more prepared with avalanche knowledge and rescue equipment than LABC skiers and snowshoers (Fitzgerald et al., 2016; Procter et al., 2014). Group size has been shown to influence the relative risk, using a ratio of number of groups and number of accidents for different group sizes, of backcountry travelers. Researchers collected this data by posting volunteer signup sheets at trailhead, intercept surveys at trailheads, social media trip reports, and field observations from a network of avalanche professionals. Smaller groups are associated with lower relative risk, with statistically significant differences in relative risk when the group size exceeds 4 members when compared to a base level of 2 members (Zweifel et al., 2016). Surprisingly, nearly 25% of groups observed were solo travelers which had a significantly lower relative risk than groups of 2 for Swiss accident data (Zweifel et al., 2016).

GIS and GPS Analysis of Travel Behavior

The widespread availability of recreational grade GPS units in cell phones and dedicated recreational navigation units has created an opportunity for inexpensive GPS data collection in a variety of research fields. GPS data has been used to analyze overlap in recreational user groups (Miller et al., 2017), to monitor trail use and the related impact on land cover change (Beeco & Hallo, 2014; Beeco et al., 2013), and to analyze urban trail use by recreational user groups (Korpilo et al., 2017).

GPS tracking is a perfect tool to measure the travel behavior of backcountry skiers. When coupled with a geographic information system (GIS), quantitative analysis of the GPS tracks yield the ability to model changes in travel behavior as a function of changing avalanche conditions. GPS track collection has been undertaken using crowd sourcing, social media, and professional organizations (Haegeli & Atkins, 2016; Hendrikx & Johnson, 2016; Hendrikx et al., 2016; Techel et al., 2015; Thumlert & Haegeli, 2017). Each of these methods has some sampling bias, but deriving a model of avalanche terrain management from observed travel behavior in different populations of backcountry skiers is a valuable resource for avalanche research and education. All research to this point has observed changes in travel behavior with increasing avalanche hazard. Generally, lower slope angles and more defensive slope shapes (e.g. ridgelines, concavities) are travelled on during period of elevated avalanche hazard.

Avalanche problem is a more specific characterization of the daily avalanche conditions that take into account the weak layer type, weak layer location, slab hardness, propagation potential, and relative avalanche size potential (Statham et al., 2018). Describing travel behavior using avalanche problem as a stratification method has only been done in a general sense, comparing persistent and non-persistent conditions. Techel et al. (2015) compared relative risk of GPS tracks sourced from social media on days with persistent avalanche hazard and found that there were no influence on the activity level of participants based on avalanche problem. Geographically, areas with the highest relative risk were those in snow climates with thinner snowpacks harboring more persistent weak layers.

By coupling GPS tracks with survey data, Hendrikx & Johnson (2016) were able to compare observed travel behavior with decision-making biases and sample demographics. In contrast to the heuristic traps presented by McCammon (2004), results show that group size, team leadership, group dynamics, and commitment to a goal do not significantly alter travel behavior (Hendrikx & Johnson, 2016). Familiarity with the terrain is shown to have the opposite effect of McCammon (2004). These discrepancies between the two research results are likely due to the sampled population. GPS track data is collected from non-accident based terrain use, whereas McCammon (2004) used avalanche fatality based data. Most backcountry outings do not results in an avalanche accident. Therefore, by collecting tracks from the population of all backcountry outings, not just accident events, Hendrikx & Johnson (2016) capture a more representative sample.

Backcountry vs Lift Access Backcountry Skiers

In contrast to traditional lift access skiing at designated ski resorts, backcountry skiers travel under their own power, in uncontrolled terrain, predominantly on public lands. Backcountry skiers represent 40% of fatalities from 2007 to 2016 (111 of 278), which is the most fatalities of any activity during that period. While there is no way to explicitly track the population of backcountry skiers in the US, we assume that the population has increased dramatically based on internet traffic from avalanche forecast websites (Birkeland et al., 2017). Conservative estimates based on internet traffic of avalanche forecast websites estimate an 8-fold increase from 1995 to 2016. Previous accident analysis has shown that 90% of avalanche victims trigger the avalanche themselves or it is triggered by someone in their party (McCammon & Haegeli, 2006).

This indicates that the vast majority of backcountry ski parties have direct control over their risk of involvement with avalanches, based on their decision-making and terrain selection.

Lift access backcountry recreationists merge the disciplines of resort skiing and backcountry skiing by utilizing the efficiency of ski lifts to gain elevation, before exiting ski resort boundaries and recreating in uncontrolled terrain. Between 2007 and 2016, lift access backcountry recreationists (LABC) comprise 10% (29 of 278) of all avalanche fatalities in the United States. Survey data from Snow sports Industries America (SIA) indicate the population of LABC has increased by 50% from the 2015/16 winter season to the 2016/17 winter season, from 2.2 million to 3.2 million (Physical Activity Council, 2017). An increase in backcountry skiers accessing terrain via ski lifts presents a unique population for targeted avalanche education and outreach.

Lift Access Backcountry Research

The subpopulation of backcountry skiers that this research focuses on is LABC skiers. Previous research has identified this population under a variety of names; including, slackcountry skiers, sidecountry skiers, and out-of-bounds skiers. To clarify the nature of the terrain being accessed by this population, we choose to use the term lift access backcountry skiers. This name highlights the fact that the only difference between traditional backcountry skiers and this population is their means of accessing the terrain. Once the ski resort boundary is crossed, the terrain should be treated as backcountry terrain.

This population is unique because of the ease of accessibility of backcountry terrain from the relative safety of the ski area (Gunn, 2010). When LABC skiers are within the resort boundaries avalanches and rescue operations are the responsibility of the ski patrol, but when they travel outside the ski resort boundary there are no avalanche or rescue support services available from the ski patrol. Signage and boundary lines clearly define the differences between backcountry and in-bounds terrain. Despite the clear communication from ski resorts, the proximity to relatively safe terrain gives some LABC skiers a false sense of security (Van Tilburg, 2010).

Research on this population have shown significant differences in their ability to evaluate avalanche hazard, their preparedness in term of rescue equipment and avalanche forecast knowledge, and their level of avalanche education (Fitzgerald et al., 2016; Haegeli et al., 2012, 2010; Silverton et al., 2009). These results are based on online survey responses and intercept surveys carried out at ski resort boundaries. The lack of preparedness and knowledge in the LABC ski population begs the question of how their travel behavior changes in response to avalanche hazard.

Avalanche Terrain Exposure Scale

Originally developed by Statham et al. (2006), the avalanche terrain exposure scale (ATES) categorizes avalanche terrain into three categories based on a specific list of variables: simple, challenging, and complex. These three categories are intended to communicate the difficulty of safely managing avalanche terrain for a given route, and indicate avalanche hazard levels that are appropriate for specific routes. The original concept of ATES applied to line geometries and characterized the entire route based on the most hazardous portion of the line (Statham et al., 2006). Eleven variables make up the parameters of ATES; they are slope angle, slope shape, forest density, terrain traps, avalanche frequency, start zone density, runout zone characteristics, interaction with avalanche paths, route options, exposure time, and glaciation. Seven of these parameters will trump all others if a certain threshold is reached, for example if the slope angle is determined to have a large percentage above thirty five degrees, then the entire slope is considered complex avalanche terrain.

In order to implement the ATES methodology into a GIS friendly format Campbell & Gould (2013) reduced the set of parameters to include forest density, slope angle, slope shape, and start zone density. A statistical runout model was used to determine the avalanche path and avalanche frequency parameters. Using a decision tree algorithm, slope angle and forest density were determined as the most heavily weighted parameters in the ATES GIS model. One major consideration of ATES mapping using GIS is the scale that the mapping is taking place. Avalanches occur at a variety of spatial scales. In order to account for this, the scale of an ATES map has to either be fixed or account for the spatial variability of scale. A scale of 20-30m is recommended in order to be accurate enough for detailed route finding in an area.

Using aerial imagery, forest density is classified as either primarily treed, mixed, or open. Slope angle is generated using 20m digital elevation models (DEM) with a neighborhood of eight cells. A simple algorithm of slope angle and forest density is used to identify treed areas that could function as terrain traps in the event of an avalanche.

Despite advances the GIS modeling capabilities, field verification is necessary for quality control and increased precision of ATES maps.

Research Questions

This thesis will present original research using GPS tracking, GIS analysis, and survey responses to model the travel behavior and decision-making biases that influence LABC skiers. Previous research has used online and intercept surveys to define the demographics of this population, but no research has looked at travel behavior or LABC specific decision-making biases. Using methods developed by Hendrikx & Johnson (2016) and Thumlert & Haegeli (2017), this research will provide a case study of LABC skiers in one geographic area, specifically, Saddle Peak, SW Montana, USA.

Two primary questions are addressed by this research: (1) How does travel behavior of LABC skiers on Saddle Peak change under 'moderate' versus 'considerable' avalanche hazard levels? (2) What demographics and decision-making biases have the greatest influence on exposure to complex avalanche terrain, as a function of the percentage of the total distance of each GPS track? These questions are addressed in Chapter 2, "Travel Behavior and Decision-Making Biases of Lift Access Backcountry Skiers".

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Abstract

Snow avalanches pose a threat to winter backcountry recreationists who travel in steep, mountainous terrain. Our research expands the existing knowledge on travel behavior and decision-making in avalanche terrain by using GPS tracking to observe the travel behavior of lift access backcountry (LABC) skiers and collecting survey data to investigate the human factors that influence their terrain choices. We sampled participants for this research in the field by handing out GPS units and surveys along the southern boundary of Bridger Bowl Ski Area, SW Montana, USA. In total 139 participants volunteered over the course of 18 days of field data collection, from February 2017 to February 2018. To analyze travel behavior, we used a logistic regression model to fit the GPS point data, with avalanche hazard (*moderate or considerable*) as the response and terrain metrics (*slope angle, slope curvature, forest density*) as explanatory variables. We derived terrain metrics from a 10m digital elevation model and 30m land cover data using a GIS. Our results show statistically significant ($p < 0.01$) changes in terrain preferences under elevated avalanche hazard, with increased travel on ridge features and decreased travel on convex features. This indicates a positive response, reducing the risk of avalanche involvement by traveling on more defensive terrain features. We analyze human factors using multiple linear regression, with percent of track in complex avalanche terrain, as defined using the avalanche terrain exposure scale, as the response variable and survey responses as explanatory variables. Both gender (*female*) and backcountry experience (*expert*) are statistically significant ($p < 0.05$) indicators of lower percentage of GPS track in complex avalanche terrain. Participants who incorrectly perceive a higher degree of avalanche mitigation in the backcountry terrain adjacent to the ski area spend a significantly higher percentage of their time in complex avalanche terrain. Our results provide a case study example of the terrain preferences and avalanche awareness of LABC skiers, and highlight specific human factors that are correlated with terrain selection.

Introduction

Snow avalanches are complex, and difficult to predict in both time and space (McClung & Schaerer, 2006). Even experienced avalanche professionals have to incorporate uncertainty about avalanche instability into their predictions (McClung, 2002). This leaves the average recreational backcountry traveler with the difficult task of trying to analyze the risk of avalanche hazard and weigh it against the recreational benefit of travelling on steep snowy slopes. The decision-making process, and the biases that influence that process, are attracting attention from researchers in many fields, e.g. (Johnson et al., 2015; Marengo et al., 2017; Techel et al., 2015); with the goal of helping recreational backcountry travelers improve their decision-making and reduce the number of fatalities due to avalanche accidents.

From 2007 to 2016 avalanches killed on average 28 people per year in the United States (Colorado Avalanche Information Center, 2018). Populations affected by avalanche fatalities include recreational users, professionals working in avalanche terrain, and public motorists and residents who drive and live near steep snowy mountains. Since 1950, activities with the highest number of avalanche fatalities are backcountry skiers (263), snowmobilers (251), climbers (182), and lift access backcountry riders (103) (Colorado Avalanche Information Center, 2018). Lift access backcountry recreation has grown in popularity in recent years, and may be underrepresented in accident statistics. This paper will focus on recreational users, specifically, lift access backcountry recreationists.

Lift access backcountry recreationists merge the two disciplines of resort skiing and backcountry skiing by utilizing the efficiency of ski lifts to gain elevation, before exiting ski resort boundaries and recreating in uncontrolled backcountry terrain. Between 2007 and 2016, lift access backcountry recreationists (LABC) comprise 10% (29 of 278) of all avalanche fatalities in the United States. Survey data from Snow sports Industries America (SIA) indicate the population of LABC has increased by 50% from the 2015/16 winter season to the 2016/17 winter season, from 2.2 million to 3.2 million (Physical Activity Council, 2017). An increase in backcountry skiers accessing terrain via ski lifts presents a unique population for targeted avalanche education and outreach.

This paper examines the behavior of a discreet subset of backcountry skiers who recreate at Saddle Peak, Bridger Mountains, Montana, USA. Specifically we investigate their travel behavior and decision-making biases using GPS tracking and field based surveys. This is a novel approach to modeling terrain preferences and decision-making in avalanche terrain with non-accident based data by sampling using field intercept methods. Our sample represents actual terrain choices in real world avalanche conditions with survey response data collected immediately post backcountry travel.

Background

Out of Bounds Skiing & Snowboarding

The type of terrain we will focus on for this research, and one growing rapidly in popularity, has been termed “sidecountry” or “slackcountry” (Shockey et al., 2008) (in Europe - *off-piste*). We prefer the term “lift-accessed backcountry” over “sidecountry” terrain. The latter term has generated some confusion in the public and has led to a misplaced belief by the public that sidecountry is somehow safer than backcountry, which is clearly not the case (Chabot et al., 2010; Fitzgerald et al., 2016). This terrain is adjacent to an existing operating ski area boundary and is typically accessed by ski lift then via an exit through an approved gate that allows skiers to leave legally defined boundaries. In the USA, some ski areas require avalanche equipment to board the lift that leads to the exit gate or a sign-out procedure, others require none. Exit signs erected by most ski areas indicate the area boundary is being crossed and that the snowpack is not controlled for avalanches by local ski patrol. Lift accessed backcountry terrain is often complex avalanche terrain and once outside the control boundary the consequence of an avalanche increases dramatically. In the event of an avalanche or skiing injury, rescue is not the responsibility of the local ski patrol. Ski areas provide these warnings to indicate that ski parties should adopt backcountry ski and avalanche practices.

Prior research on the population of LABC skiers has focused on online and intercept survey data (Gunn, 2010; Haegeli et al., 2012; Silverton et al., 2007, 2009). Intercept surveys carried out in the Wasatch Mountains of Utah USA, focused on the preparedness of LABC users for avalanche rescue and their level of avalanche education (Silverton et al., 2007, 2009). Online survey methods include profiling LABC skiers using sensation seeking tools, discrete choice surveys, and latent class analysis. Gunn (2010) characterized a high-risk cohort within the population of LABC skiers by analyzing skier’s terrain preferences under various levels of avalanche danger. Results showed that the high risk cohort was mostly under 34 years old, male, had a misunderstanding of ski resort avalanche mitigation and rescue policies, and had less regard for avalanche danger level or ski area closed terrain (Gunn, 2010). Members of this cohort also scored highly on sensation seeking scales, which is consistent with prior research on athletes in high risk activities (e.g. rock climbing, sky diving, surfing).

Using time lapse photography Saly et al (2016), recorded the travel behavior of LABC skiers on Saddle Peak in the winters of 2015/16 and 2016/17 at 10 second intervals. This method allows for passive monitoring of skiers in the backcountry and captures a high volume of skier traffic when compared to crowd sourced data or intercept survey methods. This data is limited to skier locations at the interval of the camera settings (10 seconds) and is susceptible to interruption from cloud cover, fog, and technical difficulties (Saly et al., 2016). Additionally, there is no means to collect data on demographics or decision-making via this remote sensing method.

<u>Decision-Making by Backcountry Skiers</u> McCammon (2004) presented the first empirically based research on the cognitive biases that influence backcountry decision-making (McCammon, 2004). He approached this issue by analyzing avalanche fatality case studies to estimate the risk taken by backcountry groups with varying levels of avalanche education and experience. Based on the accident reports, groups were categorized by their susceptibility to heuristic traps in their decision-making process. Six specific heuristics were highlighted in this research: familiarity, acceptance, consistency, expert halo, social facilitation, and scarcity. The heuristics were used to describe discrete subpopulations of the accidents dataset based on written reports. His findings continue to be widely utilized in avalanche education in the US.

While providing a turning point in the research of human factors in backcountry recreation, McCammon’s approach of only studying fatal avalanche accidents severely limited the scope of inference for his research. Subsequent research has utilized survey responses to evaluate participant’s terrain preferences and catalogue their demographics and decision-making biases (Bright, 2010; Eyland, 2016; Furman et al., 2010; Haegeli et al., 2012, 2010; Mannberg et al., 2017; Marengo et al., 2017). This approach yields valuable information on backcountry skier’s perception of the risk they undertake, but does not evaluate skiers based on their actual terrain choices.

<u>Group Demographics and Preparedness</u> Zweifel et al. (2016) compared the relative risk factor of different group sizes of backcountry skiers to determine what group size had the lowest relative risk. In this study relative risk was calculated by observing the frequency of different group sizes at popular trailheads and through a network of expert observers, and comparing that to the group sizes in avalanche accident statistics (Zweifel et al., 2016). Results indicate that group sizes of five or more have a significantly higher risk ratio compared to groups of size of two. One surprising finding from this study is that one quarter of observed groups were solo skiers, which is traditionally thought of as a high risk activity due to the lack of self-rescue capability in case of an avalanche. However, this research showed that solo skiers had a significantly lower risk ratio compared to groups of two in three out of four datasets.

Carrying essential rescue equipment, avalanche transceiver, probe, and shovel, and knowledge of the public avalanche forecast are considered fundamental to preparedness and objective decision-making in backcountry skiing. In a study in South

Tyrol, Italy 5,576 individuals were surveyed over a one week period. Researchers found that only 52.5% of ski groups knew the avalanche danger level, and 80.6% carried standard rescue equipment (Procter et al., 2014). Fitzgerald et al. (2016) carried out intercept surveys of backcountry and LABC skiers in southwest Montana to evaluate their preparedness. They found differences in avalanche education, knowledge of the avalanche forecast, likelihood to perform instability tests, and avalanche rescue equipment (Fitzgerald et al., 2016). In each case, the LABC skiers were less prepared and informed than their traditional backcountry counterparts.

GPS Tracking in Avalanche Research The introduction of GPS technology to cell phones and inexpensive recreational navigation devices has provided a means of data collection for land use planners and researchers interested in the impacts of recreation on ecological systems (Beeco et al., 2013; Korpilo et al., 2017). Utilizing global positioning system (GPS) tracking in decision-making research is a relatively new development in the field of avalanche science. The first application of GPS tracking to backcountry skiers was as a crowd sourced data collection model for backcountry skiers around the world (Hendrikx & Johnson, 2016b). GPS tracking has since been implemented in modeling travel behavior of helicopter ski guides in Alaska (Hendrikx et al., 2016) and Canada (Haegeli & Atkins, 2016; Thumlert & Haegeli, 2017), and recreational snowmobilers (Hendrikx & Johnson, 2016a). By implementing GPS tracks in a geographic information system (GIS) terrain metrics can be extracted to quantify each track. Results from this initial GPS analysis have shown the capability to accurately model the severity of avalanche terrain based on the decision-making of ski guides

(Thumlert & Haegeli, 2017), and highlight the travel behavior of backcountry skiers and snowmobilers (Hendrikx & Johnson, 2016a, 2016b), allowing for targeted avalanche education and outreach.

Crowd sourcing as a method for collecting GPS tracks from backcountry skiers has been used in North America and Europe (Hendrikx & Johnson, 2016b; Techel et al., 2015). Methods for data collection include cell phone applications and online social media forums. Data collected via cell phone allows users to participate in survey responses in addition to GPS tracking, which provides a more comprehensive dataset of both perceived and actual risk taking. This data shows expert level skiers using higher slope angle on average, and no evidence suggesting that heuristic traps affect the decision-making process of backcountry skiers (Hendrikx & Johnson, 2016b). An exception is that familiarity does affect travel behavior, but the direction of the relationship is opposite of that hypothesized by McCammon (2004) based avalanche fatality data. Generally, participants travel on lower slope angles on days with elevated avalanche hazard (Hendrikx & Johnson, 2016b).

<u>Avalanche Terrain Exposure Scale</u> Originally developed by Statham et al. (2006), the avalanche terrain exposure scale (ATES) categorizes avalanche terrain into three categories, simple, challenging, and complex, based on a specific list of variables. These three categories communicate the difficulty of safely managing avalanche terrain, and indicate avalanche hazard levels that are appropriate for terrain (Statham et al., 2006). This standard is widely used across western Canada to communicate terrain severity and risk to recreational backcountry users. Campbell & Gould (2013) reduced the set of

parameters to include forest density, slope angle, slope shape, and start zone density for a GIS friendly processing methodology. Using a decision tree algorithm, slope angle and forest density were determined as the most heavily weighted parameters in the ATES GIS model (Campbell & Gould, 2013). Despite advances in GIS modeling capabilities, field verification is necessary for quality control and increased precision of ATES maps.

Research Questions Previous research used online and intercept surveys to define the demographics and stated travel preferences of the LABC population. To date, no research has looked at actual real-world travel behavior or LABC specific decision-making biases. Our research will present a case study, using GPS tracking and survey responses to model the travel behavior and decision-making biases that influence LABC skiers on Saddle Peak, SW MT, USA. Two primary questions will be addressed: (1) How does travel behavior of LABC skiers on Saddle Peak change under ‘moderate’ versus ‘considerable’ avalanche hazard levels? (2) What demographics and decision-making biases have the greatest influence on exposure to complex avalanche terrain, defined by ATES, as a function of the percentage of the total distance of each GPS track?

Methods

Study Area

We collected data from the area around Saddle Peak (45.791314˚N, 110.937614˚W), in the southern Bridger Mountains, Montana, USA. Saddle Peak's location adjacent to Bridger Bowl Ski Area makes it accessible via a short hike from a ski lift and skiers can easily return the base of the ski lift without using climbing skins or hiking (Figure 1). Saddle Peak is 9,159 feet (2,791 m) tall, and has a vertical drop of 2,114 feet (644 m) from the peak to the base of the lift.

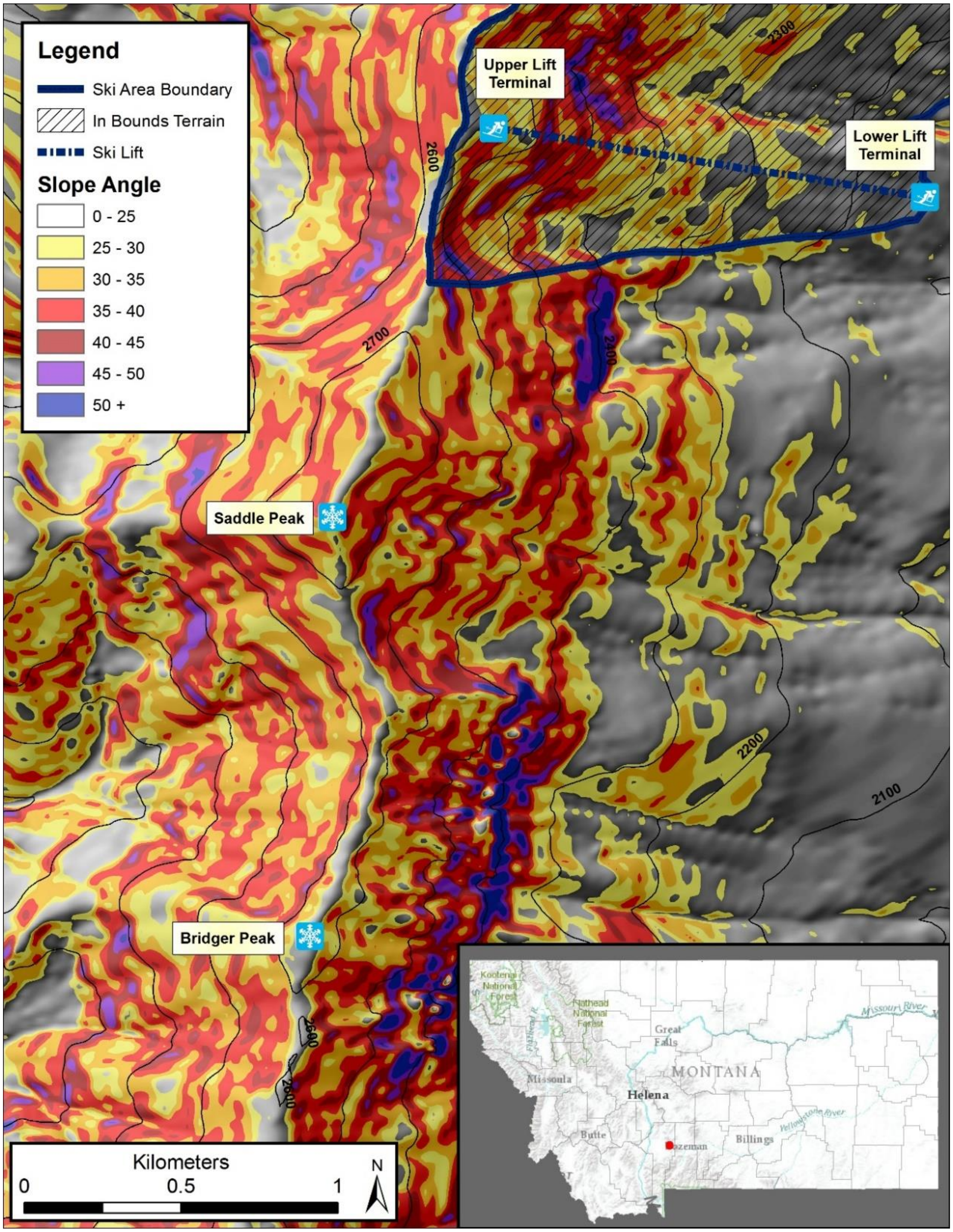


Figure 1: Map of Saddle Peak backcountry ski area with slope angle shading derived from a 10m DEM. Note the large cliff band adjacent to the ski area boundary at 2400m. GPS units were distributed on the ridgeline at the ski area boundary, and collected at the lower terminal of the ski lift. Inset map in bottom right shows location of study area in relation to Montana.

The backcountry terrain is complex, with steep wind loaded slopes above cliff bands in many areas. A variety of ski runs are accessible by hiking from the ski lift, but all options involve travelling in avalanche terrain with angles of 30˚ or higher. Despite active avalanche control work, skiers are required to wear an avalanche transceiver to use the ski lift in this portion of the ski area. The inbounds terrain accessible from this lift is all expert level, with unmarked hazards and no groomed runs or beginner options to descend. Uphill travel is prohibited within the ski area boundaries during the operating season, which means that nearly all users on Saddle Peak backcountry area utilize lift access.

The snow climate at Bridger Bowl Ski Area is generally categorized as intermountain, with some seasons more characteristic of a continental climate (Mock & Birkeland, 2000). Wind direction is predominantly out of the west, which causes heavy scouring of the western aspect of the Saddle Peak ridgeline and frequent wind loading on the eastern aspect. Large cornices dominate the landscape when viewing from the Bridger Bowl boundary up to Saddle Peak, and serve as a hazard to skiers entering the terrain from the ridgeline (Figure 2). Due to combined issues of preferential wind loading on the east slope and easy return to the ski lifts, the majority of users only ski the eastern face.

Figure 2: Photograph looking from the Bridger Bowl boundary up towards Saddle Peak. The western aspect (right side of ridgeline) is characteristically wind scoured, with cornice formation on the eastern aspect (left side of ridgeline), which is the most commonly skied side.

In February 2010, a large avalanche was triggered on Saddle Peak by a skier releasing part of a cornice onto the slope below. Multiple skiers were on the slope at the time the avalanche released and narrowly missed being caught in the avalanche. This avalanche was preceded by 3.5” (8.9 cm) of snow water equivalent, on top of a known deep persistent week layer. Luck prevailed that day, but LABC skiers on Saddle Peak made several mistakes. Including poor travel practices, misjudgment of the effect of skier compaction on a known buried weak layer, overreliance on familiarity with the terrain, and susceptibility to human factors during a high consequence avalanche hazard (Chabot et al., 2010).

Data Collection

We collected GPS tracks and survey responses from volunteer participants in the Saddle Peak backcountry area over the time span of February 2017 through February 2018. During that time, we carried out nineteen field days, with fifteen yielding data. In total, we collected 183 GPS tracks. We asked participants to carry a GPS unit when they exited the ski area boundary and return the GPS unit after their backcountry run, at the base of the ski lift. Once we recovered the GPS unit at the lower lift terminal, participants were asked to fill out a paper survey while riding the lift back up and place the completed survey in a drop box at the upper lift terminal.

Our research design aimed to minimize the time required for participation, therefore encouraging repeat participation and maximizing acceptance rates on subsequent days. Only one GPS track and survey were collected from each participant for each day of data collection, therefore multiple tracks were never recorded from one person in the course of a day. Groups of skiers who travelled together were limited to carrying one GPS unit and filling out one survey, to limit the influence of any one group on the overall dataset. No unique identifying information was collected for participants to ensure privacy. The GPS units and surveys were numbered to enable pairing the GPS track and survey response for the individual participants (Figure 3).

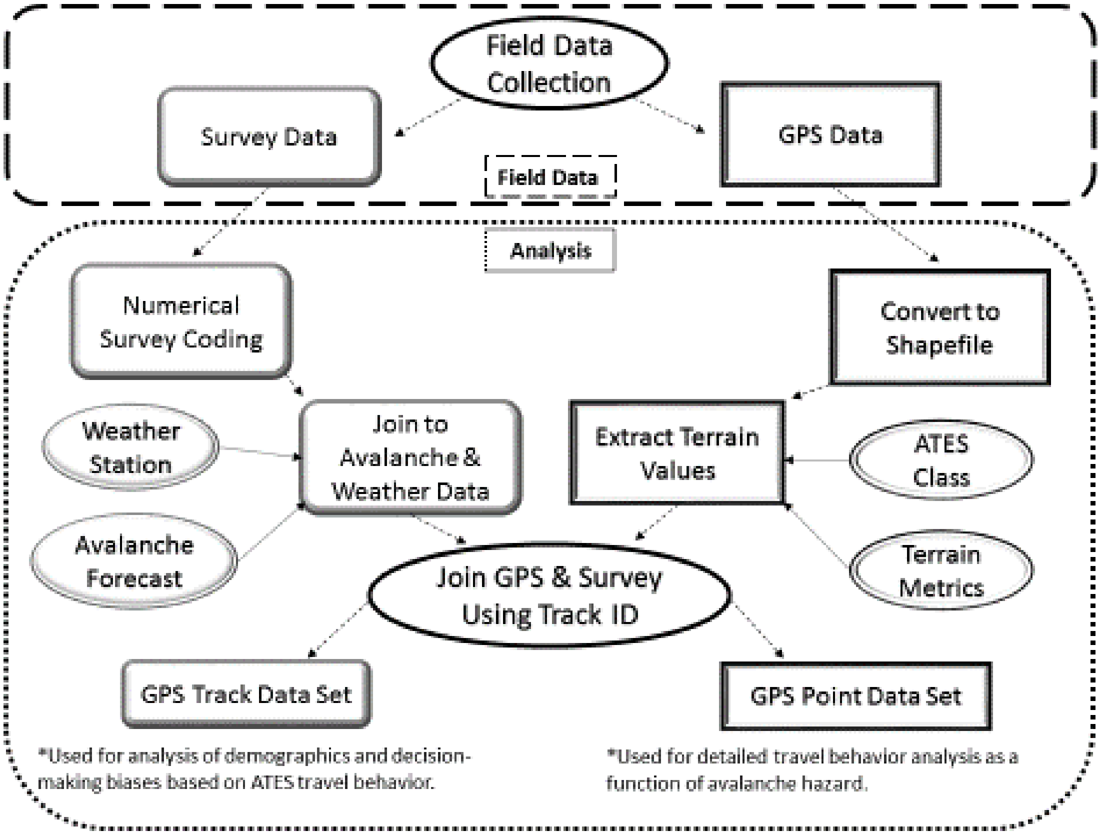


Figure 3: Workflow diagram showing the process of analyzing data collected from intercept surveys and GPS tracks. Survey data and GPS tracks are processed individually and combined post-processing. Two data sets were developed from this workflow, one based on GPS points for detailed terrain analysis, and one based on the summarized GPS track for analysis of survey responses.

GPS units used for this research were Garmin eTrex 20. Horizontal accuracy of eTrex GPS units are estimated at 5m with open sky, 7m in young forest, and 10m in closed canopy settings (Wing et al., 2005). On average, the land cover characteristics of GPS tracks were 40% open, 20% forested, and 40% sparse forest or shrub. Recording interval was set to ‘Most Often’, so that the GPS would alter the number of points collected based on the rate of travel for each participant. Between nine and eleven GPS units were used for each field day, with some units collecting multiple tracks per day, from different individuals.

We based our survey design on previous research which aimed to measure demographics and human factors in backcountry and LABC ski populations (Fitzgerald et al., 2016; Hendrikx & Johnson, 2016b). Demographic questions mirrored the response options from these previous surveys, while human factor questions were adjusted to reflect our hypotheses about specific LABC decision-making biases. The number of questions and layout of the survey were restricted by the fact that participants would complete the survey in the field while riding up a ski lift (approx. 5min). The final product was a 20 question two sided survey printed on weather proof paper that could be completed with gloved hands using a sharpie marker. Survey questions were roughly grouped in 4 sections: demographics, preparedness, LABC biases, and heuristic traps (Appendix A).

Avalanche forecast and daily weather data were compiled from online archives at the Gallatin National Forest Avalanche Center (GNFAC), and Bridger Bowl Ski Area. The GNFAC avalanche forecast provided avalanche hazard level and the primary avalanche problem. We used Bridger Bowl Ski Area weather stations to collect data at four locations around the ski area. The Alpine and Bridger weather stations were used for precipitation measurements, taken at two different elevations. The Schlasmans and Ridge weather stations were used for wind speed and direction, temperature, and relative humidity. The Schlasmans station provides accurate weather data for the east face of Saddle Peak, while the Ridge weather station provides accurate conditions for the upper elevation ridge terrain. Sampling days were selected to maximize participations, but were not biased by specific weather and avalanche conditions (Figure 4 &5).

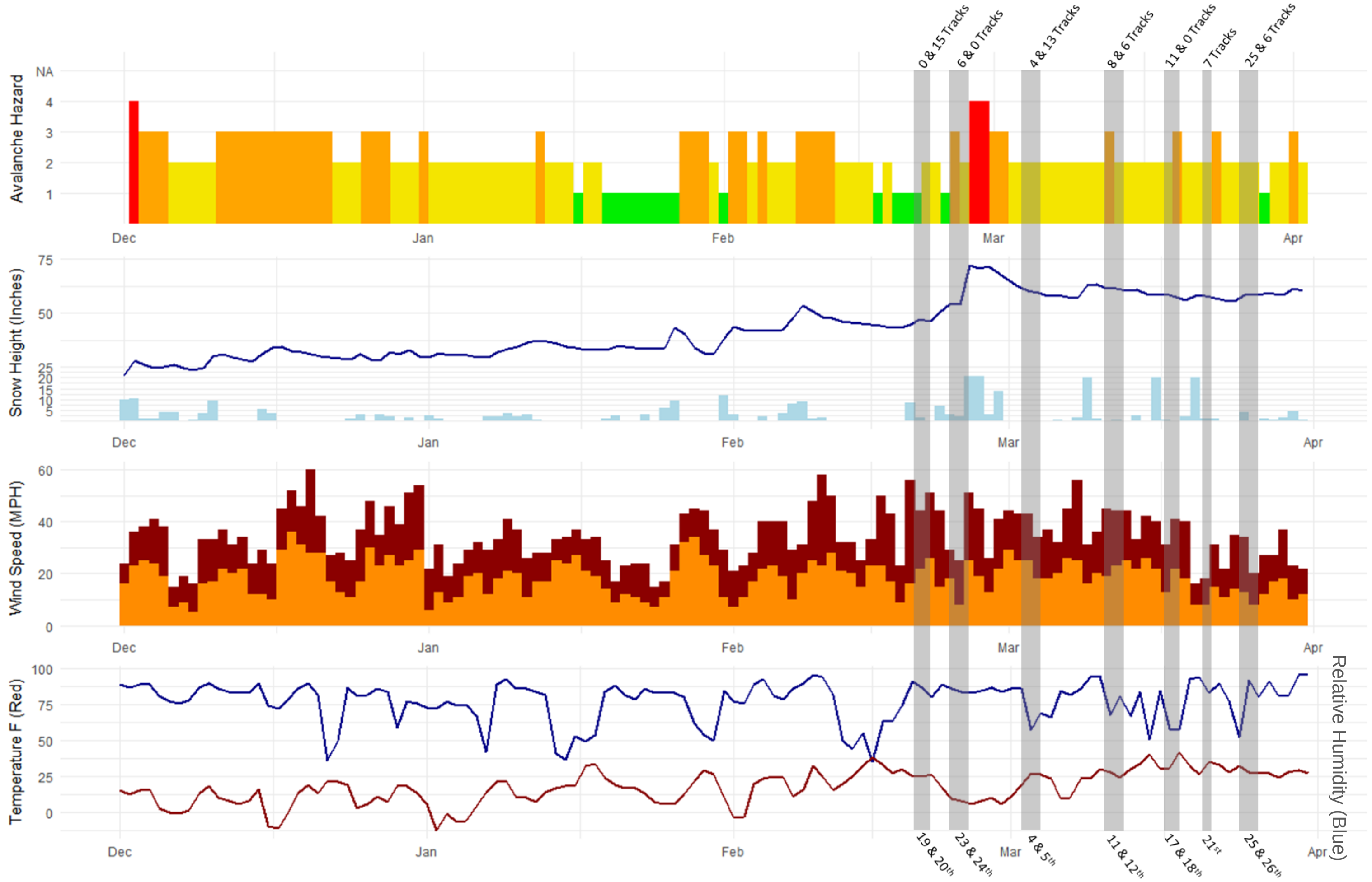


Figure 4: Avalanche hazard and weather history for Saddle Peak during 2016/2017 winter season. The first (top) plot shows avalanche hazard, second shows snow height for the season (blue line) and daily (light blue boxes), third daily wind gusts (dark red) and average (orange), fourth (bottom) daily relative humidity (blue) and average temperature (red). Sampling days highlighted with grey boxes.

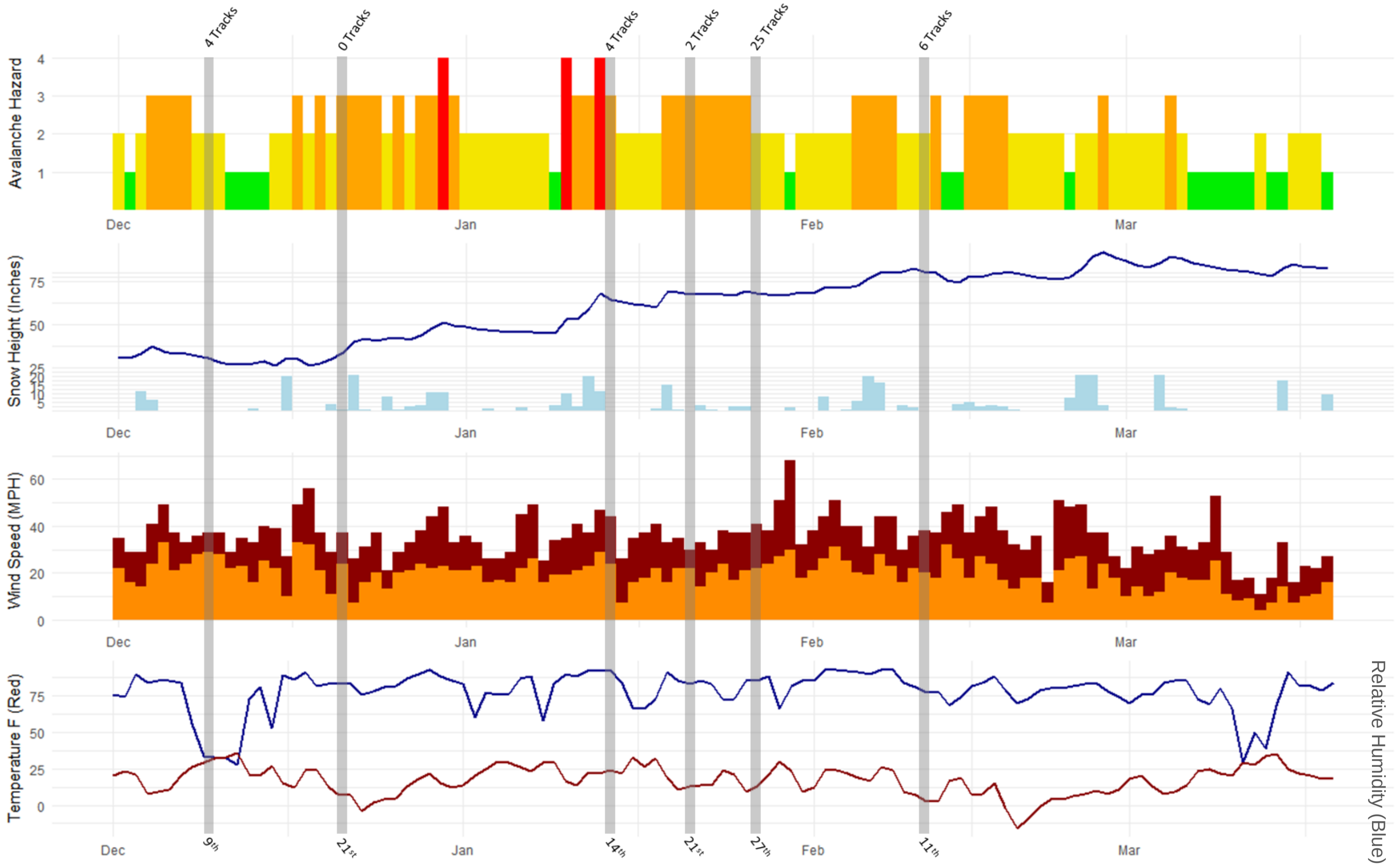


Figure 5: Avalanche hazard and weather history for Saddle Peak during 2017/2018 winter season. The first (top) plot shows avalanche hazard, second shows snow height for the season (blue line) and daily (light blue boxes), third daily wind gusts (dark red) and average (orange), fourth (bottom) daily relative humidity (blue) and average temperature (red). Sampling days highlighted with grey boxes.

Data Processing

GPS Processing GPS tracks were analyzed using a combination of Google Earth Pro, ArcGIS 10.4, Microsoft Excel, and R software packages. Using ArcGIS model builder, GPS tracks were converted to point Shapefiles, and clipped to exclude inbounds terrain and uphill travel along the Saddle Peak ridgeline. Terrain metrics of slope angle, cross slope curvature, down slope curvature, aspect, and land cover were extracted to the GPS points. The first four terrain metrics were derived from a USGS digital elevation model (DEM) with 1/3 arc second resolution (~10m cell size). The National Land Cover Dataset (NLCD) 2011 provided land cover classification for the study area with a 30m cell size. All raster layers and GPS tracks were stored in North American Datum 1983 (NAD 83), with a Universal Transverse Mercator Zone 12N (UTM 12N) projected coordinate system.

Data Cleaning Of the total 183 GPS tracks, those without corresponding surveys (n=24) were dropped from the final data set for this analysis. Multiple tracks collected from pairs of skiers travelling together (n=11) were randomly selected to include only one of the participants from this group in the final dataset. Due to the predominant wind direction and snowpack structure in the Bridger Mountains, all but two GPS tracks were located on the eastern side of the mountain range. The two western aspect tracks (n=2) were excluded from the final dataset because they were not representative of the terrain skied by the vast majority of backcountry skiers in the area. Due to GPS tracking errors and battery issues an additional seven GPS tracks (n=7) were dropped from the final dataset, leaving a total of 139 complete GPS tracks.

To answer the primary research questions, GPS data from the 139 GPS tracks was extracted in two different formats:

1) GPS point data was used to model travel behavior as a function of avalanche hazard. The total number of GPS points from the 139 GPS tracks is 17,607. However, to model travel behavior by avalanche hazard level we believe participants need to be informed of the avalanche hazard level. Therefore, we filtered the GPS point data using survey responses to only include participants who accurately indicated the avalanche forecast level. This resulted in a filtered GPS point dataset of 11,181 GPS points from 89 GPS tracks, which is 64% of the total GPS tracks sampled. By using GPS points to answer this research question, we have a much richer representation of the travel behavior through space and time than we would if we summarized the GPS points into one statistic for each track. Serial and cluster effects of GPS points from the same track are noted as a potential sample bias for the GPS point data set.

2) When modeling demographics and decision-making biases for each participant the GPS points were summarized by track, yielding 139 GPS tracks. In this analysis, we are considering the participant's GPS track and survey response as the individual for our sample population. To summarize the travel behavior of each participant, we created an Avalanche Terrain Exposure Scale (ATES) map of the Saddle Peak backcountry area. The ATES map uses multiple variables, including slope angle, land cover, and avalanche path characteristics, to rate avalanche terrain on a scale from one to three. Using the percent of track in ATES class three terrain as a response variable, allowed us to

summarize multiple terrain metrics simultaneously, instead of having to select one terrain metric to serve as a response in our statistical model.

Avalanche Terrain Exposure Scale ATES maps are widely used in Canada as a tool to communicate the difficulty of managing avalanche terrain and how prevalent avalanche hazard is in different zones within a backcountry skiing area. The scale ranges from simple (1) to challenging (2) to complex (3). An ATES map was developed for the Saddle Peak backcountry area using the workflow presented in Campbell and Gould (2013). Terrain analysis was carried out in ArcMap 10.4 and zonal statistics were extracted to a spreadsheet to verify slope angle distribution for each land cover type (Figure 6). Local avalanche experts were consulted when considering start zone density, interaction with avalanche paths, and terrain traps.

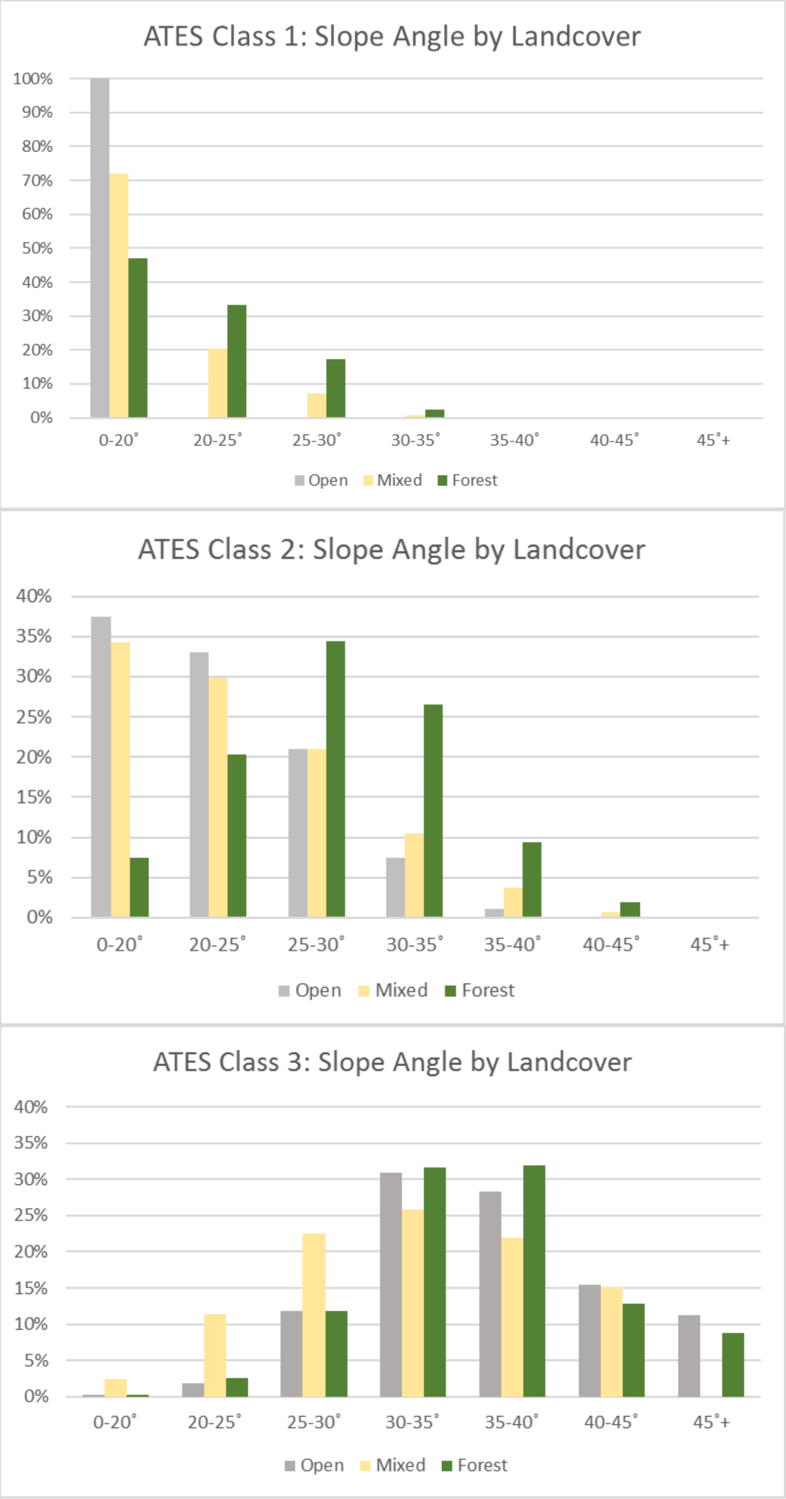
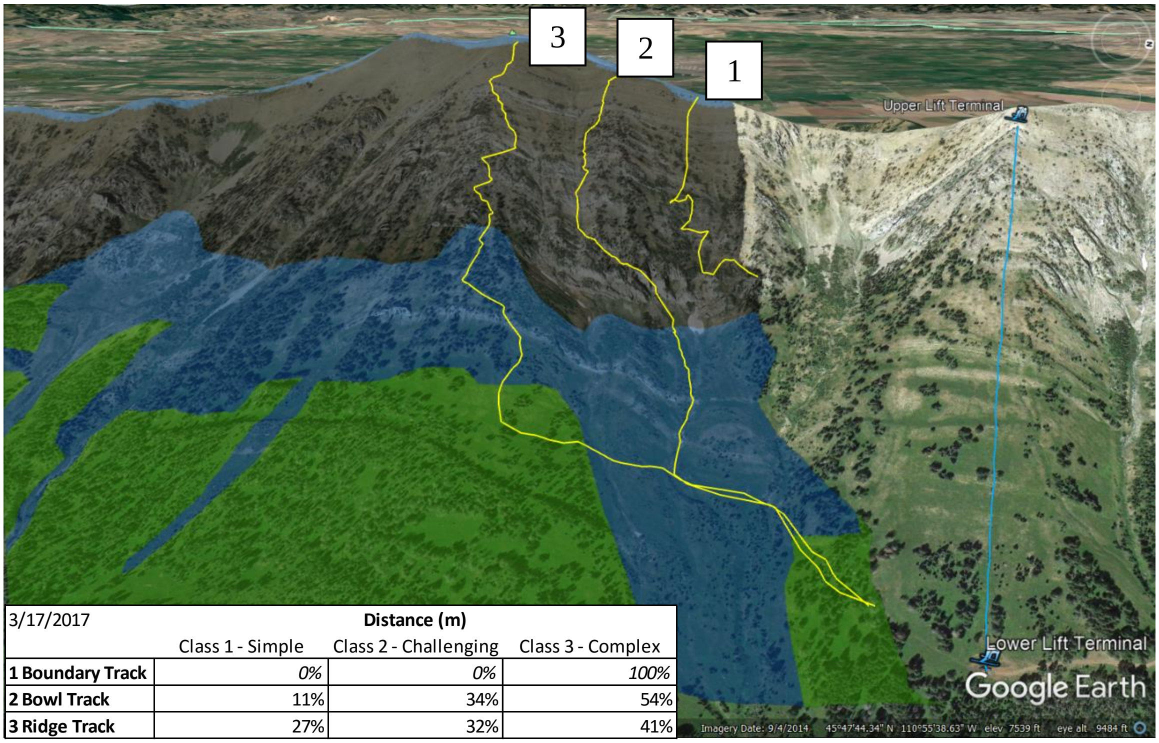


Figure 6: ATES model verification using slope angle as a function of land cover. Thresholds for slope angle percentages by land cover are defined in Campbell and Gould (2013).

To implement the ATES model in our analysis, ArcMap 10.4 was used to extract the ATES classification for each GPS point from each GPS track (ESRI, 2011). The total distance, total time, percent of total distance, percent of total time, and speed in ATES class 3 (complex) terrain was calculated for each track (Figure 7). These variables approximate the risk due to avalanche hazard for each track as a function of the portion of the GPS track that travelled in complex avalanche terrain. The main assumption with these variables is that the probability of involvement with an avalanche incident is higher, and the consequences of that involvement are higher, in complex terrain.



3/17/2017	Distance (m)		
	Class 1 - Simple	Class 2 - Challenging	Class 3 - Complex
1 Boundary Track	*0%*	*0%*	*100%*
2 Bowl Track	11%	34%	54%
3 Ridge Track	27%	32%	41%

Figure 7: Example of GPS tracks with ATES map overlay. Black indicates complex terrain, blue challenging terrain, and green simple terrain. ATES class was extracted for each GPS point along the track to summarize the severity of the terrain. The inset table refer to the boundary track (1), bowl track (2), and ridge track (3).

Analysis

Regression models were fit to answer the following research questions: (1) How does travel behavior of LABC skiers on Saddle Peak change under ‘moderate’ versus ‘considerable’ avalanche hazard levels? (2) What demographics and decision-making biases have the greatest influence on exposure to complex avalanche terrain, as a function of the percentage of the total distance of each GPS track? Regression modelling and model refinement were carried out in the software package R (R Core Team, 2016).

Travel Behavior by Avalanche Hazard

In an approach similar to Thumlert & Haegeli (2017), data was collected on days with ‘Moderate’ and ‘Considerable’ avalanche hazard, a binary categorical variable. Logistic regression is a modeling technique used to model binary response variables. The logit or log of the odds, of the outcome is modeled as a linear combination of the explanatory variables. Logistic regression was used to model the first research question using the R function ‘glm’, with the binary response variable set to avalanche hazard. The explanatory variables are slope angle, cross slope curvature, down slope curvature, and land cover. This type of model uses maximum likelihood estimation (MLE) to find the explanatory variable values that maximize the likelihood function for the binary response variable. The regression equation for this research question is:

$$logit(Avalanche\ Hazard) = \beta_0 + \beta_{Slope} * \beta_{Lndcover} + \beta_{Cxslope} + \beta_{Dwnslope} \tag{1}$$

An interaction between slope and land cover was included due to the effect of forest density on avalanche release and avalanche path demarcation and significantly better model fit when including this interaction. The variables *Cxslope* and *Dwnslope* measure the shape of the terrain in terms of convex, concave, or planar, both perpendicular to the fall line (*Cxslope)* and parallel to the fall line (*Dwnslope*). All variables in this analysis were converted to ordinal classes, in order to observe the relationship between avalanche hazard and the predetermined thresholds for each variable class (Table 1). The classification thresholds of variables were adapted from Thumlert & Haegeli (2017), who developed this logistic regression modeling technique for avalanche hazard and terrain metrics. Model assumptions, model fitting, and plots are shown in Appendix B.

Table 1: Terrain metric classification scheme, after Thumlert & Haegeli (2017)

Slope Angle		**Land Cover**		**Down Slope Curvature**		**Cross Slope Curvature**	
Class	*Value Range (˚)*	*Class*	*Value (NLCD 2011)*	*Class*	*Value Range*	*Class*	*Value Range*
0-30	0-30	Treed	Forest	Planar	0.1 to -0.1	Planar	0.1 to -0.1
30-45	30-45	Sparse	Shrub/Scrub	Concave	> 0.1	Ridge	> 0.1
45+	45-62	Sparse	Herbaceous	Convex	< -0.1	Gully	< -0.1
		Open	Barren Land				

Average marginal effects (AME) provide a method to interpret the effect of explanatory variables on the full distribution of response variables (Leeper, 2017). AME calculates the effect of each explanatory variable at every value of the response, and gives the average effect for each level of the explanatory variables. This provides a single number summary of the effect of each explanatory variable on the response, which highlights the most influential explanatory variables. AME was calculated for the travel behavior logistic regression model using the R package ‘margins’ (Leeper, 2017). Analysis of differences in sample demographics between considerable and moderate avalanche hazard was carried out using the *Mann-Whitney U Test* and *Fisher’s Exact Test* in the R package ‘MASS’ (Venables & Ripley, 2002).

Human Factors by Percent of Track in Complex Terrain Multiple linear regression was used to model human factors and percent of track in complex terrain because percent of track is a continuous response variable and the survey responses are a combination of continuous and categorical variables. The research question that drove this analysis is: What demographics and decision-making biases have the greatest influence on exposure to complex avalanche terrain, as a function of the percentage of the total distance of each GPS track? The model uses the percent of the total GPS track distance in complex avalanche terrain as the response variable. The model fitting process involved explanatory variables that reflect the demographics of survey participants, their perception of LABC avalanche hazard, and their self-rated influence of heuristic traps, as identified by McCammon (2004).

Demographics included as explanatory variables for research question two are: age, gender, years of ski experience, backcountry ski experience, and level of avalanche education. Age and years of ski experience are continuous variables, while gender, backcountry ski experience, and level of avalanche education are binary (Table 2). We determined variable levels based on statistical analysis with the goal of having enough participants in each level of the explanatory variables to produce reliable models. See Appendix A for original survey questions. Collinearity was taken into account in the model fitting process using the R packages ‘GGally’ and ‘lmtest’ (Schloerke et al., 2017; Zeileis & Hothorn, 2002). For each pairwise combination of variables, collinearity was calculated and output in a matrix plot (Appendix B). Variance inflation factor was calculated for each regression model, with a threshold of 10 used to indicate significant effect on model fit (O’brien, 2005). Following a process of model fitting to exclude variables without significant coefficients, gender and backcountry ski experience were included in the final model.

Table 2: Demographic survey response variables tested in model fitting.

Demographic Explanatory Variables		
Variable	*Class*	*Value Range*
Age	Continuous	15 to 66
Ski Experience	Continuous	1 to 58
Gender	M	Male
	F	Female
Backcountry Experience	Novice or Intermediate	< 5 Years
	Expert	> 5 Years
Formal Avalanche Education	Yes	< Level One Course
	No	>= Level One Course

Explanatory variables used to measure decision-making biases are: participant’s perception of rescue and avalanche mitigation in the backcountry, familiarity with the backcountry terrain, whether other skiers influenced participant’s perceived safety, rescue equipment, and forecast knowledge (Table 3). The same process of matrix plots and variance inflation factor was used to evaluate collinearity in this model as the above demographics model (Appendix B). Perception of avalanche mitigation measures and familiarity with the terrain were included in the final model because they had significant coefficients in the human factors model. Both variables are evaluated on a Likert type five-point scale, and included in the regression model as continuous variables.

Table 3: Survey questions aimed at evaluating human factors tested in model fitting.

Hueristic & Decision Bias Explanatory Variables		
Variable	*Class*	*Value Range*
Rescue Perception	Continuous	Likert 1 to 5
Mitigation Perception	Continuous	Likert 1 to 5
Familiarity	Continuous	Likert 1 to 5
Herding	Continuous	Likert 1 to 5
Rescue Equipment	Prepared +	Prepared + Airbag or Avalung
	Prepared	Beacon, Probe and Shovel
	Not Prepared	No Probe or Shovel
Forecast Knowledge	Yes	Knows Avalanche Hazard
	No	Doesn't Know Avalanche Hazard

The final regression model was a combination of demographic and human factor explanatory variables. To satisfy the statistical assumptions of multiple linear regression, the response variable (percent of track in complex terrain) was log transformed prior to model fitting. Using the extra sum of squares test, a three-parameter model including gender, backcountry experience, and perception of avalanche mitigation as explanatory variables was determined to be the the best-fit model. In addition to the manual model fitting process described above, the R package ‘leaps’ was used for automated variable selection using step-wise model fitting (Lumley & Miller, 2017). The final three-parameter model outputs between both methods were identical. Model assumptions were diagnosed in R using plots and linear model tests, and are addressed in Appendix B. The final regression equation for this research question is:

$$\log(Y_{\%TimeComplex}) = \beta_{Intercept} + \beta_{Gender(1)} + \beta_{Exp(1)} + \beta_{Mitigation} \tag{2}$$

Results

We collected data over 19 days with a total of 139 useable GPS tracks and survey responses between February 2017 and February 2018. The avalanche hazard was rated moderate for twelve days, considerable for six, and low for one. We collected GPS tracks on 11 out of 12 moderate hazard days, 4 out of 6 considerable hazard days, and 0 out of 1 low hazard days for a total of 15 days of data collection. Of the 139 participants who provided GPS and survey data, 119 of them were sampled on moderate hazard days, 20 were sampled on considerable hazard days, and none were sampled on low hazard days. Over all 19 field days, we collected an average of 7.3 tracks per day, with 10 tracks per day on moderate hazard days and 3.3 tracks per day on considerable hazard days. Total sample rates were appoximtely 75% of LABC skiers under both moderate and considerable avalanche hazard. Partial survey responses were included in the final dataset, so sample sizes vary depeding on survey question.

Demographics

The median age of participants is 36 years old, with median years of skiing of 27 years. The sample is composed of 90% males (n=123) and 10% females (n=13). Participants using alpine ski equipment comprise 51% (n=70) of the sample, with 32% (n=45) using backcountry ski equipment, and 22% (n=22) percent using a snowboard. Group sizes ranged from 39% (n=50) solo skiers, 40% (n=52) groups of two, 14% (n=18) groups of three, and 7% (n=9) in groups of four or more.

Participant's avalanche education varied from 16% (n=22) with no avalanche education, 35% (n=48) with awareness level, 34% (n=47) with a U.S. recreational level one avalanche course, and 15% (n=20) with U.S. level two or higher education. Self-rated backcountry experience is 6% (n=8) novice, 16% (n=22) intermediate, and 78% (n=107) expert. During their foray into backcountry terrain, 72% (n=97) of participants had an avalanche transceiver, probe, and shovel. All participants are required to wear an avalanche transceiver to ride the ski lift in this region of the ski area. In addition to the basic rescue gear, 13% (n=18) of participants carried either an airbag or Avalung as an additional safety measure.

Our results indicate that 40% (n=19) of solo skiers do not carry a beacon, probe, and shovel compared to 22% (n=17) of skiers who travel with partners. Using Fishers Exact Test, we found that there is a significant association between solo skiers and not carrying basic rescue equipment (*Odds Ratio 2.4, p-value 0.04*). Demographic results are summarized in Figure 8.

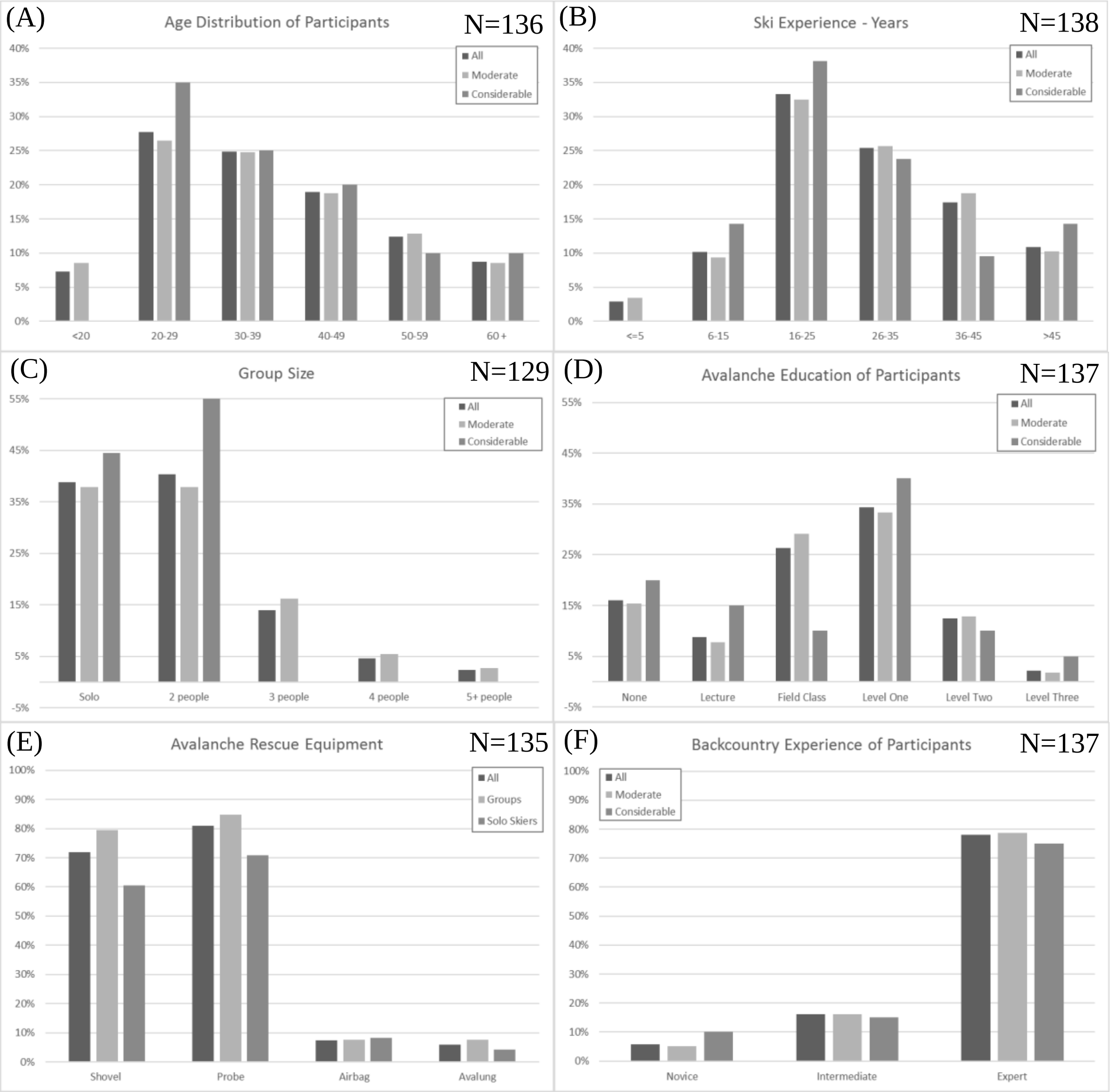


Figure 8: Demographic plots from top left to bottom right showing age, ski experience, group size, avalanche education level, avalanche rescue equipment, and backcountry experience of participants. Note scale on axis changes.

While traveling in backcountry terrain, 61% (n=78) of participants carried out some kind of instability test. Traveling tests (37%, n=47) and ski cuts (33%, n=42) were the most common form of instability test, with 17% (n=22) performing cornice tests and 3% (n=4) performing a formal instability test. Despite Bridger Bowl Ski Patrol posting the public avalanche forecast at the upper terminal of the ski lift, only 64% (n=89) of participants accurately reported the current avalanche hazard.

Travel Behavior and Avalanche Hazard

To illustrate the changes in travel behaviour by avalanche hazard we created heat maps from the GPS tracks (Figure 9). The heat maps are based on participant's GPS tracks who were aware of the avalanche forecast level. GPS track density is calculated using raster analysis where the length of the GPS tracks within a 30m radius of each raster cell are divided by the area of the cell neighboorhood. We use a stretched classification technique to color code the heat maps, specifying 'standard deviation' as the stretch type with 'n=5' standard deviation included in the symbology.

The map of moderate avalanche hazard shows highly concentrated use near the ski area boundary and along a ridge feature that descends from the false summit of Saddle Peak known as 'North Shoulder'. Overall we see widespread use of terrain across the Saddle Peak backcountry area. The horizontal stripe of heavy use is due to the return route to the ski area and does not represent travel in significant avalanche terrain. The map of considerable hazard highlight three primary route choices: the boudary line, the North Shoulder, and a ridge feature that descends from the true summit of Saddle Peak. The terrain use is more concentrated under considerable hazard, with the are of heaviest use restricted to a narrow swath around the North Shoulder run.

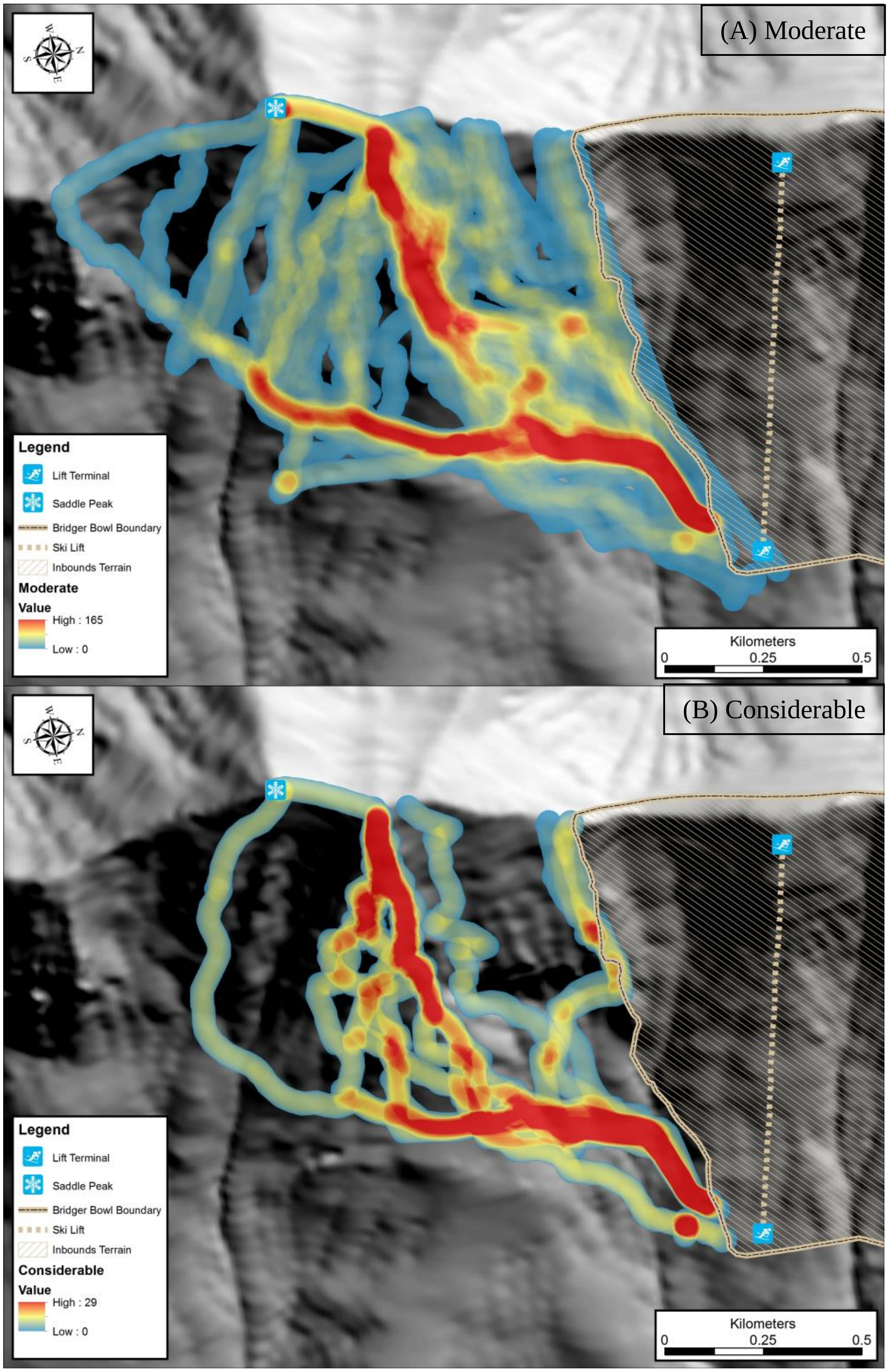
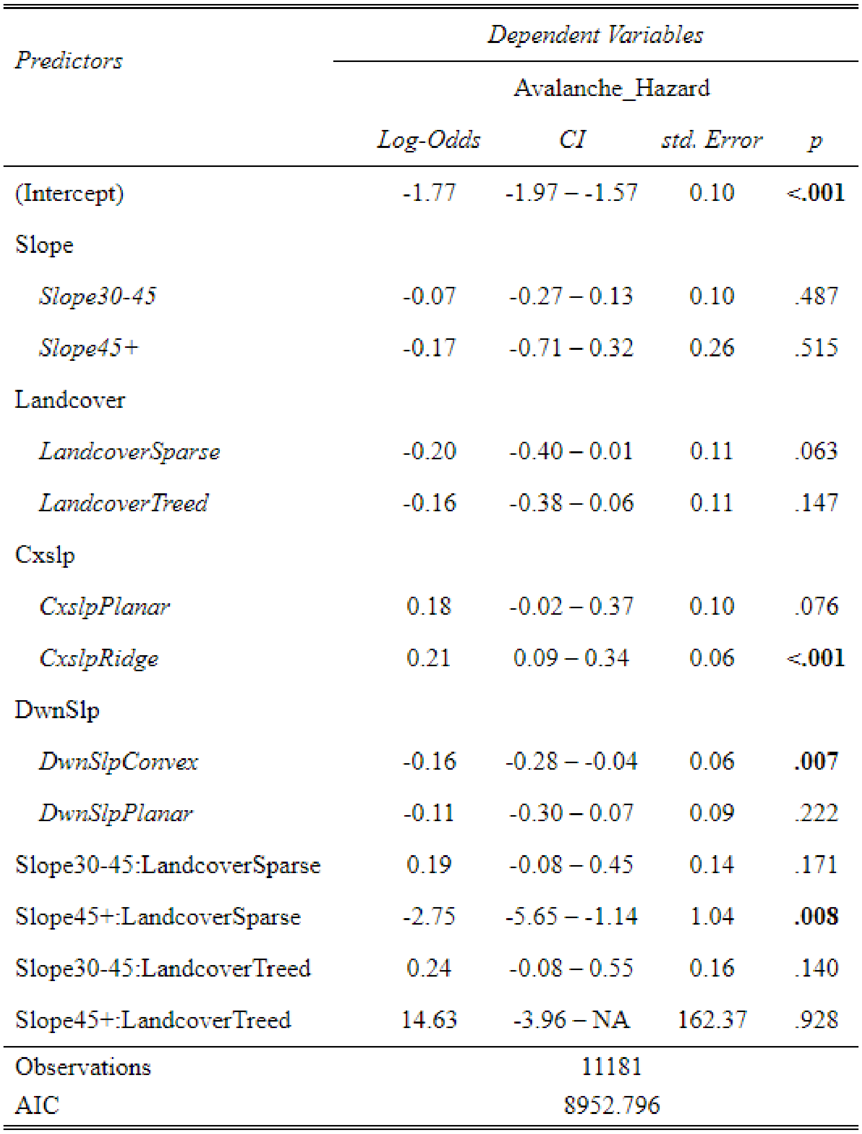


Figure 9: Heat map showing GPS Track density. Moderate hazard tracks, n=77. Considerable hazard tracks, n=12. Both maps have concentrated tracks along the central ridge and ski area boundary, but the moderate hazard has a much wider distribution across Saddle Peak and a wider swath along the central ridge.

Results from the logistic regression model developed to measure the correlation between travel behavior and avalanche hazard show significant changes in terrain metric values between the two levels of avalanche hazard (Table 4). Cross-slope curvature has a significant positive coefficient for ridge shape features (*Log Odds 0.21, p <.001*) and a marginally significant positive coefficient for planar features (*Log Odds 0.18, p .076*). This indicates that the log odds of travelling on ridge and planar shaped features versus gully shaped features is higher under considerable avalanche hazard than moderate avalanche hazard. Down slope curvature has a significant negative coefficient for convex features (*Log Odds -0.16, p .007*), meaning that the log odds of travelling on convex features is lower for considerable avalanche hazard than moderate avalanche hazard. Figure 9 qualitatively supports these results, with concentrated terrain use on routes that are predominantly cross slope ridge features and avoid convex rollovers.

Table 4: Output from travel behavior and avalanche hazard logistic regression model. Results show significant changes of some terrain variables when moving from moderate to considerable avalanche hazard. Bold are significant p-values at the 0.05 level.



Predictors	*Dependent Variables*			
	Avalanche_Hazard			
	Log-Odds	*CI*	*std. Error*	*p*
(Intercept)	-1.77	-1.97 – -1.57	0.10	**<.001**
Slope				
Slope30-45	-0.07	-0.27 – 0.13	0.10	.487
Slope45+	-0.17	-0.71 – 0.32	0.26	.515
Landcover				
LandcoverSparse	-0.20	-0.40 – 0.01	0.11	.063
LandcoverTreed	-0.16	-0.38 – 0.06	0.11	.147
Cxslp				
CxslpPlanar	0.18	-0.02 – 0.37	0.10	.076
CxslpRidge	0.21	0.09 – 0.34	0.06	**<.001**
DwnSlp				
DwnSlpConvex	-0.16	-0.28 – -0.04	0.06	**.007**
DwnSlpPlanar	-0.11	-0.30 – 0.07	0.09	.222
Slope30-45:LandcoverSparse	0.19	-0.08 – 0.45	0.14	.171
Slope45+:LandcoverSparse	-2.75	-5.65 – -1.14	1.04	**.008**
Slope30-45:LandcoverTreed	0.24	-0.08 – 0.55	0.16	.140
Slope45+:LandcoverTreed	14.63	-3.96 – NA	162.37	.928
Observations	11181			
AIC	8952.796			

In addition to the slope curvature variables the interaction between land cover and slope angle show a significant negative correlation with slopes over 45˚ and sparse land cover (*Log Odds -2.75, p .008*). This result could be influenced by relatively small sample size of GPS points over 45˚ terrain, which is shown in the high standard error (*SE*

1.04). Overall, the model indicates participants skied on planar or ridge terrain during elevated avalanche hazard and tended towards open land cover over sparse in steep terrain, and this is also visually apparent (Figure 9). The intercept term, while significant in the model output, does not have a meaningful interpretation for this analysis due to the default alphabetical assignment of base levels for the explanatory variables.

Average marginal effects for this model showed that open land cover, 30˚ to 45˚ degree slopes, cross slope planar and ridge features, and down slope concave features have the greatest effect on the predicted values of the logistic regression model. Plots of AME for the logistic regression model included in Appendix B. Comparison between samples collected under moderate and considerable, using the R package 'MASS', avalanche hazard showed no significant differences in regards to demographics, or preparedness (Venables & Ripley, 2002). The only marginally significant ($p < 0.10$) difference found between the two samples indicated that participants who travelled under considerable avalanche conditions were three times more likely to carry out some kind of instability test ($p = 0.07$, *Odds Ratio 3.12).*

Human Factors and Percent of Track in Complex Terrain

To visualize changes in travel behavior based on the human factors we evaluated in our survey we created heat maps for the explanatory variables that had significant results in our statistical model: gender, backcountry experience, and avalanche mitigation. We used the same methods described in 'Travel Behavior and Avalanche Hazard' (p 49) to create all heat maps for this research question. For gender, we split the GPS tracks by males and females and calculated the GPS track density in ArcMap10.4

(Figure 10). The male tracks show an area of heavy use along the North Shoulder with moderate to high use along the ski area boundary and widespread tracks in the entire Saddle Peak backcountry zone. Female tracks are much more concentrated, with the majority of tracks concentrated along the North Shoulder or a similarly shaped but steeper line adjacent to it. There is very limited track density along the boundary line and overall less widespread use of the terrain compared to males. One limitation of this approach is the small sample size for female skiers (n=13, 10%).

To map GPS tracks by backcountry experience we divided our sample by those who self-rated as experts and those who self-rated as either novice or intermediate (Figure 11). The expert tracks have a wide distribution across Saddle Peak, but a notable lack of concentration along the ski area boundary compared to non-experts. Non-experts have high concentrations along the boundary line and along the North Shoulder, with less widespread distribution in terrain selection.

Avalanche mitigation perception measures whether or not participant’s think there is avalanche control work outside the ski area boundary. We compared GPS tracks between participants who perceived no avalanche control or some level of avalanche control (Figure 12). The no avalanche control group has a widespread distribution with a concentrated stripe along the North Shoulder. The avalanche control group shows a very strong concentration of tracks adjacent to the ski area boundary and generally stays closer to the boundary compared to the no avalanche control group.

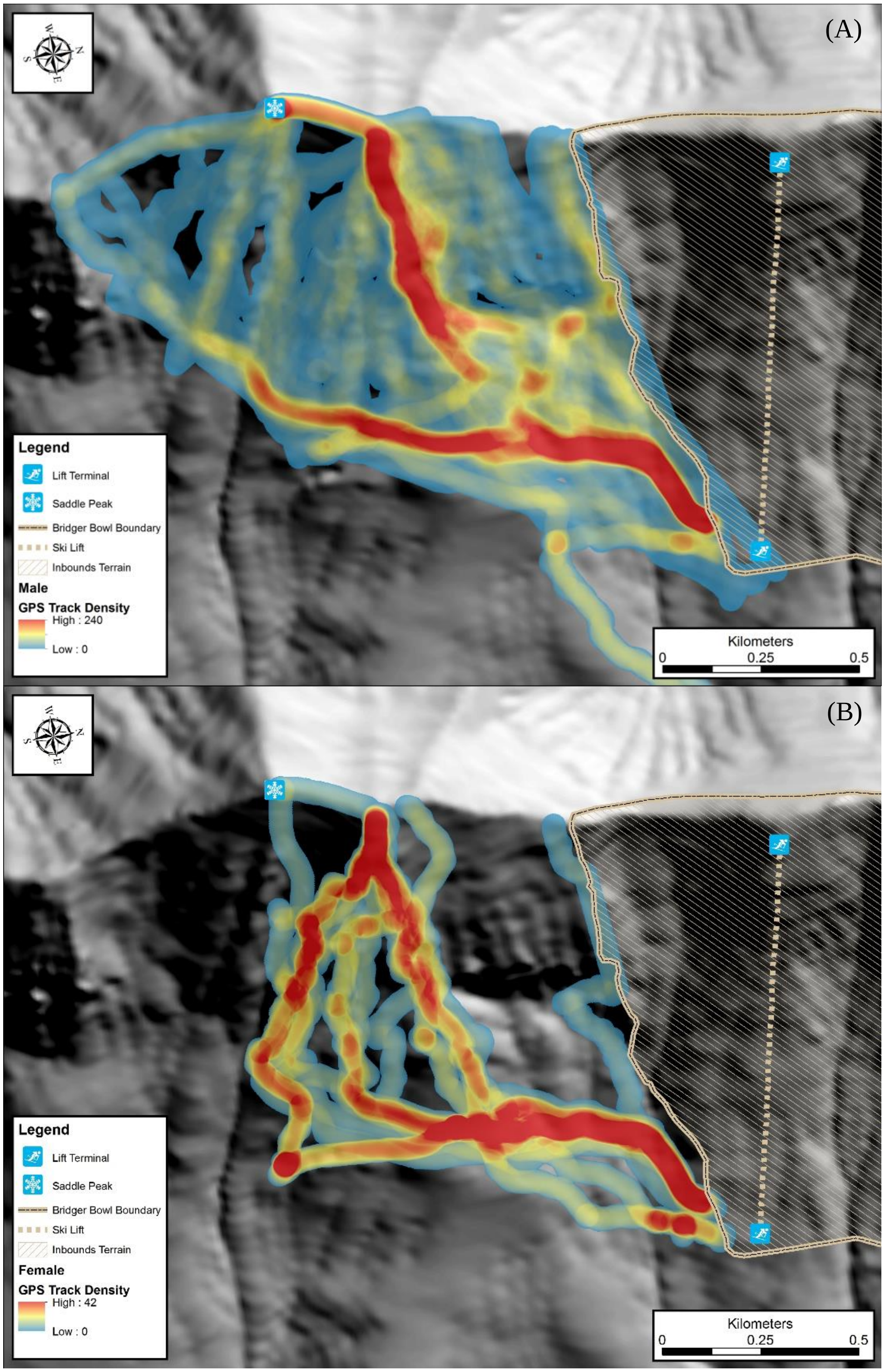


Figure 10: GPS track density split out by males n=123 (A) and females n=13 (b). Male tracks are more widespread and show a higher density close to the ski area boundary. Female tracks are highly concentrated along the false peak of Saddle Peak, descending predominantly ridge features.

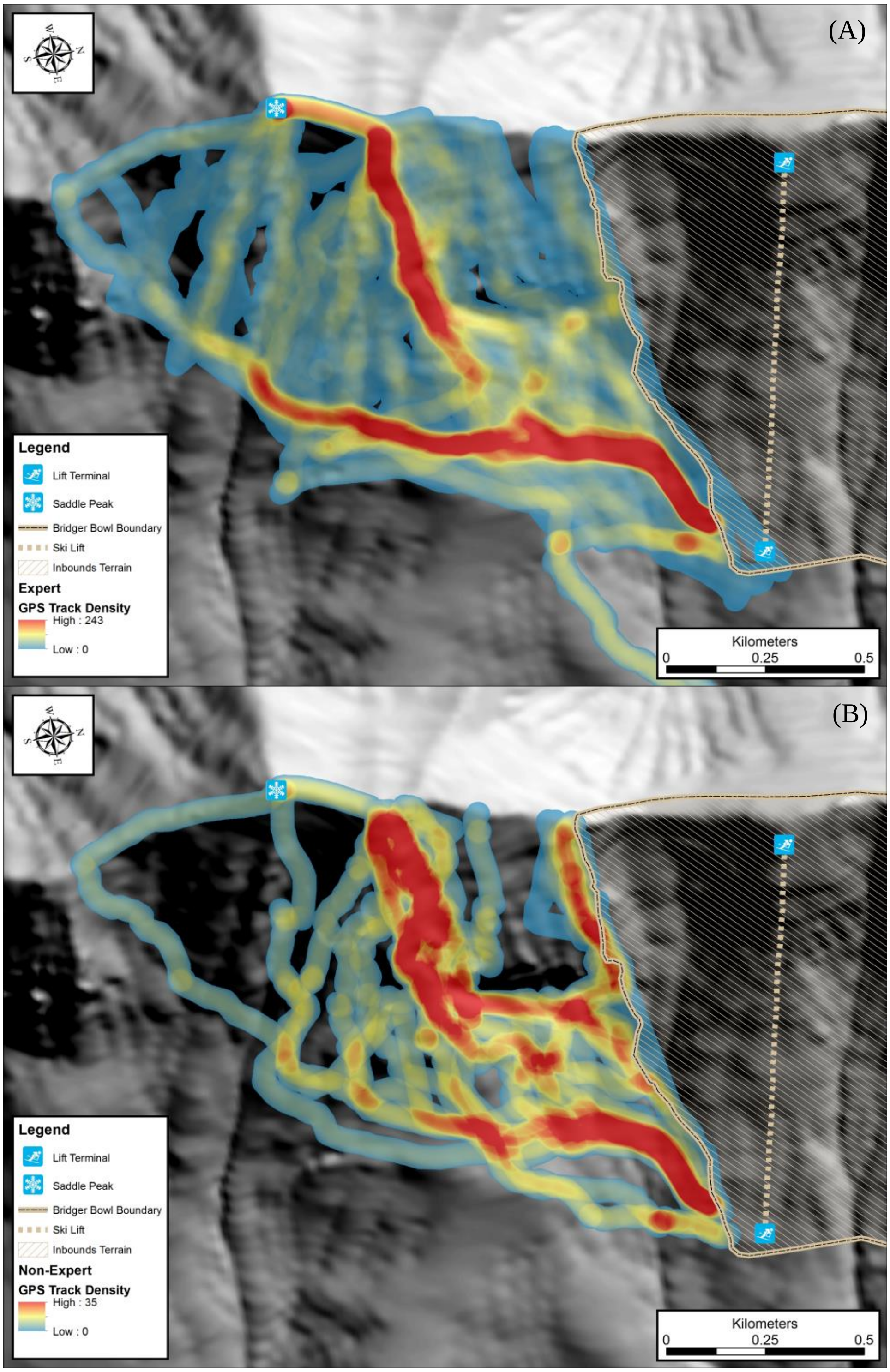


Figure 11: GPS track density split out by self-rated backcountry experts n=107 (A) and novice or intermediate n=30 (B). The expert tracks show a lower concentration of tracks along the ski area boundary but overall wide distribution of tracks across Saddle Peak. Non-experts have a much higher concentration along the ski area boundary.

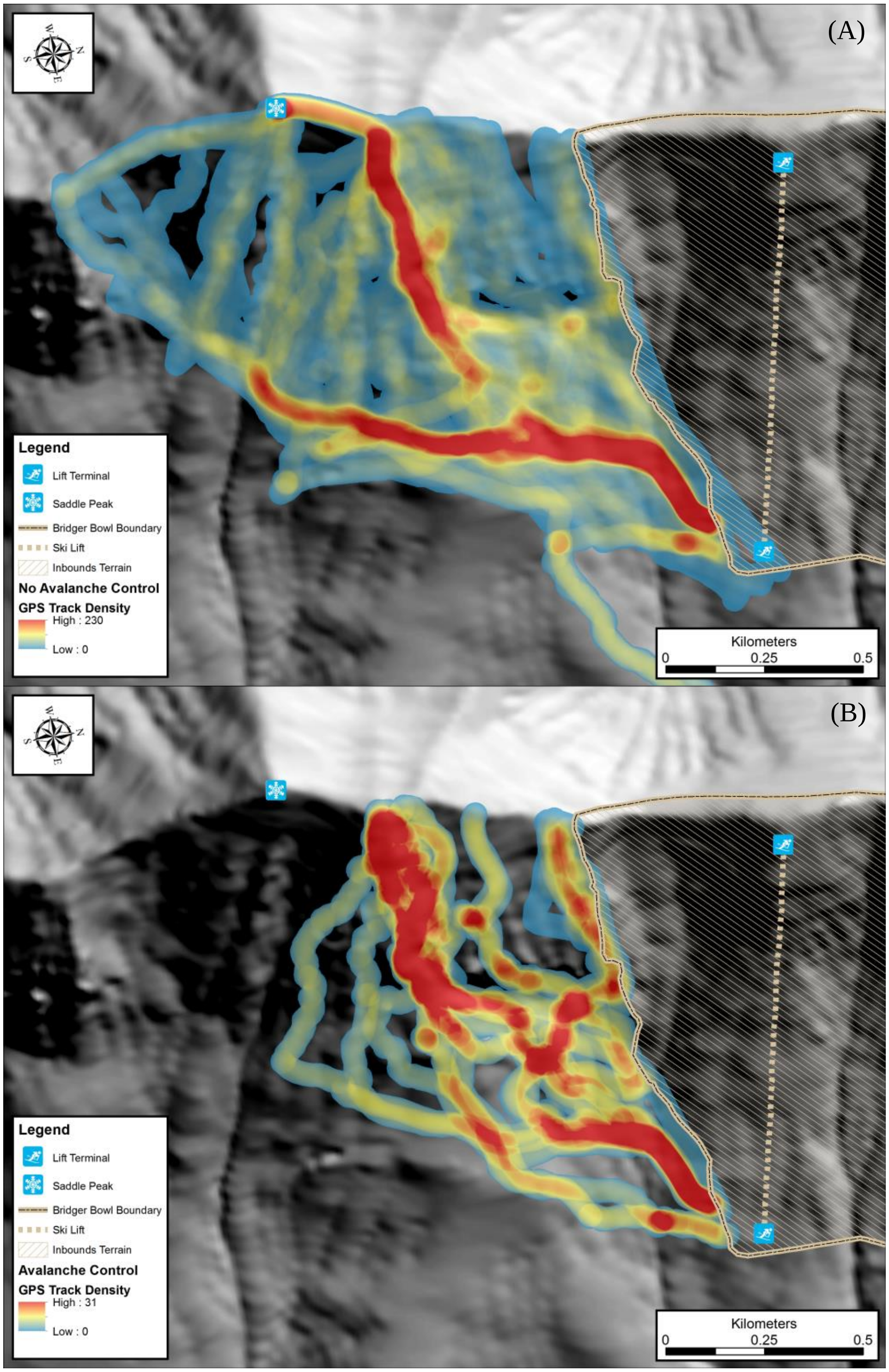
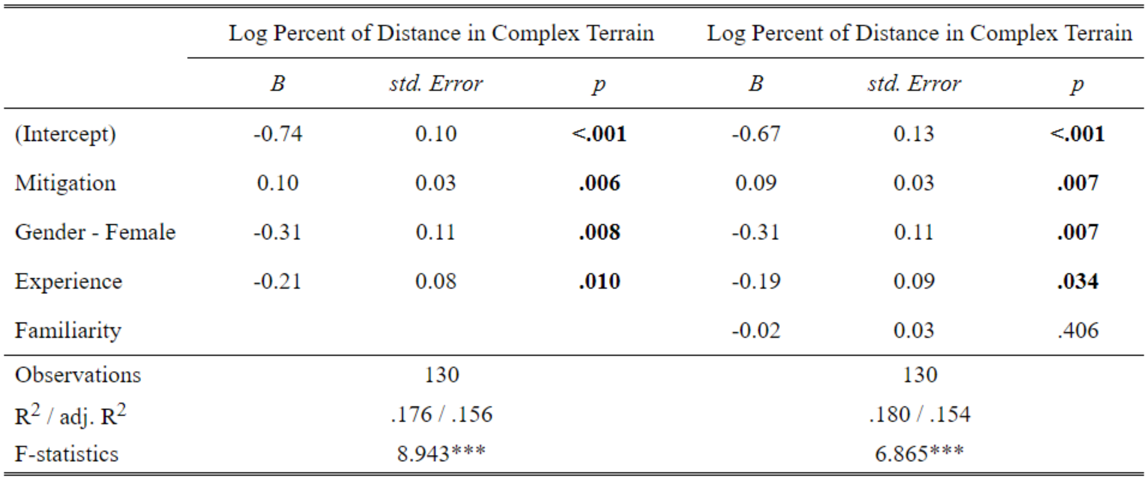


Figure 12: GPS track density by perception of avalanche mitigation. No avalanche mitigation n=108 (A) avalanche mitigation n=25 (B). Note the high concentration of tracks along the boundary for participants who perceive some amount of avalanche mitigation.

Results from the multiple linear regression model addressing the influence of participant demographics, heuristic traps, and perception of LABC risk, show gender, backcountry experience, and perception of avalanche mitigation as significant variables (Table 5). Gender (*β -0.31, p .008*) and backcountry experience (*β -0.21, p 0.10*) are negatively correlated with percent of track in complex terrain. This indicates that participants whose are female or have a higher level of backcountry experience have a lower percentage of their total GPS track spent in complex avalanche terrain.

Perception of avalanche mitigation has a positive correlation (*β 0.10, p .006*) with percent of track in complex terrain indicating that participants who think the Bridger Bowl Ski Patrol mitigates the avalanche hazard in the backcountry are more likely to have a higher percentage of their GPS track in complex avalanche terrain. We did not find any significant differences within the levels of our explanatory variables when we included an interaction term for avalanche hazard level.

Table 5: Multiple linear regression model showing the correlation between avalanche mitigation perception, gender, experience, and familiarity with the log of the percent of distance in complex terrain. Familiarity was dropped from this final model due to lack of significance.



	Log Percent of Distance in Complex Terrain			Log Percent of Distance in Complex Terrain		
	B	*std. Error*	*p*	*B*	*std. Error*	*p*
(Intercept)	-0.74	0.10	**<.001**	-0.67	0.13	**<.001**
Mitigation	0.10	0.03	**.006**	0.09	0.03	**.007**
Gender - Female	-0.31	0.11	**.008**	-0.31	0.11	**.007**
Experience	-0.21	0.08	**.010**	-0.19	0.09	**.034**
Familiarity				-0.02	0.03	.406
Observations		130			130	
R^2 / adj. R^2		.176 / .156			.180 / .154	
F-statistics		8.943***			6.865***	

Discussion

Population Demographics

Compared to prior research, the mean age of participants in this study is notably older than survey research on LABC skiers in western Canada and Utah (Gunn, 2010; Silverton et al., 2007). Results of previous research indicate the mean age of participants in their late 20's, with the median age of the population in the mid to late 30's. This may be due to the tendency for younger skiers to take time to participate in social media outlets that would advertise online surveys. The research design of this study focused on a sub-population of LABC skiers in the USA, but gave equal opportunity to participate to any skier present during the data collection timeframe. No online follow up was necessary to participate in the study. Previous intercept surveys, e.g. Fitzgerald et al (2016), carried out at Bridger Bowl LABC areas did not report statistics on age of their sample.

Chabot et al. (2010), also cited Saddle Peak as having a large contingent of longtime local skiers, who represent a different demographic than the typical backcountry ski population (Chabot et al., 2010). Our observations of the population on Saddle Peak support that conclusion, which was contrary to our hypothesis of the population demographics prior to the study. While the younger population of LABC skiers do travel on Saddle Peak, the generally older 'regulars' were there every day we collected data, regardless of avalanche or weather conditions. This could be due to the younger population being less confident in their ability to manage the Saddle Peak terrain under adverse weather and avalanche conditions.

The proportion of male to female participants in this sample is consistent with prior LABC skier research, with approximately 10% of the sample composed of female skiers (Gunn, 2010). A larger proportion of females, 20% of the total sample, was found in global crowd sourced data collection (Hendrikx & Johnson, 2016b). Larger proportions of female skiers and snowshoers, 30% of total sample, were found in field research based in the Tyrolean Alps and online surveys in Norway (Mannberg et al., 2017; Procter et al., 2014). Since the true gender distribution in backcountry skiers is unknown, we cannot say whether these discrepancies are based on sampling strategy, regional differences, or variance between different sub populations of backcountry skiers.

Group sizes in this research were generally smaller than those found in non-lift accessed backcountry research, with 81% of participants travelling in groups of one or two. In contrast, Swiss researchers have reported approximately 60% of participants travelling in groups of one or two (Zweifel et al., 2016). The main contribution to these differences is the large percentage (38%) of solo travelers on Saddle Peak. Previous research on Saddle Peak has shown 30% of participants travelling solo (Fitzgerald et al., 2016). In crowd-sourced data Hendrikx & Johnson (2016b) found similar percentages of solo skiers in their backcountry data set.

For LABC terrain this may be due to the adjacency to the ski area. When travelling inbounds, avalanche control and rescue services from professional ski patrol minimize the necessity to travel in groups compared to uncontrolled backcountry terrain. Backcountry or LABC skiers with more backcountry experience may have a higher likelihood of travelling solo in avalanche terrain. Nearly 80% of participants in this study consider themselves expert level backcountry skiers, which could indicate high self-efficacy when travelling solo in avalanche terrain. Crowd-sourced and online data collection are likely to attract more experienced participants who are invested enough in the sport to take time for participation in research.

Regarding preparedness and knowledge of avalanche hazard, our sample was strikingly similar to research from the European Alps, which focused on traditional backcountry skiers (Procter et al., 2014). The proportion of participants who knew the forecasted avalanche hazard level was 64.0% in our sample, compared with 52.5% of skiers in the European sample. Fitzgerald et al. (2016) found very similar percentage of participants who checked the avalanche report (67%) compared to results from this study. Despite the higher percentage in comparison to the European study, the fact that the avalanche forecast is posted at the top of the ski lift leaves no reason why this number should not be higher for LABC skiers on Saddle Peak.

Preparedness was measured by whether participants were carrying an avalanche transceiver, probe and shovel. For this study, 71.8% of participants had necessary rescue equipment compared to 80% in previous studies on Saddle Peak and 80.6% of skiers in the European sample (Fitzgerald et al., 2016; Procter et al., 2014). By comparison, a study of LABC skiers in the Wasatch Mountains of Utah USA in 2007, had far lower adherence to carrying avalanche rescue equipment (36% Transceiver, 31% Shovel, 32% Probe) (Silverton et al., 2007). This could be due to increased communication about the hazards of LABC skiing since the earlier research was carried out (11 years ago), and concentrated community outreach from the local avalanche forecasting and education network at Bridger Bowl Ski Area (Chabot et al., 2010). Bridger Bowl's policy of requiring all skiers on the ridge terrain and Schlasmans lift to wear avalanche transceivers could also influence skier's likelihood of including shovel and probe in their equipment.

Travel Behavior

Saddle Peak is a relatively small piece of backcountry avalanche terrain, with limited variety in run choices. No ski runs avoid complex avalanche terrain and all run choices involve managing wind loaded slopes, potential terrain traps, and steep avalanche terrain. Despite these limitations, the logistic regression model, using GPS point terrain metrics as explanatory variables, clearly highlights statistically significant changes in travel behavior between moderate and considerable avalanche hazard levels. Due to the relatively homogenous slope angles on Saddle Peak, we see limited changes in slope angle use between avalanche hazard levels. However, a more subtle change in micro terrain selection is shown by participant's preference for travelling on ridge shape features and avoiding convex rollovers under considerable avalanche hazard.

This response to elevated avalanche hazard shows that areas with higher likelihood of acting as avalanche trigger points (convex rollovers) and areas with high consequences in the event of an avalanche (gully features) are avoided when the likelihood of triggering avalanches is higher (considerable hazard) (McClung & Schaerer, 2006). These are encouraging results, which indicate LABC skiers are subtly changing their travel behavior in response to elevated avalanche hazard. This is a rational response to an increase in the probability of triggering an avalanche.

Previous online survey research has shown that LABC skiers are more likely to change their travel behavior in response to recreational goals than avalanche hazard, when compared to avalanche professionals (Haegeli et al., 2010). The high percentage (78%) of self-rated *expert* backcountry skiers in this sample could influence their awareness of elevated avalanche hazard, and their ability to change their travel behavior accordingly. Further research comparing the change in travel behavior due to avalanche hazard of multiple populations of backcountry users would help test this hypothesis. Major limitations of this dataset is the small sample size (n=20) of GPS tracks collected under considerable avalanche hazard and the relatively low diversity in terrain options on Saddle Peak. Our GPS track filtering process increased the sample size limitation by only including the 64% (n=12 considerable, n=77 moderate) of participants who were aware of the avalanche hazard level based on survey responses.

Thumlert & Haegeli (2017) showed similar findings on changes in travel behavior by avalanche hazard in the GPS tracks of helicopter ski guides. Their research used a much larger dataset that spanned a more diverse range of terrain options and avalanche conditions. While our research goals and sampling methods are different, the fact that our sample of recreational skiers show similar adaptations in their travel behavior compared to professional guides is an encouraging result. The lack of tracks under considerable hazard reflect the lack of users, as participation rates remain approximately 75%. These methods have potential to be further developed and used to analyze backcountry users in different regions as well as applied to more detailed analysis of travel behavior within groups of skiers travelling together.

Decision-Making Biases

The main challenge to analyzing decision-making for this study is the relatively homogeneous slope angle and widespread complexity of the terrain on Saddle Peak. Methods developed by Hendrikx & Johnson (2016b) for analyzing differences in GPS tracks were ineffective for Saddle Peak because they only considered slope angle percentiles. Initially, the lack of significant differences in the slope angles of terrain used by different user groups indicated a lack of response between survey questions and travel behavior. This is due in part to the relatively small sample size collected for this study, as well as the lack of drastically different terrain options in the Saddle Peak backcountry area (Figure 10).

Figure 10: Photograph of Saddle Peak, showing the complex terrain and relative lack of safe terrain options. All ski runs are generally east facing, with many options involving navigating above or through large cliff bands. The Bridger Bowl Ski Area Boundary is shown in red with backcountry terrain to the left. Photographer: Diana Saly (2016)

Using ATES mapping methodology we achieved a meaningful summary of many terrain metrics. We extracted ATES values for every point from a participant's GPS track and the total distance and total time for each ATES class was calculated. The final summary statistics we selected as a response variable is the percent of distance in complex avalanche terrain. This statistic functionally highlights how far from the ski area boundary each participant travelled, because returning to the ski area from ski runs further from the boundary requires more travel in challenging and simple terrain.

With this interpretation of the response variable we can see that the regression model used to quantify demographics and decision-making biases are also capturing influence on distance travelled from the ski area boundary. In the case of Saddle Peak, the ski runs closest to the boundary have the highest consequences, with all options involving travelling above large cliffs, on slopes steep enough to avalanche. Therefore, the delusional sense of safety that comes from staying closer to the ski area boundary comes with very high consequences if an avalanche incident should occur. Saly et al. (2016) captured an avalanche incident of this nature on January 14th, 2016, when a group of skiers remotely triggered an avalanche on Saddle Peak. Luckily, they were able to ski back to in-bound terrain before being caught and swept over the cliff band.

Results from the regression models indicate that participant's perception of avalanche mitigation measures taken by ski patrol in backcountry terrain adjacent to the resort has a significant effect on the percent of their total track spent in complex terrain. In this case, participants who perceive greater avalanche mitigation are more likely to ski closer to the resort boundary. This finding is supported by Gunn (2010), who found that the highest risk cohort of LABC skiers have a misunderstanding of ski resort policies on avalanche mitigation measures. Factors that decreased participant's proximity to the resort boundary are gender and backcountry experience. To change the perception of avalanche mitigation in LABC areas we need to continue to reach out to resort skiers about their mindset when leaving resort boundaries. Increased signage and terrain maps of LABC terrain could help increase awareness of avalanche risk. LABC terrain is the same as backcountry terrain as far as avalanche danger, despite the complacent mindset fostered by skiing in-bounds terrain adjacent to LABC areas.

Our results indicate significantly different travel behavior, based on ATES mapping, for males and females. However, the gender of the participant was the only data collected and did not include whether the group that participant was travelling in was a mixed gender group. Our field observations estimate that most, if not all, female participant's were travelling in mixed gender groups. All survey data collected for this research focused on individual participants, not group dynamics, with the exception of questions about group size and group terrain management. GPS tracks submitted by the same user on different days are not identifiable within the data set and could introduce cluster biases into the data. Environmental variables such as wind, temperature, precipitation, new snow, and ski quality were not included in the modeling procedure in this research. The scope of inference for this research is limited to Bridger Bowl Ski Area LABC skiers. Despite these limitations, this study provides a case study of the travel behavior and decision-making tendencies of LABC skiers.

We did not find statistically significant evidence for the heuristic traps presented by McCammon (2004) in this data set. Familiarity and social facilitation were explicitly tested and did not have a significant effect on the travel behavior of participants as summarized by GPS tracks and ATES mapping. Additionally, we tested the concept of herding, or groupthink, without significant results. It is difficult to say whether these factors played a role in the decision-making of participants in this study, but they do not appear to be as influential as the explanatory variables discussed above. Hendrikx & Johnson (2016b) also found a lack of evidence to suggest statistically significant influence of heuristic traps based on observed travel behavior in avalanche terrain.

Previous research based on online survey responses has shown significant positive relationships between familiarity, avalanche safety equipment, and tracks on the slope with self-rated likelihood to ski a slope (Marengo et al., 2017). Furman et al. (2010) also found significant positive correlations with familiarity, untracked slopes, group leadership, presence of other groups, and commitment when surveying students prior to level one avalanche courses. The discrepancies between our results and previous research is likely due to the nature of data collection via online survey and field intercept surveys coupled with GPS tracks. Hypothetical decisions based on a limited set of variables provided by survey prompts do not reflect the complexity of the backcountry environment or the physical and emotional investment of climbing to the top of a ski run. On the contrary, field measurements of decision-making in avalanche terrain could fail to recognize variables that have significant contributions to the decision-making process. Both research methods have faults, but it is intriguing that using these two methods to evaluate decision-making in avalanche terrain yield opposite results. Future research including an online survey of self-rated likelihood of skiing a slope and GPS data collection via crowd sourcing could shed light on these apparently opposing results.

For future research, data collection from multiple LABC areas would help develop a more robust data set to analyze decision-making biases. A natural extension of looking at avalanche hazard level as a response variable to terrain metrics would be to look at travel behavior under different avalanche character (Statham et al. 2018). The difference between a moderate hazard day with a deep slab problem or a wind slab problem is a major focus of avalanche education. To quantify whether those concepts are reflected in backcountry skier's terrain preferences would be highly informative to avalanche educators and forecasters. Including weather and ski quality variables in travel behavior modelling would help constrain the variables influencing participant's decisions. Additional analysis on the effect of formal avalanche education on participant's likelihood of being prepared for avalanche rescue and being informed on the avalanche hazard could demonstrate the efficacy of avalanche education. Finally, publicizing the ease and availability of tracking travel in avalanche terrain could help backcountry recreationists objectively analyze their own travel, and learn to carefully manage terrain before they may learn the hard way from an avalanche incident.

Conclusions

By collecting GPS tracks and surveys responses via intercepting participants in the field, we have broadened the scope of GPS tracking research in avalanche terrain to include participants who may not volunteer their time and energy to submit GPS tracks online or via social media or web based platforms. There are inherent biases in this sampling strategy, most notable being the isolated population that this data was sampled from. Participation was voluntary for this research, which also introduces a convenience sampling bias.

In general, the results show that LABC skiers in this area respond as avalanche professionals would hope, in the case of increasing avalanche danger. In addition to subtly changing their terrain preferences to safer terrain features, the average number of skiers sampled on days with considerable hazard was a third of the number collected on days with moderate hazard. This change in overall number of skiers clearly shows an avoidance strategy to decision-making under elevated avalanche hazard. Saddle Peak does not afford a risk-free option to travel during days with elevated avalanche hazard, therefore, many skiers choose to avoid the area entirely in those conditions. We found significant differences in travel behavior, as summarized by ATES, based on participants gender, backcountry experience, and perception of avalanche mitigation.

Broadening the scope of data collection to LABC areas with different snowpack characteristics, terrain options, and avalanche safety cultures would help expand the scope of inference for this field of research. During the time period sampled for this research there was a lack of persistent avalanche problems in SW Montana. Future research could benefit avalanche educators by highlighting the travel behavior of LABC skiers under persistent and non-persistent avalanche problems. GPS tracking could also shed light on the avalanche safety culture differences between geographic regions in the western US and different population of backcountry users.

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CONCLUSIONS

Summary

Previous research using GPS tracking and survey analysis have focused on traditional backcountry skiing populations and sampling via volunteer track submission. This paper aims to build upon that literature by applying existing methodologies to a new population, LABC skiers. Two main goals of this research are: (1) Detailed modeling of travel behavior in avalanche terrain under different avalanche hazard levels (2) Quantitative analysis of human factors that have the greatest influence on LABC skiers. Results of these research goals, and thoughts on further developing the research methods to broaden the scope of knowledge to additional LABC populations are presented below.

Travel Behavior by Avalanche Hazard

The first lesson learned from modelling the travel behavior of LABC skiers is that the spatial extent of the study area and homogeneity of the terrain drive the necessity for more detail-oriented analysis. Using the techniques previously developed by Hendrikx et al. (2016) for modeling terrain preferences based on summarizing individual terrain metrics (i.e. slope angle) would have resulted in an incomplete picture of the travel behavior for this population. Two methods were implemented in this research that allow for more nuanced and comprehensive terrain preference analysis: (1) Logistic regression as a modeling technique that accepts multiple terrain metrics as explanatory variables and describes the changes in those terrain metrics as a function of different avalanche hazards

(Thumlert & Haegeli, 2017), and (2) ATES mapping as a means to calculate response variables provides a well defined method for categorizing terrain and a metric to evaluate the influence of multiple survey responses on travel behavior.

The former method provides a detailed analysis of terrain preferences by taking into account every GPS point that compose a complete GPS track. The impact of serial effects or spatial autocorrelation on the output of this modeling technique are unknown and deserve additional analysis in future research. Despite that limitation, this method promises to be fruitful for future analysis of travel behavior based on changes in avalanche hazard or avalanche problem. Including a mixed effect for weather or snow quality variables could help improve the accuracy of this modeling method.

Using ATES mapping to summarize avalanche terrain has potential for standardizing terrain analysis for future researchers. The body of literature on ATES mapping clearly defines both GIS and field-based methods for mapping avalanche terrain; therefore, this method could help minimize subjectivity in categorizing the level of risk for GPS tracks. Future research could consider total time in complex terrain as a response variable that directly effects the formula for risk. More exposure time, regardless of hazard level, increases overall risk for a route through avalanche terrain. Furthermore, by implementing avalanche character as a proxy for avalanche likelihood and distribution, future researchers could quantitatively estimate the risk of a given travel behavior (Statham et al., 2018).

Human Factors in LABC Skiers

As a pilot study for the demographics, heuristics, and decision biases that influence LABC skiers, this research was successful. By highlighting a few significant variables through quantitative analysis and integration of GPS tracking, our results help define the challenge of communicating to the growing population of skiers that are venturing outside ski resort boundaries. With more careful survey design, larger sample sizes, and representation of LABC populations from a variety of regions across the US, future research could build on these results and provide a more definitive set of human factors for LABC populations as a whole.

By sampling directly from the population of LABC skiers on Saddle Peak, this research invites a broader range of participants than has been previously captured with volunteer GPS track submission. Despite the intention of collecting a more representative sample, this data is composed of close to 80% self-rated expert backcountry skiers. Attempting to diversify this sample to novice and intermediate skiers could illustrate the progression of terrain management practices that comes with gaining experience in backcountry skiing. Interestingly, despite being 80% self-rated experts, the avalanche education of this sample seems relatively low. This is likely an effect of older median age than most studies of backcountry populations. Future studies could investigate the ability for self-rated experts to evaluate avalanche risk versus individuals who have spent time and money on avalanche education.

Future Work

Specific recommendations for future work are listed below, which are based on limitations and lessons learned from this research. My hope is that these recommendations can help future research continue to build knowledge of decision-making and travel behavior in avalanche terrain.

1. The study site for this research was limited in terms of terrain options, snowpack variability, and population diversity. Due to the predominant winds on Saddle Peak and the relatively homogeneous terrain, there are limited opportunities for selecting terrain with radically different characteristics. We observed this trend with the dramatic drop in users on days with elevated avalanche conditions, indicating a general avoidance strategy. By selecting a study site with a variety of slope angles, aspects, forest density, and slope shapes, future research could hope to see changes that are more dramatic in terms of travel behavior with changing avalanche and snowpack conditions. One of the original goals of this research was to observe travel behavior under a variety of avalanche problems, specifically focusing on persistent vs non-persistent character. The stars did not align for this comparison, as there were no persistent avalanche characters listed as the primary avalanche problem throughout the year long data collection period. While this is impossible for researchers to control, selecting study site in a more continental snow climate would increase the likelihood of collecting data under persistent conditions. LABC areas in Colorado or Utah are likely candidates for observing these conditions. Finally, the sample collected in this research had a strong bias toward self-rated expert backcountry experience. This demographic dominates all GPS tracking data that has been collected to date. Perhaps, choosing a LABC area closer to a major population center, such as Salt Lake City, Denver, or Seattle, our with less serious terrain, would help balance the experience level of participants and shed light on how novice and intermediate backcountry users travel under a variety of avalanche conditions.

2. The survey design used in this research was based on previous work by Hendrikx & Johnson, to allow comparison between backcountry and LABC data sets. In retrospect, more careful survey design, focused on the LABC decision-making environment, could provide targeted information on the human factors influencing this population. Specifically, questions targeted at the influence of tracks on the slope, the role ski quality played in their decision to leave the resort boundary, and how weather and snowpack conditions influence participant's likelihood of avoiding Saddle Peak all together. By collecting data on participant's perception of the environmental variables at play, researchers could improve statistical models by including mixed effects or interaction terms based on these responses. We were challenged by balancing the survey design with the ability to complete it in the field in a winter environment.

3. Using GPS points in regression analysis inherently causes a high degree of spatial autocorrelation or serial correlation in the data. For this study, adding a random effect to the logistic regression model was considered but was not implemented due to the limited sample size and data structure. For future research, a random effect based on the time of season, avalanche character, or environmental variables could help address the issue of spatial autocorrelation.

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APPENDICES

APPENDIX A

FIELD SURVEY

Participation in this Research is Voluntary

MONTANA STATE UNIVERSITY

Snow Science

Q1 Age: ______ **Q2** Gender: **Male** **Female** **Q3** Number of years skiing/riding: ________

Q4 What is your primary mode of travel for the day? (Circle one)

Alpine Skis	**Backcountry Skis**	**Snowboard**	**Split Board**

Q5 Describe your backcountry experience level: (Circle one)

Novice: Little to no winter backcountry experience	**Intermediate:** Less than 5 years' backcountry experience	**Expert:** More than 5 years' backcountry experience

Q6 Which of the following formal avalanche training opportunities have you completed? (Circle all that apply)

None	**Evening awareness lecture**	**Field based awareness course**	**Level One**	**Level Two**	**Level Three**

Q7 Which pieces of avalanche safety equipment you are carrying today? (Circle all that apply)

Beacon	**Probe**	**Shovel**	**Airbag Pack**	**Avalung**

Q8 What was the avalanche forecast for the Bridger range today as posted by the Gallatin Avalanche Center?

Don't know	1 Low	2 Moderate	3 Considerable	4 High	5 Extreme

Q9 Did you observe any of the following signs of instability? (Circle all that apply)

None	**Recent Avalanches**	**Whoomphing**	**Shooting Cracks**	**Active Wind Loading**

Q10 What, if any, instability tests did you carry out to evaluate the snowpack? (Circle all that apply)

Travelling Tests (hand pits, Ski pole probe etc.)	**Snow Pit Tests**	**Cornice Cutting**	**Ski Cutting**

Q11 Did your observations and assessment of the snowpack agree with the local avalanche forecast for Saddle Peak?

Don't Know	**Not at all**	**Somewhat**	**Closely**	**Very Closely**

Q12 How did your stability assessment effect your terrain use on Saddle Peak Today?

We skied more conservative terrain than we expected.	**Our assessment was consistent with our terrain choice.**	**We skied more aggressive terrain than we expected.**

Q13 Based on your understanding, what level of assistance does the ski area provide in the case of an avalanche rescue? (Circle where you fall on this scale)

No Rescue Assistance **Some Rescue Assistance** **Full Rescue Assistance**

Q14 Based on your understanding, what degree of avalanche mitigation does the ski area provide for the lift access backcountry terrain you travelled in today? (Circle where you fall on this scale)

No Avalanche Control **Some Avalanche Control** **Complete Avalanche Control**

Q15 How familiar are you with the terrain on Saddle Peak? (Circle where you fall on this scale)

Not at all Familiar **Somewhat Familiar** **Very Familiar**

Q16 Are you skiing with partners today, if so what is your group size?

Solo | **2 People** | **3 People** | **4 People** | **5+ People**

Q17 Travel Practices. When travelling on Saddle Peak, as a group we…

	Never	Rarely	Sometimes	Most of the Time	Always
Cross potential avalanche paths one at a time.	○	○	○	○	○
Spot each other when in dangerous terrain.	○	○	○	○	○
Ski slopes one at a time.	○	○	○	○	○
Place someone in a safe spot for rescue.	○	○	○	○	○
Plan and discuss an escape route.	○	○	○	○	○
Plan and discuss communications.	○	○	○	○	○

Q18 In retrospect, how would you rate your terrain use on Saddle Peak today? (Circle where you fall on this scale)

Conservative **Moderate** **Aggressive**

Q19 To what degree did seeing other people on Saddle Peak make you feel safer in your terrain choice?

No Effect **Somewhat Safer** **Much Safer**

Q20 To what degree did you feel rushed by the presence of other people on Saddle Peak?

No Effect **Somewhat Rushed** **Very Rushed**

Q21 Are you a current or former MSU student?

Current MSU Student | **MSU Alumni** | **No MSU Affiliation**

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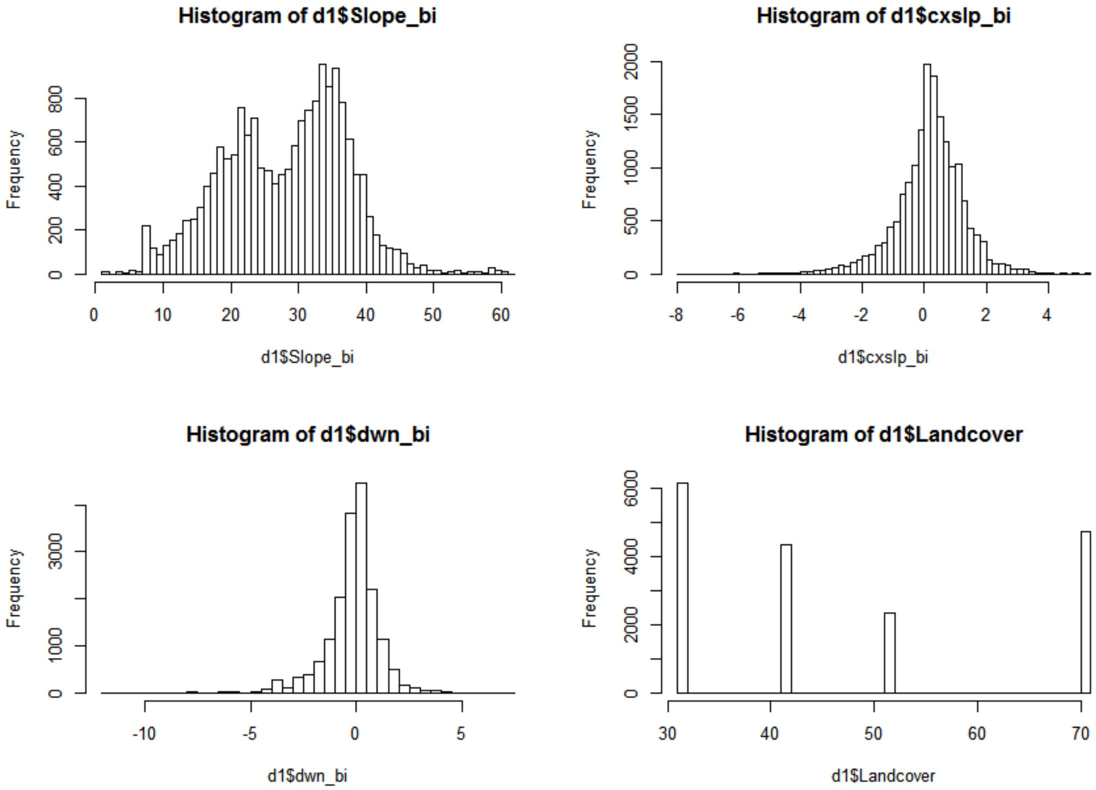
APPENDIX B

R-CODE AND PLOTS

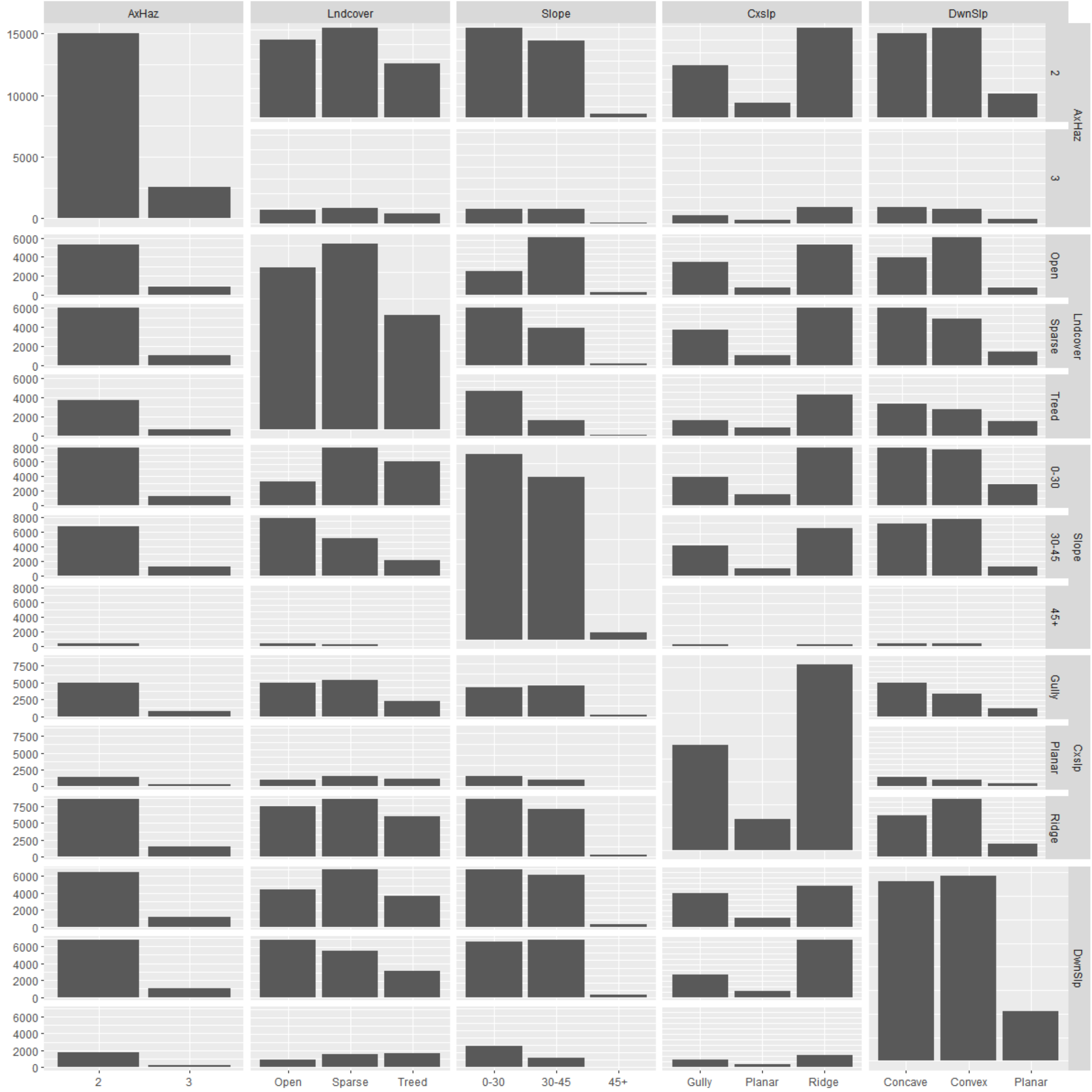
LOGISTIC REGRESSION R-CODE AND PLOTS

```
#Analysis of Travel Behavior by Avalanche Hazard Using Logistic Regression
#This R Script shows the workflow for fitting the logistic regression model for the entire
#dataset, it does not include the filtering process of selecting on participants who know
#the avalanche forecast

library(readr)
DatabyPoint2_19_18 <-
read_csv("J:/Thesis/Statistical_Analysis/2018_Master/DatabyPoint_2_19_18.csv")
d1 = DatabyPoint2_19_18

library(car)
library(margins)
library(sjPlot)
library(sjmisc)
library(GGally)
library(lmtest)

AxHaz <- factor(d1$Fx_Daily_MaxHaz)
Lndcover <- factor(d1$Lndcvr_cat)
Slope <- factor(d1$Slope_cat2)
Cxslp <- factor(d1$cxslp_cat)
DwnSlp <- factor(d1$dwn_cat)
Aspect <- factor(d1$Aspect_cat)

d2 <- data.frame(AxHaz, Lndcover, Slope, Cxslp, DwnSlp)
View(d2)
length(AxHaz)
str(d2)
summary(d2)

#Plots of individual explanatory variable distributions

hist(d1$Slope_bi,breaks = 50)
hist(d1$cxslp_bi,breaks = 50)
hist(d1$dwn_bi,breaks = 50)
hist(d1$Landcover,breaks = 50)
```



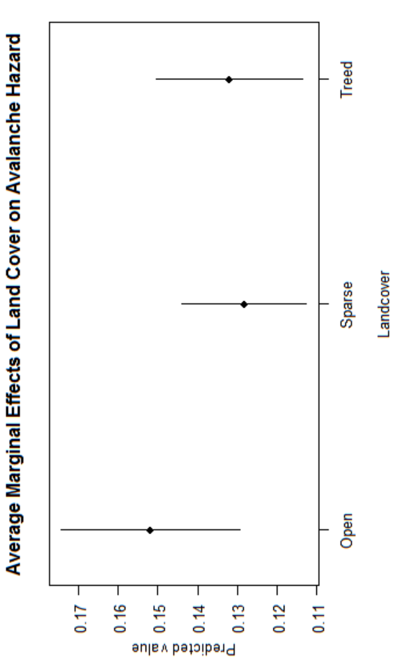
#Plot of all variables in dataframe with interactions between variables

ggpairs(d2)

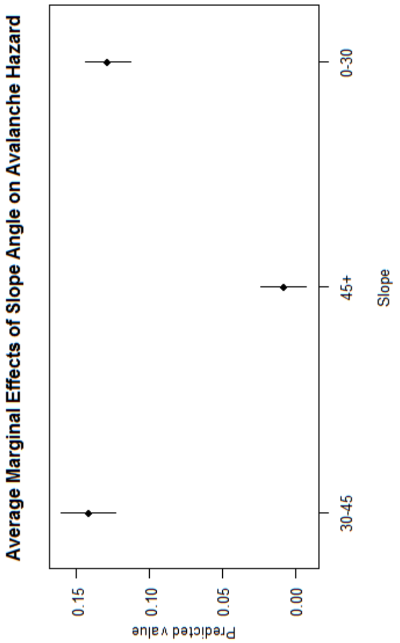


```
#Plots of individual explantory variables by avalanche hazard

plot(AxHaz ~ Slope)
plot(AxHaz ~ Slope1)
plot(AxHaz ~ Slope2)
plot(AxHaz ~ Cxslp)
plot(AxHaz ~ DwnSlp)
plot(AxHaz ~ Lndcover)
plot(AxHaz ~ Aspect)

m1 <- glm(AxHaz ~ Lndcover + Slope + Cxslp + DwnSlp,family = binomial(link =
"logit"),data=d2)
```

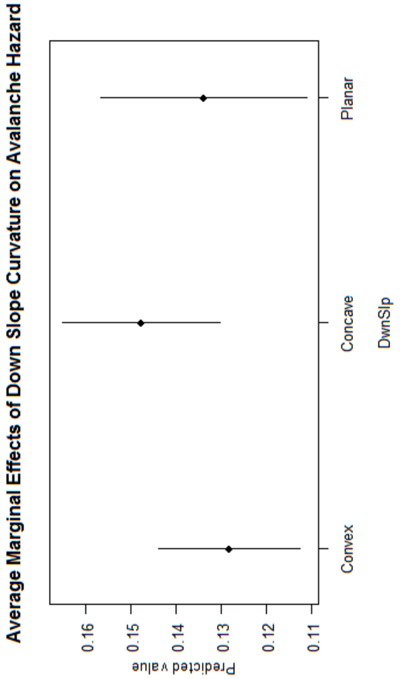
```
summary(m1)

m2 <- glm(AxHaz ~ Lndcover * Slope + Cxslp + DwnSlp, family = binomial(link =
summary(m2)

#Test for model fit and interaction
anova(m2,m3, test = "Chisq")

#Tests of model assumptions
#Variance Inflation Factor - Tests collinearity of variables
vif(m2)

#Tests Autocorrelation between adjacent observation in data frame
#Fails due to repeated measures from same GPS Track
dwtest(m2)

#Model Interpretation
#Confidence Intervals of log odds
confint(m2)
#Confidence intervals of odds ratio
exp(cbind(OR = coef(m2),confint(m2)))

#Average Marginal Effects
#Shows impact of each explanatory variabel across all values of other explantory
variables

mar <- margins(m2)
summary(mar)

#2x2 matrix of AME plots
par(mfrow = c(2,2))
cplot(m6, "Slope",main = "Average Marginal Effects of Slope Angle on Avalanche
Hazard")
cplot(m6, "Lndcover",main = "Average Marginal Effects of Land Cover on Avalanche
Hazard")
cplot(m6, "Cxslp",main = "Average Marginal Effects of Cross Slope Curvature on
Avalanche Hazard")
cplot(m6, "DwnSlp",main = "Average Marginal Effects of Down Slope Curvature on
Avalanche Hazard")
```



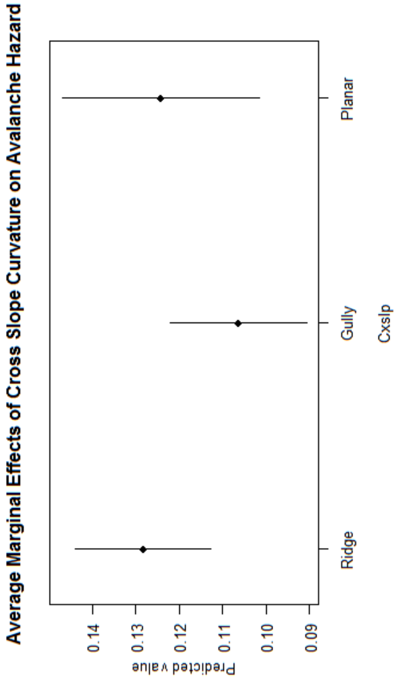
Average Marginal Effects of Land Cover on Avalanche Hazard



Average Marginal Effects of Slope Angle on Avalanche Hazard



Average Marginal Effects of Down Slope Curvature on Avalanche Hazard



Average Marginal Effects of Cross Slope Curvature on Avalanche Hazard

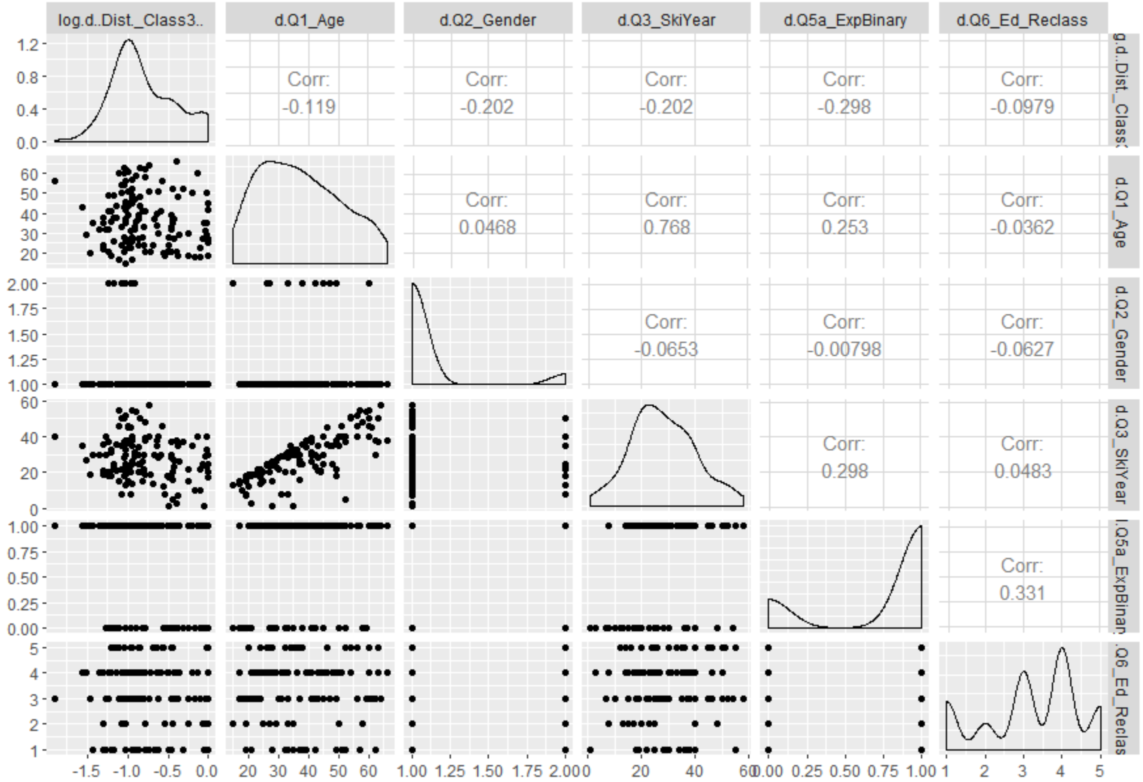
```
#HTML output table of regession model
#Log Odds
sjt.glm(m2,show.aic = T,show.se = T,group.pred = T,emph.p = T,show.header =
T,exp.coef = F)
#Odds Ratio
sjt.glm(m2,show.aic = T,show.se = T,group.pred = T,emph.p = T,show.header =
T,exp.coef = T)
```

```
#Comparison of Populations by Avalanche Hazard

library(readr)
DatabyTrack2_20_18 <-
read_csv("J:/Thesis/Statistical_Analysis/2018_Master/DatabyTrack2_20_18.csv")
d <- DatabyTrack2_20_18

Axhaz <- as.factor(d$Fx_Daily_MaxHaz)

#Testing for significant differences in the population demographics on considerable vs
#moderate sampling days.

wilcox.test(d$Q1_Age ~ Axhaz)
wilcox.test(d$Q3_SkiYear ~ Axhaz)

#Fisher's Exact test of independence for sample proportions (Small Samples)
#Testing whether population proportions are associated with avalanche hazard level

library(MASS)

#Gender
tbl1 = table(Axhaz,d$Q2_Gender)
tbl1
fisher.test(tbl1)

#Travel Mode
tbl2 = table(Axhaz,d$Q4_Travel)
tbl2
fisher.test(tbl2)

#Backcountry Experience

tbl3 = table(Axhaz,d$Q5_Experience)
tbl3
fisher.test(tbl3)

#Formal Avalanche Education
tbl4 = table(Axhaz,d$Q6_Education)
tbl4
fisher.test(tbl4)

#Rescue equipment
tbl5 = table(Axhaz,d$Q7_Equipment)
tbl5
```

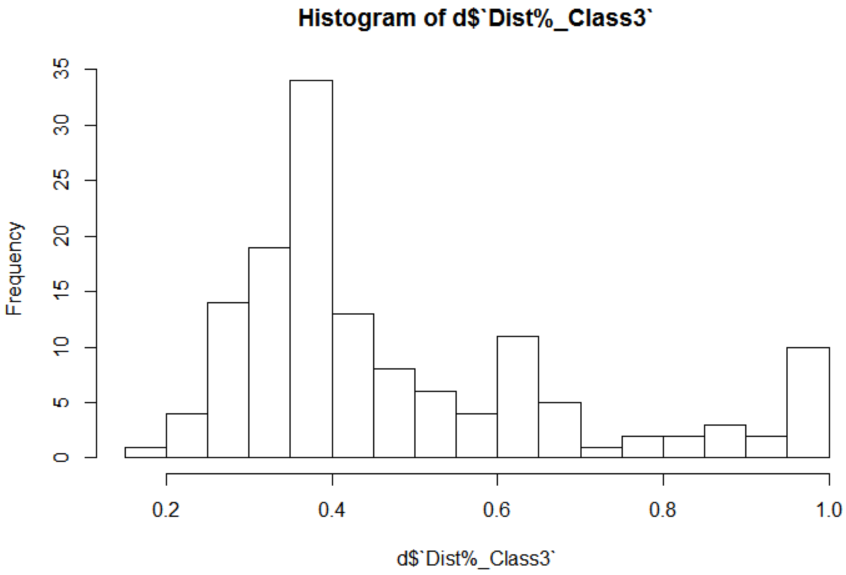
```
fisher.test(tbl5)

#Forecast Knowledge
tbl6 = table(Axhaz,d$Q8a_FxAcc)
tbl6
fisher.test(tbl6)

#Instability Observations
tbl7 = table(Axhaz,d$Q9_Obs)
tbl7
fisher.test(tbl7)
fisher.test(tbl7,conf.level = .9)

        Fisher's Exact Test for Count Data

data:  tbl7
p-value = 0.07138
alternative hypothesis: true odds ratio is not equal to 1
90 percent confidence interval:
  1.064372 10.880046
sample estimates:
odds ratio
  3.118781

#Travel Practices
tbl8 = table(Axhaz,d$Q17_TravelPractices)
tbl8
fisher.test(tbl8)
```

MULTIPLE LINEAR REGRESSION R-CODE AND PLOTS

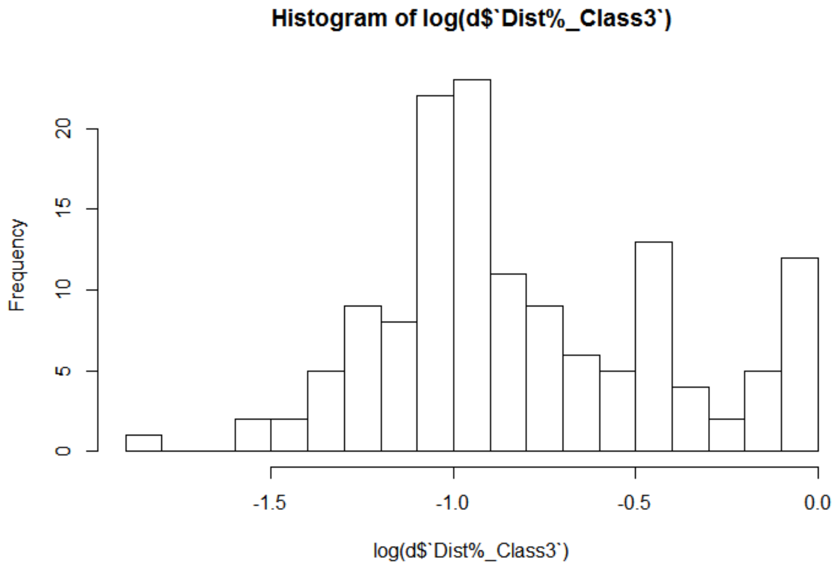
```
#Human Factor and Percent of Distance in Complex Terrain
#Multiple Linear Regression

library(readr)
DatabyTrack2_20_18 <-
read_csv("J:/Thesis/Statistical_Analysis/2018_Master/DatabyTrack2_20_18.csv")
d <- DatabyTrack2_20_18

library(car)
library(lmtest)
library(leaps)

#Demographics Influence and % Distance in Comlex Terrain

d1 <- data.frame(log(d$`Dist%_Class3`),d$Q1_Age,d$Q2_Gender,d$Q3_SkiYear,
              d$Q5a_ExpBinary,d$Q6_Ed_Reclass)

#Step-wise regression for variable selection and model fitting

m.ss = regsubsets(log(d$`Dist%_Class3`) ~ d$Q1_Age + d$Q2_Gender + d$Q3_SkiYear
          + factor(d$Q5a_ExpBinary) + factor(d$Q6a_Formal_Ed) + d$Q13_Rescue +
          d$Q14_Mitigation + d$Q19_Herding + d$Q15_Familiarity +
          factor(d$Q7_Equip_Bi) + factor(d$Q8a_FxAcc),data=d)
summary(m.ss)

mss <- lm(log(d$`Dist%_Class3`) ~ d$Q2_Gender + d$Q14_Mitigation +
d$Q6a_Formal_Ed + d$Q15_Familiarity,data=d)
summary(mss4)

#Best fit model with 4 parameters does not have significantly better fit that 3 parameter
model

anova(m3aL,mss4)

#Matrix of Plots and Correlation Between Explanatory Variabels
#Indicated collinearity between Ski year & Age, Experience & Age, Experience & Ski
Year, Education & Experience
#MLR models checked for influence of collinearity using variance inflation factor
library(GGally)
ggpairs(d1)
```



```
#Historgram and Density Plot of Response Variable
hist(d$`Dist%_Class3`,breaks = 20)
dt <- density(d$`Dist%_Class3`)
plot(dt)
```

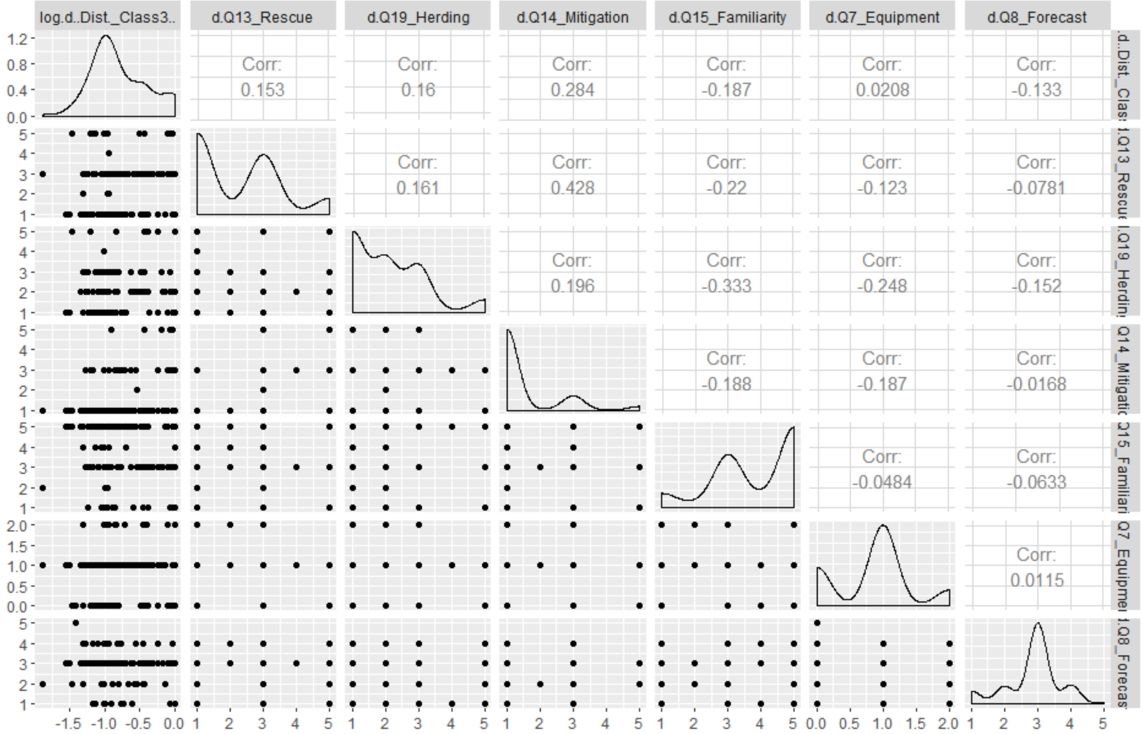


```
#Histogram and Desnity Plot Log Transformed Response Variables
hist(log(d$`Dist%_Class3`),breaks = 20)
dt1 <- density(log(d$`Dist%_Class3`))
plot(dt1)
```



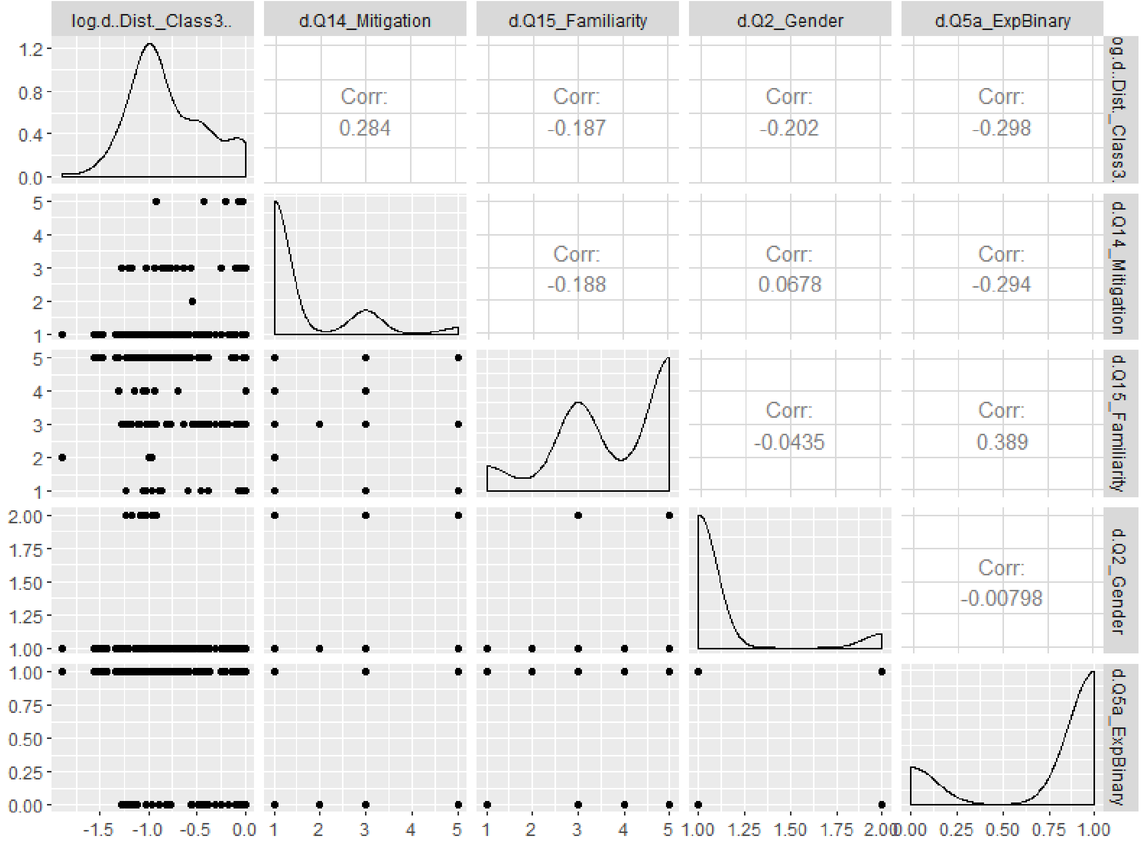
```
#Models of Demographics by % Distance in Class 3 Terrain

m1 <- lm(log(d$`Dist%_Class3`) ~ d$Q1_Age + d$Q2_Gender + d$Q3_SkiYear +
factor(d$Q5a_ExpBinary) + factor(d$Q6a_Formal_Ed),data=d)
summary(m1)

#Check for variance Inflation due to collinearity
#VIF > 5 indicates regression output could be severely impacted by collinearity
vif(m1)

m1a <- lm(log(d$`Dist%_Class3`) ~ d$Q2_Gender + d$Q3_SkiYear +
factor(d$Q5a_ExpBinary) + factor(d$Q6a_Formal_Ed),data=d)
summary(m1a)
vif(m1a)

m1b <- lm(log(d$`Dist%_Class3`) ~ d$Q2_Gender + d$Q3_SkiYear +
factor(d$Q5a_ExpBinary),data=d)
summary(m1b)
vif(m1b)

m1c <- lm(log(d$`Dist%_Class3`) ~ d$Q2_Gender + factor(d$Q5a_ExpBinary),data=d)
```

```
summary(m1c)

# Cheching for interaction effect of avalanche hazard on either demographic variable

m1d <- lm(log(d$`Dist%_Class3`) ~ d$Q2_Gender + factor(d$Q5a_ExpBinary)*
factor(d$Fx_Daily_MaxHaz) ,data=d)
summary(m1d)

m1e <- lm(log(d$`Dist%_Class3`) ~ d$Q2_Gender * factor(d$Fx_Daily_MaxHaz) +
factor(d$Q5a_ExpBinary),data=d)
summary(m1e)

#Significant variabels are gender and experience, which will be included in combined
model
#################################################

#Models looking at human factors and decision bias on exposure to complex terrain

d2 <- data.frame(log(d$`Dist%_Class3`), d$Q13_Rescue, d$Q19_Herding,
        d$Q14_Mitigation, d$Q15_Familiarity, d$Q7_Equipment,d$Q8_Forecast)

#Testing for multi-collinearity
#Several collinear explanatory variables, models checked using VIF

library(GGally)
ggpairs(d2)
```

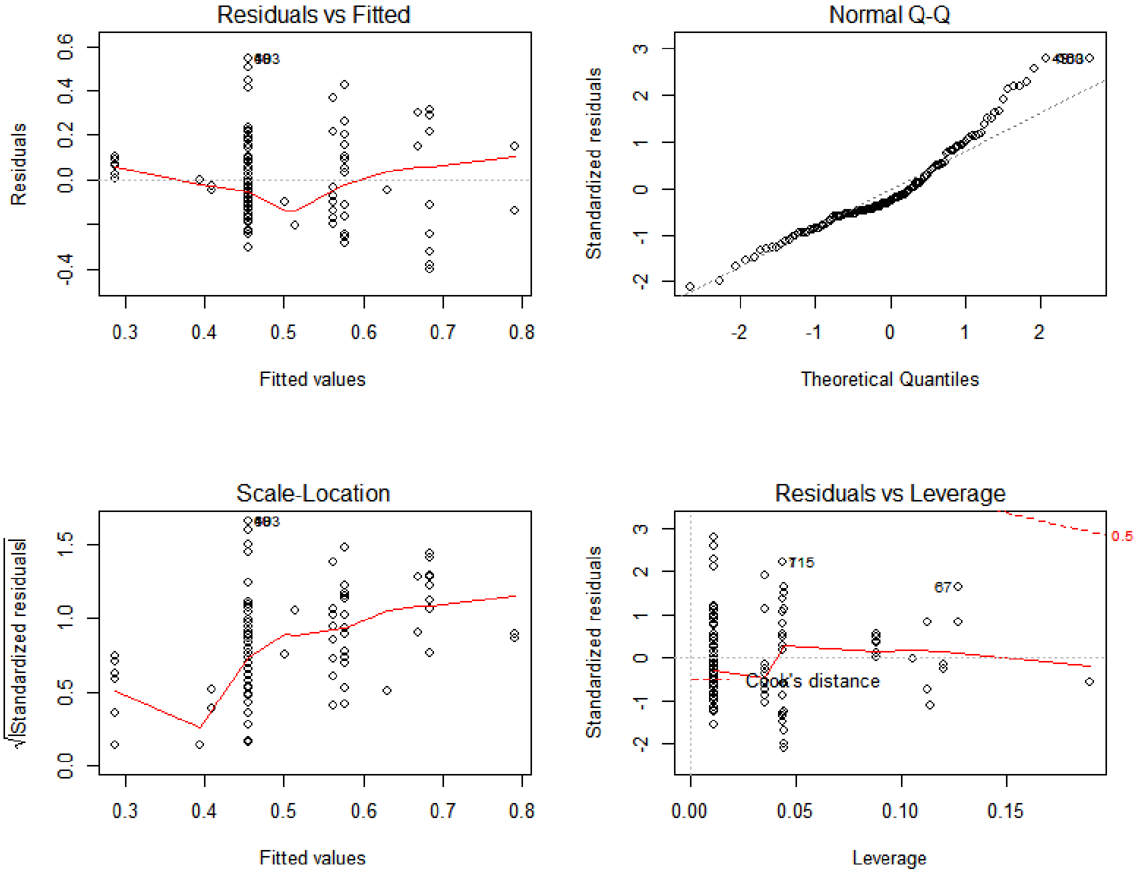


```
#Model Fitting

m2 <- lm(log(d$`Dist%_Class3`) ~ d$Q13_Rescue + d$Q14_Mitigation
+d$Q19_Herding+d$Q15_Familiarity+ factor(d$Q7_Equipment) +
d$Q8_Forecast,data=d)
summary(m2)
vif(m2)

m2a <- lm(log(d$`Dist%_Class3`) ~ d$Q13_Rescue + d$Q14_Mitigation
+d$Q15_Familiarity + factor(d$Q7_Equipment) + d$Q8_Forecast,data=d)
summary(m2a)
vif(m2a)

m2b <- lm(log(d$`Dist%_Class3`) ~ d$Q14_Mitigation +d$Q15_Familiarity
+factor(d$Q7_Equipment) + d$Q8_Forecast,data=d)
summary(m2b)
vif(m2b)

m2c <- lm(log(d$`Dist%_Class3`) ~ d$Q14_Mitigation +d$Q15_Familiarity +
d$Q8_Forecast,data=d)
summary(m2c)
vif(m2c)
```

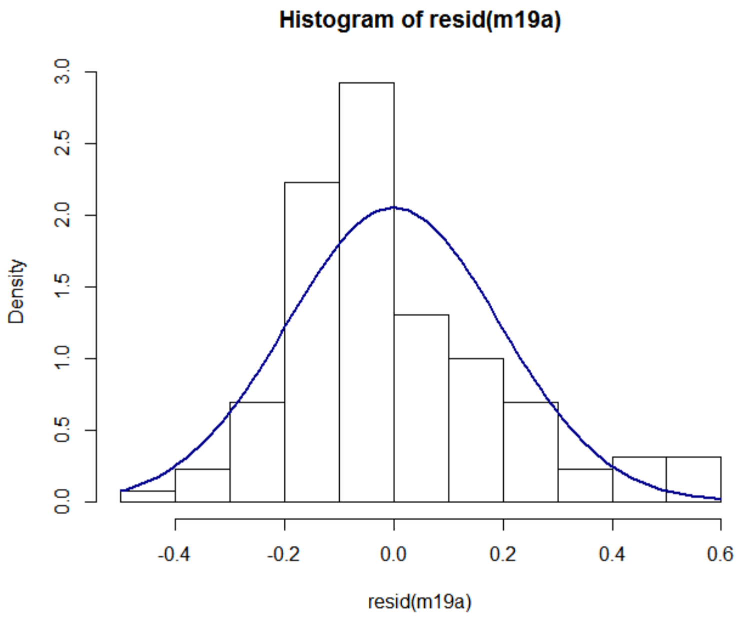
```
m2d <- lm(log(d$`Dist%_Class3`) ~ d$Q14_Mitigation + d$Q15_Familiarity,data=d)
summary(m2d)
vif(m2d)
#Significant variables are mitigation and familiarity, which will be included in combined
model

############################################################

#Combined Models with Demographics and Human Factors

d3 <-
data.frame(d$`Dist%_Class3`,d$Q14_Mitigation,d$Q15_Familiarity,d$Q2_Gender,d$Q5
a_ExpBinary)

#Testing for multi-collinearity
#Several collinear explanatory variables, models checked using VIF

library(GGally)
ggpairs(d3)
```



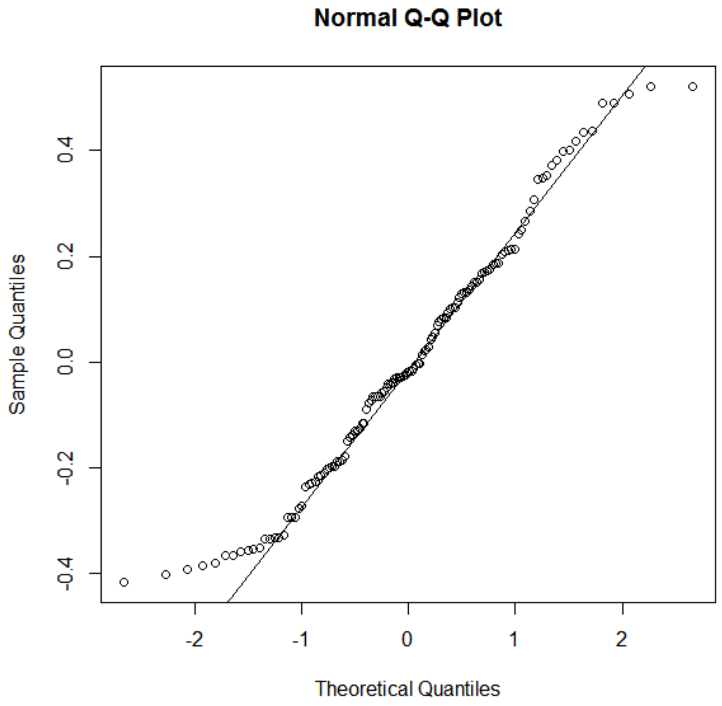
```
#Plots of final variables with potential interactions
plot(d$`Dist%_Class3`~d$Q5a_ExpBinary)
plot(d$`Dist%_Class3`~ d$Q2_Gender)
coplot(d$`Dist%_Class3`~ d$Q5a_ExpBinary | factor(d$Q2_Gender))
plot(d$`Dist%_Class3`~ d$Q14_Mitigation)
coplot(d$`Dist%_Class3`~ d$Q14_Mitigation | factor(d$Q2_Gender))
coplot(d$`Dist%_Class3`~ d$Q14_Mitigation | factor(d$Q5a_ExpBinary))

#Model Fitting
m3 <- lm(d$`Dist%_Class3` ~ d$Q14_Mitigation + d$Q15_Familiarity +
factor(d$Q2_Gender) +
         factor(d$Q5a_ExpBinary),data=d)
summary(m3)
vif(m3)

m3a <- lm(d$`Dist%_Class3` ~ d$Q14_Mitigation + factor(d$Q2_Gender) +
          factor(d$Q5a_ExpBinary),data=d)
summary(m3a)
vif(m3a)

#Checking for model fit
#Model including familiarity is not statistically significantly better

anova(m3a,m3)

#Check Model Assumptions
#Residual Plots
par(mfrow = c(2,2))
plot(m3a)
```



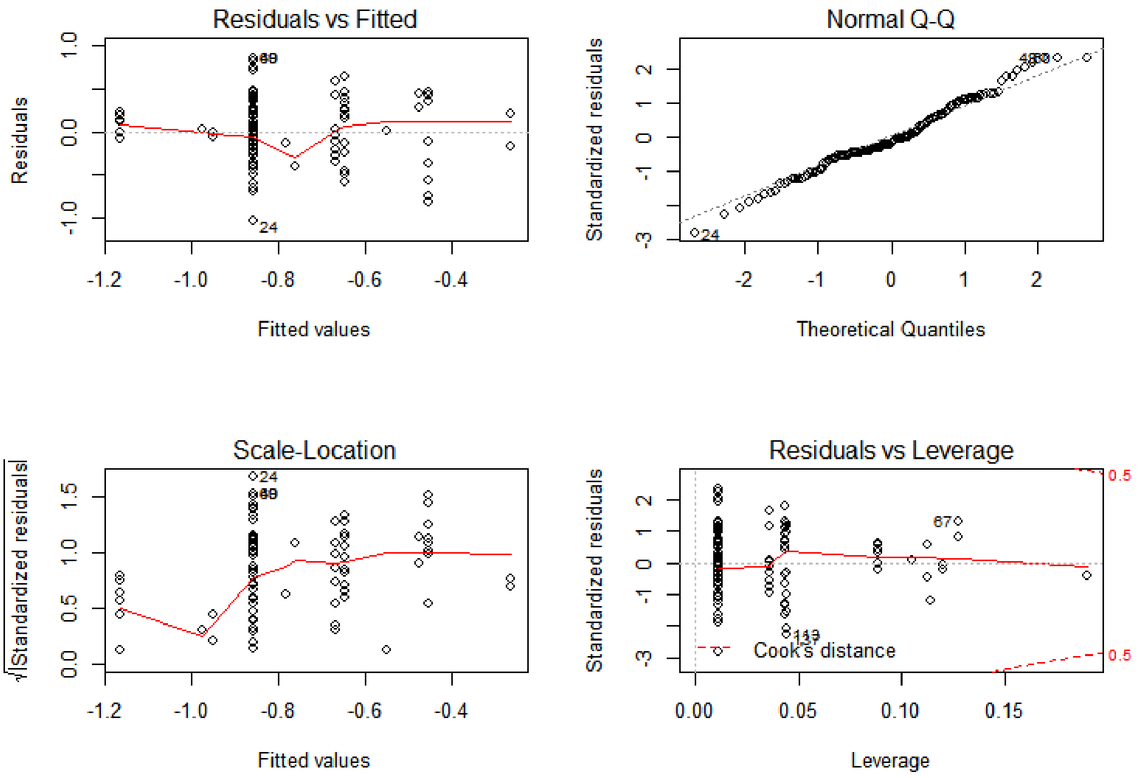
```
#Histogram of Residuals with normal distribution density curve
resid(m3a)
par(mfrow = c(1,1))
hist(resid(m3a),freq = FALSE, breaks = 10)
m <- mean(resid(m3a))
std <- sqrt(var(resid(m3a)))
curve(dnorm(x, mean=m, sd=std),
     col="darkblue", lwd=2, add=TRUE, yaxt="n")
```



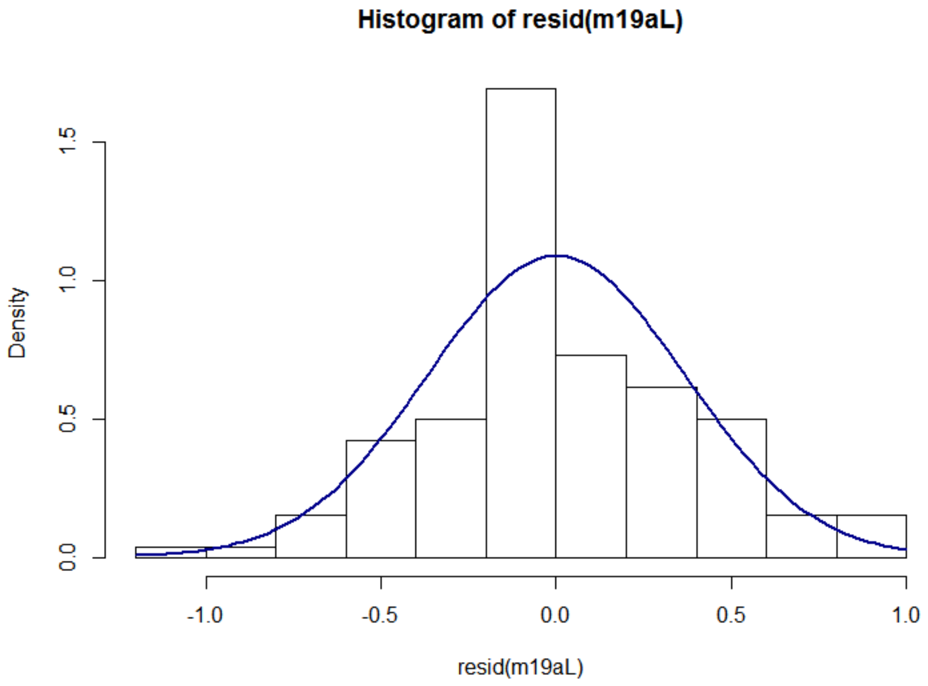
```
#Noramlity of residuals
par(mfrow = c(1,1))
qqnorm(resid(m3a))
qqline(resid(m3a))
```



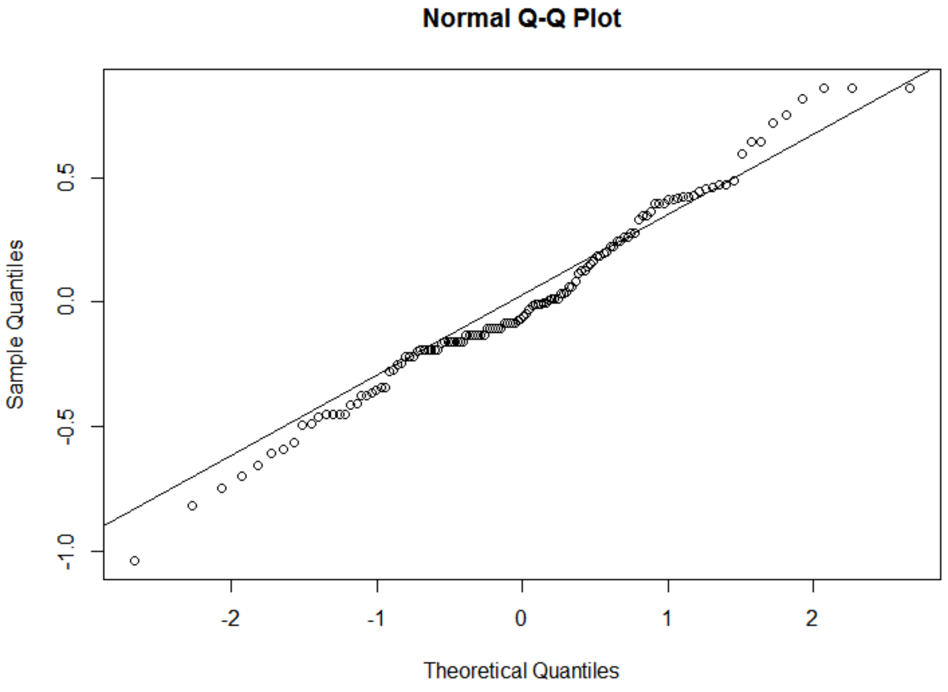
```
#Significant tests for normality
library(car)
library(lmtest)
#Breush-Pagan Test
bptest(m3a)
#Non-Constant Variance Test
ncvTest(m3a)

#Model fails NCV test, indicating non-constant variance

#Log Transform of Response Variable to Satisfy Assumptions
m3L <- lm(log(d$`Dist%_Class3`) ~ d$Q14_Mitigation + d$Q15_Familiarity +
factor(d$Q2_Gender) +
        factor(d$Q5a_ExpBinary),data=d)
summary(m3L)
vif(m3L)

m3aL <- lm(log(d$`Dist%_Class3`) ~ d$Q14_Mitigation + factor(d$Q2_Gender) +
          factor(d$Q5a_ExpBinary),data=d)
summary(m3aL)
vif(m3aL)

#Re-checking model fit
#Model with familiarity is not statisticallyl significantly better fit
anova(m3L,m3aL)

#Re-checking assumptions
par(mfrow = c(2,2))
plot(m3aL)
```



```
resid(m3aL)
par(mfrow = c(1,1))
hist(resid(m3aL),freq = FALSE, breaks = 10)
m <- mean(resid(m3aL))
std <- sqrt(var(resid(m3aL)))
curve(dnorm(x, mean=m, sd=std),
    col="darkblue", lwd=2, add=TRUE, yaxt="n")
```



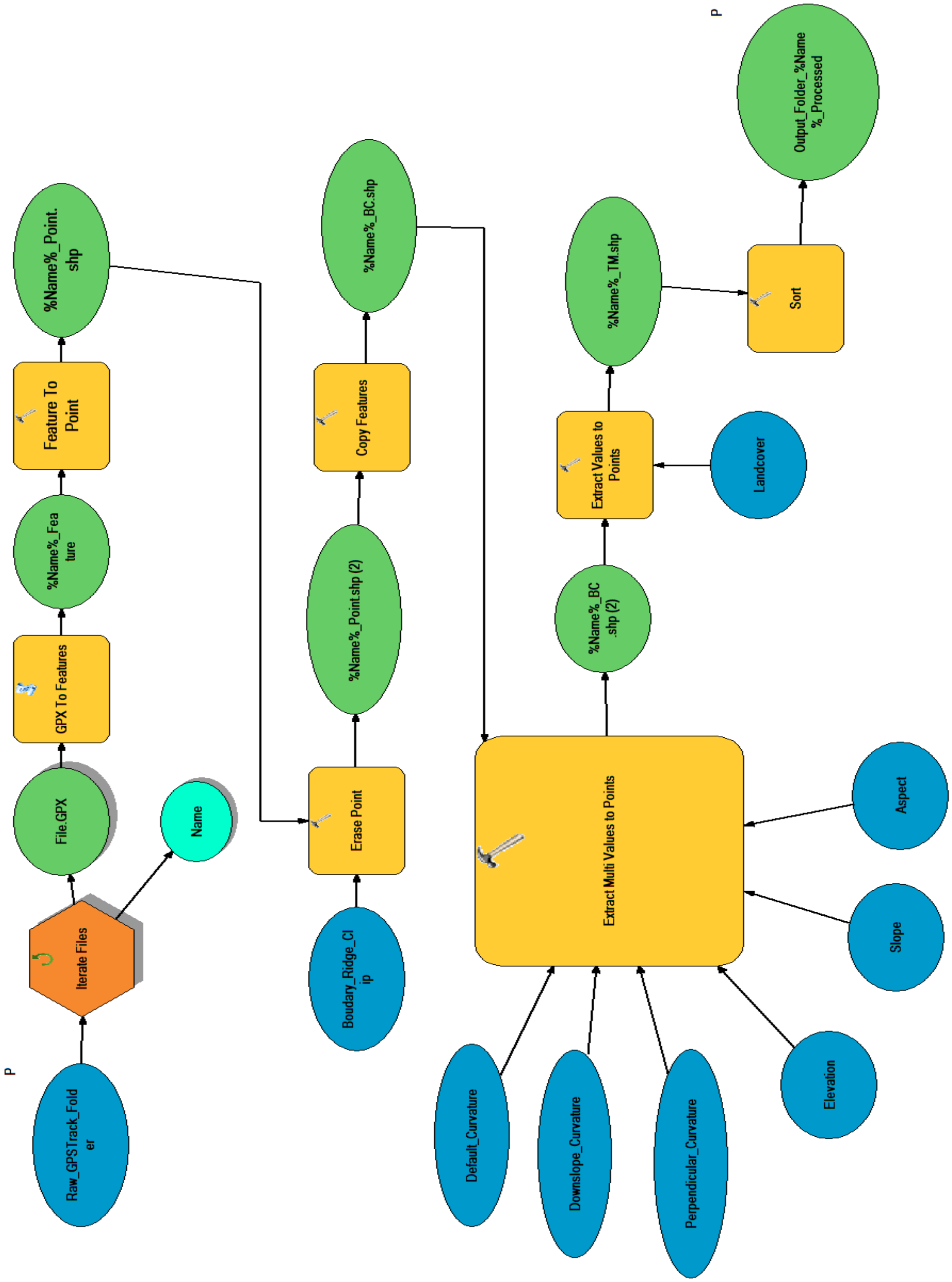
```
par(mfrow = c(1,1))
qqnorm(resid(m3aL))
qqline(resid(m3aL))
```



```
library(car)
library(lmtest)
bptest(m3aL)
ncvTest(m3aL)

#Passes both test of constant variance

##################################

#Checking for interaction with avalanche hazard

m3b <- lm(d$`Dist%_Class3` ~ d$Q14_Mitigation * factor(d$Fx_Daily_MaxHaz) +
factor(d$Q2_Gender) +
            factor(d$Q5a_ExpBinary),data=d)
summary(m3b)

m3c <- lm(d$`Dist%_Class3` ~ d$Q14_Mitigation + factor(d$Q2_Gender) *
factor(d$Fx_Daily_MaxHaz) +
           factor(d$Q5a_ExpBinary),data=d)
summary(m3c)

m3d <- lm(d$`Dist%_Class3` ~ d$Q14_Mitigation + factor(d$Q2_Gender) +
           factor(d$Q5a_ExpBinary) * factor(d$Fx_Daily_MaxHaz),data=d)
summary(m3d)

#No significant interaction with any explanatory variables

#HTML table of final model regression output
library(sjPlot)
library(sjmisc)
sjt.lm(m3aL,m3L,pred.labels = c("Mitigation","Gender - Female","Experience - Expert",
                               "Familiarity"),depvar.labels =
        c("Log Percent of Distance in Complex Terrain","Log Percent of Distance in
Complex Terrain"),
      show.se = T,show.ci = F,show.fstat = T,emph.p = T)
```

APPENDIX C

ArcGIS Model Builder – GPS Track Processing Model


P
Raw_GPSTrack_Folder
Iterate Files
Name
File.GPX
GPX To Features
%Name%_Feature
Feature To Point
%Name%_Point.shp
Boudary_Ridge_Clip
Erase Point
%Name%_Point.shp (2)
Copy Features
%Name%_BC.shp
Default_Curvature
Downslope_Curvature
Perpendicular_Curvature
Elevation
Slope
Aspect
Extract Multi Values to Points
%Name%_BC.shp (2)
Extract Values to Points
Landcover
%Name%_TM.shp
Sort
Output_Folder_%Name%_Processed
P