# SPATIAL AND TEMPORAL VARIATIONS IN SNOW STABILITY AND SNOWPACK CONDITIONS THROUGHOUT THE BRIDGER MOUNTAINS, MONTANA

by

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## ABSTRACT

This research investigates snow stability and snow properties throughout a small mountain range in southwest Montana over the course of a snow season. Although previous research has addressed avalanches and snow at smaller spatial scales, this is the first field-based study to investigate snow stability over a mountain range in order to better understand the spatial distribution of avalanches and improve their prediction.

Using helicopter access, six two-person sampling teams collected data from over 70 sites on each of two sampling days. Variables for terrain, snowpack, snow strength and snow stability were generated from the field data, and analyzed using descriptive statistics, correlation analysis, multiple regression, canonical correlation, cluster analysis, and analysis of variance.

Results from the first sampling day show stability is only weakly linked to terrain, snowpack and snow strength variables due to relatively homogenous weather conditions leading up to that day. The second field day's results demonstrate a stronger relationship between stability and the other variables due to increasingly heterogenous weather conditions. On both days stability decreased on high elevation, northerly facing slopes. Overall results suggest that the Bridgers consist of a single avalanche region - where site-specific slope factors such as elevation and aspect are better predictors of stability than location within the mountain range.

Further results show that at higher elevations and more northerly aspects in the mountain range: 1) average snow strength increases, 2) snow depth increases, 3) sub-surface snow temperatures decrease, and 4) absolute values of temperature gradient increase. Analyses also indicated that the relationship between surface snow strength and terrain are different on the two sampling days, probably reflecting temporal changes in surface snow composition.

This work is dedicated to

the late Melvin G. Marcus,

whose encouragement got me started,

and

Ginger H. Birkeland,

whose encouragement kept me going.

## ACKNOWLEDGEMENTS

I enjoyed the help and expertise of many people while doing this research. I am grateful to the late Mel Marcus, who passed away while teaching a field course in the snowy San Juan Mountains of Colorado when I was halfway through collecting my data. Like many others, I benefitted from Mel's child-like enthusiasm, broad scientific insight, positive outlook, and emphasis on field science. Mel also provided a flexible academic environment, allowing me to keep my job in Montana while pursuing my degree in Arizona. I am grateful to Will Graf, who filled in as the chair of my committee and provided numerous helpful comments, to Lee Dexter for providing expertise on snow and encouragement during data analysis, to Bob Balling for joining my committee and teaching me about statistics, and to Tony Brazel for helping me assess my project before the snow fell. Thanks to all the faculty, staff, and my fellow graduate students in the Department of Geography for providing a stimulating intellectual environment.

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# Chapter I

# Introduction

## OVERVIEW

Knowledge of regional snowpack conditions is critical for predicting snow avalanches, which are a significant hazard in mountain environments. Because snow conditions are not uniform in complex terrain, an understanding of spatial variations in snowpack properties is important in snow and avalanche research and prediction. In spite of the known variations in snowpack, traditional methods of data collection have focused on single location study plots, such as at ski areas. These data are then extrapolated to a larger area on the basis of practical experience instead of scientific understanding. The connections between these point data and the snowpack properties of the surrounding terrain must be better understood for accurate avalanche prediction and explanation of avalanche processes.

The purpose of this research is to investigate the spatial variability of snowpack properties as a function of terrain at the physical scale of a small mountain range and the temporal scale of a snow season. In particular, this study will focus on patterns of snow stability, which are of primary importance for understanding the distribution of avalanches. A secondary purpose is to investigate spatial patterns of snow strength and general snowpack characteristics. This study will be useful for avalanche professionals and scientists studying the distribution of snow avalanches and snow properties.

Avalanches, which are defined as the rapid descent of material (rock, ice, snow, or all three) down a slope (Small and Witherick, 1989), have been studied by geographers since the late 19th century (Cornell, 1875). Much research has focused on rock avalanches and slides, as part of the general category of mass movement on hillslopes (Crozier, 1986; Selby, 1993). Although less research has been done on snow avalanches, the interdisciplinary nature of snow avalanche research is remarkable, crossing several boundaries within geography, including natural hazards, biogeography, climatology, and geomorphology. Natural hazards research focuses upon "human responses to geological, meteorological and hydrological risks" (Mitchell, 1989, p. 412), and therefore clearly includes snow avalanches and the resultant responses of people living and recreating in mountain environments. Further, avalanches are a well known influence on the biogeography of alpine zones, where large areas are cleared of coniferous trees by frequent avalanche activity, and where pioneer species such as aspen and alder are quick to establish (Price, 1981). Avalanche research also falls under climatology, where "interest is primarily with the weather phenomena which favor avalanche situations" (Barry, 1992, p. 357). Finally, avalanches are of interest to geomorphologists. Since medium to small avalanches are not capable of moving large boulders or much debris, avalanches have only a small affect on landform development (Selby, 1993). Still, it is the field-based approach of geomorphologists to their study of landforms and associated processes which can be readily transferred to the study of snow avalanche phenomena, an approach used in this research. In essence, this study addresses a classic question in physical geography: how do physical features (specifically, snow stability, strength, depth and subsurface temperature) vary through space (over a mountain range) and time (through a snow season), and what are the implications of that variability for prediction?

Atmospheric and geomorphic variables interact with each other to determine snow stability (Figure 1). Terrain provides the background for the other variables, influencing the past and current weather, though not always in the same direction. Past weather, in turn, is critical since past snowfall, wind, temperatures and radiation inputs determine snowpack properties, structure, and strength. Snowpack structure controls the potential for avalanche release, because the presence of a slab, weak layer, and bed surface are required (McClung and Shaerer, 1993). Ultimately, snow stability is a function of the strength of the snow and the stresses

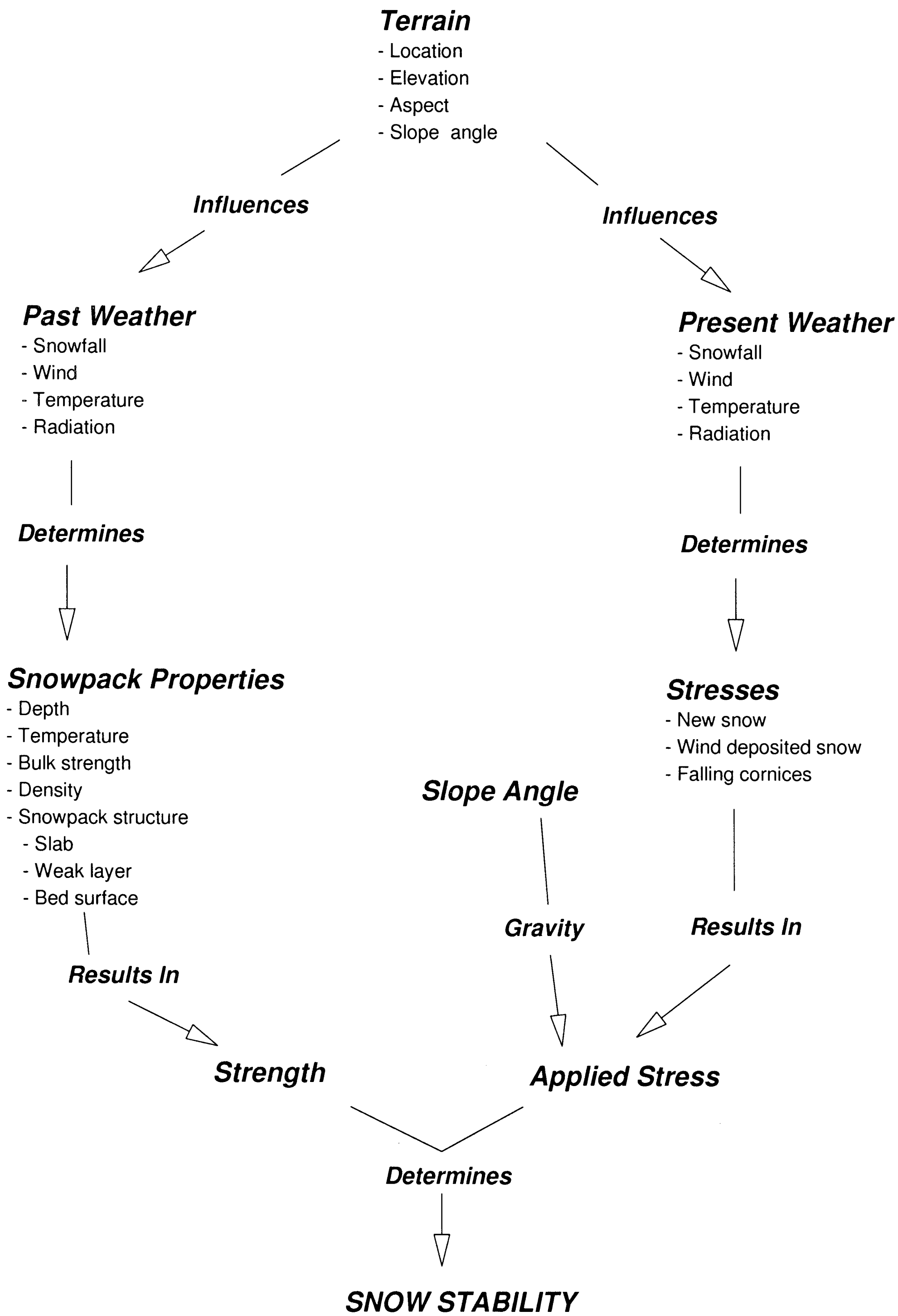


FIGURE 1: Simplified conceptual model showing how numerous variables interact to determine snow stability.

being applied to it. Common natural stresses which trigger avalanches include new snow, windblown snow, and falling cornices, while typical artificial triggers include explosives, skiers, and snowmobilers. In short, not only are the interactions of the variables that determine stability complicated, but the spatial changes in those variables makes their analysis even more complex.

The study area for this research is the Bridger Range, a single ridge of mountains located approximately 5 km north of Bozeman, Montana. The study involves the collection of snowpack data at over 70 sample sites throughout the range on two different sampling days, and the statistical comparison of terrain variables (location, elevation, aspect with respect to sun, and slope angle) and snowpack variables (stability, strength, depth, subsurface temperature). This work also links the above spatial data with data typically gathered by avalanche workers: 1) surface weather data (temperature, winds, and snowfall), and 2) detailed study plot snowpack information (depth, densities, temperatures and crystal types of various layers, as well as stability tests).

A geographic approach is required in snow and avalanche research to explain spatial variations in snowpack properties. This study improves our understanding of regional processes affecting snowpack stability, which may improve statistical and process-oriented avalanche forecasting models, neither of which currently effectively deal with the problem of regional variations in snowpack characteristics. In addition to theoretical considerations, this research has practical applications. On average 17 people are killed by avalanches in the United States every year, a mortality toll that exceeds the average annual mortality due to earthquakes (Voight and others, 1990). With increasing recreation and development pressure on mountain environments, death and damage tolls will continue to escalate. Results of this study constitute a critical step toward the better understanding of spatial variations in snowpack which may help to improve avalanche forecasting methods and which, in turn, could help to mitigate rising death tolls.

## BACKGROUND

Geographers have investigated avalanche phenomena since Strabo, who commented in *Geographica IV* 6, 6 in the year A.D. 16 that

> "It is difficult to protect oneself against ice sheets sliding down from above which are capable of hurling entire caravans into the gaping abysses. Many such sheets lie one on top of another because one snow layer after the other turns to ice and the sheets on the surface disengage themselves from the ones below before they are melted entirely by the sun" (Bader and others, 1939, p. xi).

More recent physical geography texts have addressed snow avalanches in general terms since the late 19th century (Cornell, 1875), and contemporary geographical research has focused on a variety of avalanche related topics that are not directly pertinent to this study. Such work has investigated avalanche climatology (e.g., Butler, 1986; Mock and Kay, 1992; Mock, 1995; Mock, 1996), avalanche path vegetation (e.g., Butler, 1989), avalanche path characteristics and geological controls (e.g., Butler, 1979; Butler and Walsh, 1990; Walsh and others, 1990), and avalanche runout distances (e.g., McClung and Mears, 1995). However, geographers have also investigated snowpack variability in relation to terrain (e.g., Dexter, 1986; Elder, 1995), snow strength variability in relation to terrain features and avalanche release (e.g., Birkeland, 1990; Birkeland and others, 1995), and avalanche forecasting (e.g., Armstrong and Ives, 1977; McClung and Tweedy, 1994). The following literature review focuses on the sub-fields most closely associated with the current research: 1) studies of spatial variations in snowpack properties, 2) previous work on snow strength and stability, and 3) research on avalanche forecasting, and the limitations in current forecasting models.

**Spatial studies of snowpack properties**

Most spatial snowpack studies have focused on the relationship of terrain to snow water equivalence (SWE) because of the importance of the snowpack to mountain hydrology and water supplies. McPartland (1971) investigated snow depth (which was highly correlated to SWE) in southwest Montana, and found elevation to be the most important terrain feature explaining changes in depth. Exposure to wind was of secondary importance and variables such as aspect and location were not effective in predicting depth. Caine (1975) evaluated data from the San Juan mountains of Colorado, and Toews and Gluns (1986) analyzed British Columbia data; both studies found a linear increase in SWE with elevation. Birkeland (1996) studied forested areas within Big Sky Ski Area in southwest Montana and also found that elevation was the most important variable in explaining the variance of depth and SWE. Elder (1995) investigated a small alpine watershed (120 ha) in California with 616 m of relief. Unlike McPartland (1971) and Birkeland (1996), he found that net solar radiation (a function of aspect) was the most important factor controlling SWE, while elevation and slope angle were of secondary and tertiary importance.

Pipp (1997) collected snow depth and SWE within the study area for this research in the Bridger range. Depth and SWE increased with elevation at his sites, which were protected from wind effects. However, these increases were modified by the proximity to a major pass (Ross Pass) which decreased the snow accumulation gradient. He concluded that areas around such terrain features might not be representative of the entire range and that measurement site selection was a critical factor.

The work that most closely parallels the present research was by Dexter (1986) in an area of about ten square kilometers in the Colorado Front Range. Like Pipp (1997), Dexter avoided areas exposed to wind because of increased variability in those locations. Depth increased with elevation in the early and mid-season, though by late in the year that pattern was not observed. Depth also decreased with increasingly southerly aspect.

Spatial studies that address snowpack properties other than depth and SWE are rare. Dexter (1986) also measured snow temperatures 0.30 m below the snow surface, a depth generally below the level of diurnal temperature fluctuations. He also calculated the temperature gradient, which is a function of depth and the snow temperature. Snow temperature decreased with increasing elevation in the early- and mid-season, and was constant in the late season. Snow temperature increased with increasingly southerly aspect in the early-season, but was not related to aspect in the mid- and late-season. Subsurface temperature was also the most stable variable measured, an important result since temperatures serve as a starting point for thermodynamic modelling of the snowpack. Temperature gradient decreased with elevation, indicating that depths increased with elevation faster than temperatures decreased.

In summary, previous research linking terrain with snowpack variables shows that elevation and aspect control snow depth and SWE. In the majority of the research, elevation was the most important control of SWE, though one detailed study found that net radiation was dominant (Elder, 1996). In general, depth and SWE were shown to increase with increasing elevation and northerly aspect. Much more limited data are available on snow temperatures, but they suggest that snow temperatures decrease with increasing elevation and increasingly northerly aspect through the majority of the season.

This study differs from the above body of research. First, previous work that required field measurements (i.e., McPartland (1971), Dexter (1986), Birkeland (1996), Pipp (1997), Elder (1996)) was conducted in relatively small (less than 10 square km) areas, while studies over larger areas used widely spaced snow course data (i.e., Caine (1975); Toews and Gluns (1986)). This research is the first field-based study that analyzes field data over an area on the scale of hundreds of square kilometers. Second, all of the above research with the exception of Elder (1995) analyzed data exclusively from wind protected areas, thereby controlling for the effects of wind deposition. Another unique aspect of this research is that sampling locations include both wind protected and wind exposed locations.

**Spatial studies of snow strength and stability**

While several studies have assessed snow strength at a specific point (e.g., LaChapelle and Atwater, 1961; Bradley, 1966; 1968; Martinelli, 1971; LaChapelle and Armstrong, 1977), only recently has any research taken a more geographic approach by investigating the spatial variability of snow strength. In the 1980s snow mechanics researchers suggested that avalanches released from zones of localized shear weakness (Gubler and Armstrong, 1983; Gubler and Bader, 1989; Bader and Salm, 1990). These findings led to more geographic studies exploring snow strength variations (Birkeland, 1990; Birkeland and others, 1995) and snow stability patterns (Conway and Abrahamson, 1984; Fohn, 1988; Jamieson and Johnson, 1992; Jamieson, 1995) on individual slopes with areas on the order of $10^2$ to $10^4$ $m^2$.

Only two field-based studies investigated snow strength variations at a scale larger than the local scale discussed above, and no studies have addressed stability at that scale. In addition to measuring depth and temperatures, Dexter (1986) described snowpack structure and strength. He collected data three times during the season from 39 points over an area of about 10 square kilometers with an elevational range of 400 m. In general, strength increased with elevation. However, when sites were broken down by aspect, strength increased with elevation on northerly facing slopes, but it decreased with elevation on southerly facing slopes. Bradley (pers. comm., 1988) also measured bulk strength properties by collecting snow resistance data on a couple different slopes over an area of about one square kilometer. The preservation of early season snow on northerly facing slopes correlated with weak basal layers in the mid-season snowcover.

Although data have been gathered showing local snow strength variability over limited particular slopes, only two studies have dealt with slightly larger areas, and no studies have focused on strength patterns over hundreds of square kilometers, such as the areas covered by avalanche forecast centers. More importantly, there have been no studies assessing variations in snow stability factors at this large scale, which is the key consideration for forecasting avalanches. The current research addresses these gaps in the literature, thereby providing valuable information to avalanche scientists, as well as helping regional avalanche forecasters.

**Avalanche forecasting**

Researchers have made significant efforts to produce reasonable statistical and process-oriented avalanche forecast models. Numerous statistical methods have focused on the close link between avalanches and readily measurable meteorological parameters. Techniques used have included multiple regression (Judson and Erickson, 1973), discriminant analysis (Bovis, 1977a; 1977b; Fohn and others, 1977), index paths for forecasting in a given area (Judson, 1983; Judson and King, 1985), nearest neighbor techniques (Buser, 1983; 1989; Buser and others, 1985; 1987), binary regression trees (Davis and others, 1992; Davis and Elder, 1994), and a combination of techniques (McClung and Tweedy, 1994). Still, these techniques only assessed conditions of areas smaller than those covered by regional avalanche forecast centers (such as ski areas (e.g., Obled and Good, 1980) or highway corridors (e.g., Bovis, 1977a)). Furthermore, none of the models effectively take snowpack factors into account. Since they rely heavily on meteorological data they can help to predict avalanches that involve new snow during a current storm; they are less effective at predicting avalanches that fail in older layers.

In addition to statistical models, efforts have been made at refining process-oriented models (Judson and others, 1980; 1986), but these models are far too inaccurate for operational use. The most promising suite of process-oriented models are being developed in France, where researchers have been making progress on a snowpack evolution model (Lafeuille and Brun, 1988; Brun and others, 1989; Brun, 1990; Brun and others, 1992). This model, dubbed CROCUS, requires a great deal of high resolution meteorological data to arrive at a snowpack depth, temperature, and structure profiles. The model SAFRAN interpolates meteorological data over the mountainous terrain to produce inputs for CROCUS (Durand and others, 1993). Current research using CROCUS to predict snow stability factors with an expert systems model, MEPRA (Giraud, 1992), have had modest success. This set of three nested models currently provides a useful tool for conventional forecasters who have access to sufficiently high resolution meteorological data, but this approach is not yet usable by avalanche forecasters outside of Europe who are generally faced with poor mountain meteorological data.

Although increasingly sophisticated statistical and process-oriented forecasting tools are becoming available, conventional avalanche forecasting is, and will probably stay, the only completely holistic forecasting method for the near future (Buser and others, 1985). Conventional avalanche forecasting is a complex process which attempts to assess terrain, weather and snowpack variability over a region of interest to produce an evaluation of the present and future avalanche conditions. Typically, the terrain is fixed and the forecaster uses information about the weather and the dynamics of the snowpack to predict how snowpack properties, and snow stability, vary over a region.

LaChappelle (1980) discussed the nature of the data used for conventional avalanche forecasting, and McClung and Shaerer (1993) classified the variables into three categories (Table 1). Their classification is based on the ease of interpretation of a particular factor and its relevance for assessing snow stability, with higher classes containing data that are more difficult to interpret and which provide less direct evidence for avalanche prediction. Class III variables are the most general and easily available data, provide indirect evidence of snow stability, and consist of meteorological

TABLE 1: Factors used for avalanche forecasting, as defined by McClung and Schaerer (1993), with class IV factors (terrain) added. Data in higher classes are more difficult to interpret and generally have less usefulness for avalanche prediction. Factors marked in ***bold/italics*** are investigated in the present study.

| Class IV Factors (Terrain) | Class III Factors (Meteorological) | Class II Factors (Snowpack) | Class I Factors (Stability) |
|---|---|---|---|
| - ***location*** | - new snow amount | - ***snow depth*** | - ***stability tests*** |
| - ***elevation*** | - new snow density | - ***snow temperature*** | - current avalanches |
| - ***aspect*** | - new snow type | - ***surface penetrability*** | - explosive tests |
| - ***slope angle*** | - snowfall intensity | - ***bulk snow strength*** | - fracture propagation |
| | - precip. intensity | - snow profile | |
| | - wind speed | | |
| | - wind direction | | |
| | - air temperature | | |
| | - radiation | | |
| | - relative humidity | | |

factors such as wind speed and direction, precipitation, precipitation intensity, temperature, snow type, radiation, and humidity (Table 1). Snowpack factors make up the more specific Class II variables, and include several of the variables measured in this research, including snow depth, snow temperature, surface penetrability, and snow strength. Class I data are what Fredston and Fesler (1994) refer to as "bull's eye" information, and provide direct information on the stresses and strengths within the weak layer. These data include current avalanches, stability tests, explosive tests, and fracture propagation in the snowpack.

Neither LaChapelle (1980) nor McClung and Shaerer (1993) include terrain in any variable class, perhaps because terrain is fixed at each point during the snow season while the other variables are all changing. However, terrain changes radically in space and provides the background for the interplay of the other variables. Only point data are available for Class I, II, and III data, and the interpolation of those data to other locations must be made based on terrain. I propose adding terrain variables as Class IV factors (Table 1). These variables are fixed at the time-scale of a snow season, but change in space. Their values are known and can be modelled using digital elevation models, but their interaction with other factors is not clearly understood. This research investigates the linkages between selected Class IV, Class II, and Class I factors.

How the data are used for decision making varies depending on the climate (LaChapelle, 1966) and the size of the forecast area (LaChapelle, 1980). For example, regional scale (i.e., one or several mountain ranges with areas from hundreds to thousands of square kilometers) forecasters tend to make increased use of Class III meteorological variables, while micro-scale (i.e., ski areas with areas of tens of square kilometers) forecasters rely heavily on Class I stability factors (Figure 2). Interestingly, the use of the available data also varies markedly between forecasters with similar

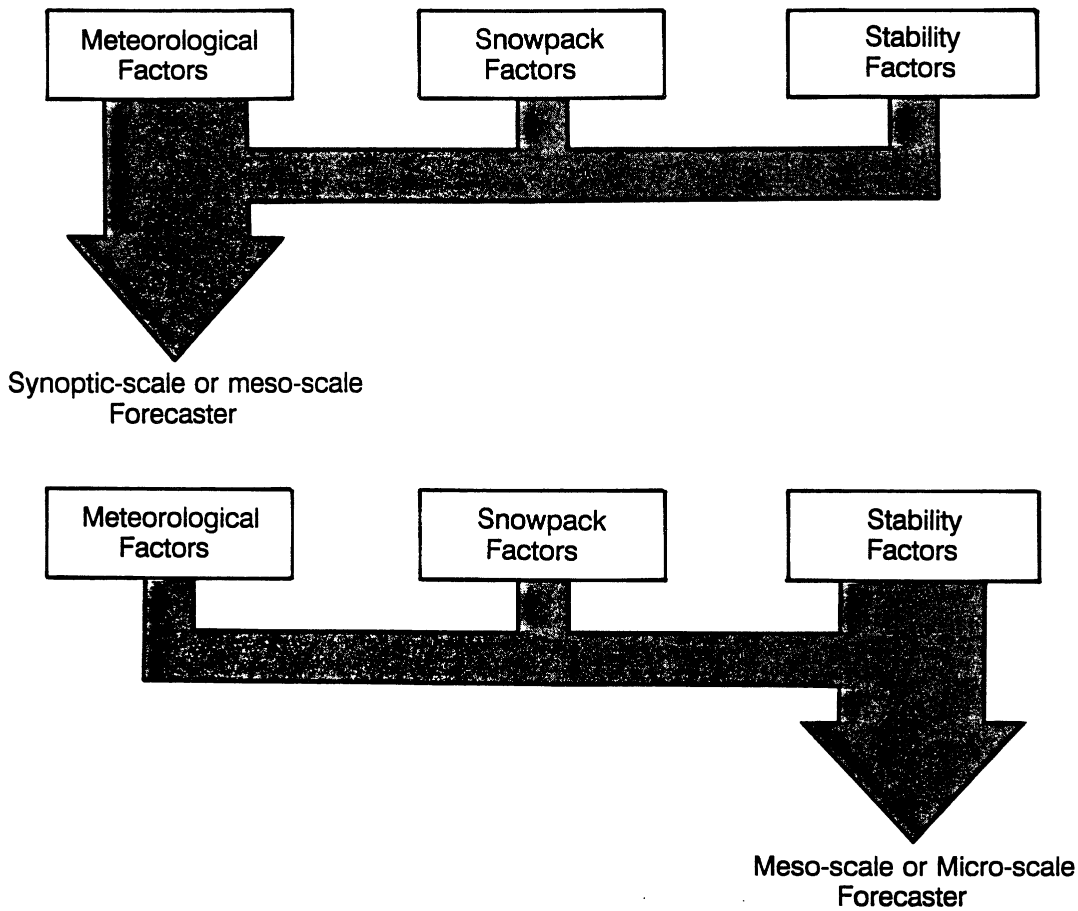


FIGURE 2: Schematic of types of avalanche forecasting and principal data classes (from McClung and Shaerer (1980) based on LaChapelle (1980)).

forecasting accuracy, even when they are forecasting for the same region (Armstrong and LaChapelle, 1977; LaChapelle, 1980; Buser and others, 1985). Four forecasters at Red Mountain Pass in southwestern Colorado listed 31 factors that they considered important for forecasting, but only wind speed and direction were shared amongst the four (LaChapelle, 1980). In short, "there is more than one way to predict an avalanche" using conventional methods (LaChapelle, 1980, p. 78), inferring that the methods used are somewhat subjective. Thus, experience is needed for accurate conventional forecasts, and teaching forecasting methods is difficult.

Though not addressed in the literature, all operational avalanche forecast centers define specific "avalanche regions" within their forecast areas. Much as biogeographers define regions by species composition or climatologists define regions by similar temperatures and precipitation, avalanche forecasters simply define avalanche regions as areas with similar avalanche conditions. A great deal of variability in avalanche conditions exist within regions, largely as a result of local slope factors such as elevation and aspect. Indeed, the domination of these local variables over location indicates the existence of a definable avalanche region. This study will be the first to explore the idea of avalanche regions by investigating the relative importance of location and local slope factors in predicting snow stability in a small mountain range.

In addition, this research may refine statistical and process oriented avalanche forecasting models and improve conventional forecast techniques. Available forecasting models suffer from a lack of knowledge of the spatial variations in snowpack properties. Further, since those spatial variations are not clearly understood, conventional forecasters currently depend on poorly understood empirical rules of thumb, such as "slopes with similar aspects and elevations will have similar snowpack and snow strength conditions" (Perla and Martinelli, 1978). The present study, which is the first investigation of Class I snow stability factors at the scale of a small mountain range, increases our knowledge of these poorly understood patterns.

## SPECIFIC RESEARCH QUESTIONS

A survey of the literature indicates that no snow research has been conducted at the regional scale (several hundred square kilometers), a critical scale for operational avalanche forecast centers. No studies have characterized snow stability and snowpack properties over a large area of complex terrain on a given day. Finally, no research has evaluated the changes in regional snow stability or snowpack characteristics over a snow season.

To explore snowpack strength and stability at a previously unstudied scale, as well as to address the concerns of avalanche professionals, this work addresses two sets of specific research questions. The primary set of research questions is:

On a given day, and over the snow season,

1) how does snow stability vary in relation to terrain?

2) how does snow stability vary in relation to terrain and snowpack?

3) how does snow stability vary in relation to terrain, snowpack, and snow strength?

Thus, this research begins at the most basic level by attempting to link definable Class IV terrain variables with snow stability (path 1 in Figure 3).

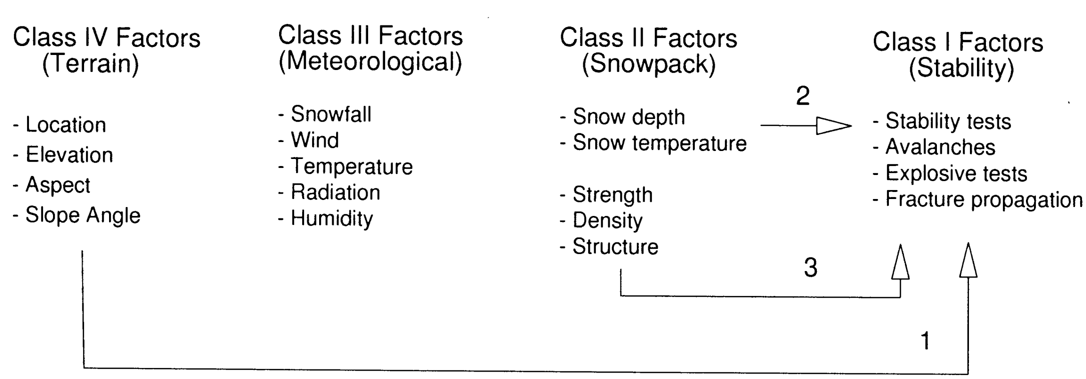


FIGURE 3: Relationships between terrain, snowpack, snow strength, and snow stability addressed by the present research.

The complexity of the analysis is increased by considering whether easily measured Class II snowpack variables can help to improve the assessment of stability (a combination of paths 1 and 2 in Figure 3). Finally, more time-intensive Class II snow strength variables are added to see if their inclusion improves estimates of snow stability (combining paths 1, 2, and 3). Answering the above questions will help to identify the data requirements for assessing stability patterns. Hypothetically, linkages between snow stability and terrain exist, the addition of more specific Class II snowpack factors will improve the predictability of stability patterns, and these relationships change over the course of the season.

A secondary set of research questions address the spatial patterns of snow strength and snowpack variables:

On a given day, and over the course of the season,

1) how does snow strength vary in relation to terrain (path 1 in Figure 4)?

2) how does snow strength vary in relation to terrain and snowpack (paths 1 and 2 in Figure 4)?

3) how do snowpack characteristics vary in relation to terrain (path 3 in Figure 4)?

As with the stability data, the analysis of snow strength starts at a simple level, attempting to link snow strength to Class IV terrain variables before considering whether the addition of easily measured snowpack variables can

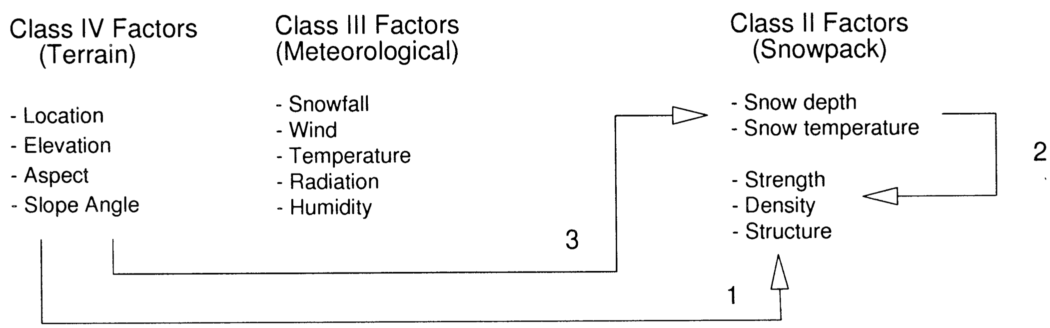


FIGURE 4: Relationships between terrain, snowpack and snow strength addressed by the present research.

improve snow strength prediction. Hypothetically, snow strength and snowpack variables link with terrain, adding Class II snowpack variables improves the explanation of patterns of snow strength, and these relationships change over time.

# Chapter II

# Research Methodology

## ENVIRONMENTAL SETTING

### Topography and vegetation

The area chosen for study is the Bridger Range, located five kilometers northeast of Bozeman, Montana (Figure 5). The Bridgers are an ideal location for this study because: 1) the relatively simple topography of the range facilitates the comparison of terrain features with snow stability and strength, 2) the vegetation characteristics, snow climate, and steep slopes are conducive to widespread avalanche activity, and 3) the location of Bridger Bowl Ski Area provides good weather instrumentation and easy access.

The topography in the Bridger Range is relatively uncomplicated compared to other mountain ranges, simplifying the study of the effects of terrain on snow stability variations. The Bridgers are an overturned anticline, and consist of a single ridge of mountains approximately 10 km wide

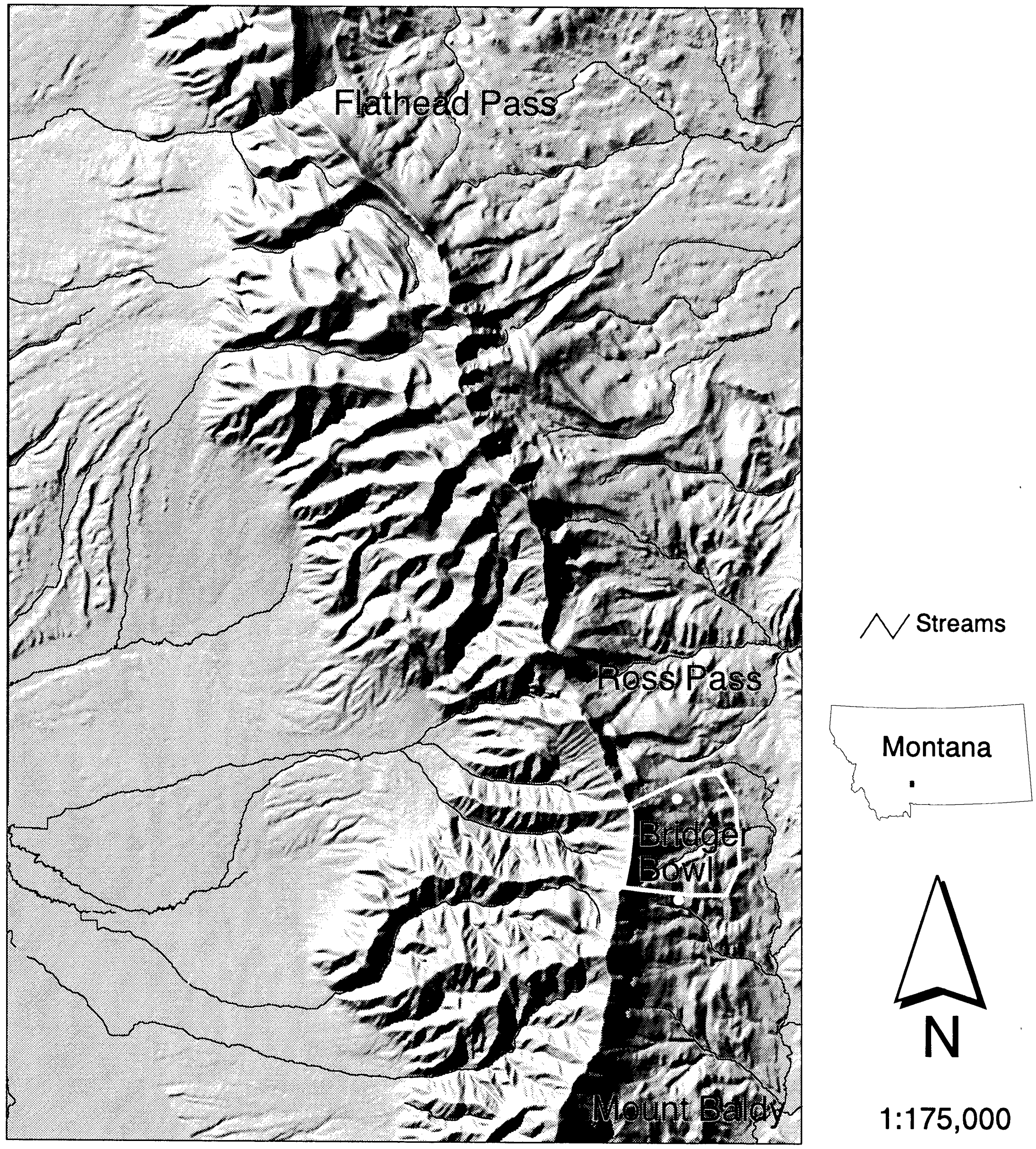


FIGURE 5: Hillshade map of the Bridger Range. The yellow line outlines the approximate boundaries of Bridger Bowl Ski Area, the yellow point in the northern part of the ski area is Bridger Bowl's Alpine study plot and the point on the southern boundary is the Natural Resources Conservation Service's Bridger snow course. Map generated from U.S. Geological Survey 30 m digital elevation models with a vertical exaggeration of two and an illumination angle of 315 degrees.

running north-south for 40 km. Rising 1400 m above the Gallatin Valley to the west, the highest peaks are 2900 m above sea level. The east side of the range was lightly glaciated 20,000 to 70,000 years before present, resulting in numerous small cirques (Montagne, pers. comm., 1993).

Although vegetation affects avalanches by anchoring snow, only dense tree cover in the starting zone (approximately 1000 conifers/hectare) is sufficient to prevent avalanche initiation (McClung and Shaerer, 1993). The scattered trees on the steep, upper elevation avalanche slopes in the Bridgers are sparser than this critical level in most areas. Most woody vegetation on high elevation slopes throughout the Bridgers shows clear evidence of avalanche damage, including flagging and scarring.

### Climatology

The Bridger Mountains are located in the Intermountain or Middle Alpine avalanche region of the United States (LaChapelle, 1966; Mock, 1995), and are characterized by fairly substantial winter precipitation, low winter temperatures, varying winds, dry snow, and a changeable snowpack depending on the given winter. Snow covers vary from shallow, unstable snowpacks with depth hoar formation and full depth avalanches to more stable snowpacks with extensive surface avalanches. The Bridger Bowl Ski Patrol collects daily snowfall data at the Alpine study plot (located in a sheltered area at 2,260 m near the north boundary of the ski area (Figure 5)). Though a reliable data record only goes back to 1984-85, records indicate that Bridger Bowl receives an average of 6.44 m of snow from November 1st to March 31st. The Natural Resources Conservation Service (NRCS) collects monthly snow depth and snow water equivalence (SWE) data at their Bridger site (on the southern edge of the ski area at 2210 m (Figure 5)). The average maximum SWE since 1961 at this site is 0.78 m.

Besides snowfall, winds affect snowpack properties and are a major contributor to avalanche formation. In the Bridgers, ridgetop winds are predominantly westerly, causing wind loading on the eastern side of the range and significant cornice development on the ridge (Montagne and others, 1968; Latham and Montagne, 1970; McCarty and others, 1986). At lower elevations the strongest winds are predominantly southerly, funnelled between the Bridgers and the Bangtail ridge to the east (Birkeland, 1990). However, sustained north, west and even east winds are occasionally observed every season.

A detailed climatological analysis of heavy snowfall events (greater than 0.32 m of snow in 24 hours) recorded at Bridger Bowl Ski Area since 1968 demonstrates that most large storms in the Bridgers occur during strong northwesterly flow (Birkeland and Mock, 1996), a pattern resulting from the position of the surrounding mountains. Mountain ranges to the west include the Tobacco Root and Pioneer Mountains in southwest

Montana, and the Bitterroot Range on the Montana/Idaho border. To the southwest of the Bridger Range lie Montana's Madison Range, the Beaverhead Mountains on the Montana/Idaho border, and Idaho's Lemhi Range, Lost River Range, Pioneer Mountains, Beaverhead Mountains, and Sawtooth Range. The predominantly northwest-southeast alignment of these ranges, all with peaks higher than 3,000 m, reduces the Pacific moisture reaching the Bridger Range from the southwest and west, thereby creating a more continental climate compared to areas farther west. On the other hand, northwest of the Bridger Range are areas of relatively lower relief, including the northwest-southeast oriented Swan Range, Lewis and Clark Range, and Big Belt Mountains.

**Avalanche activity**

The snow climate, steep topography, and lack of significant vegetation in the higher elevations of the Bridgers combine to create extensive and dangerous avalanche terrain. Although no formal mapping has been done, I estimate there are over 1000 avalanche paths in this small range of about 250 square kilometers. Bridger Bowl Ski Area is located in terrain typical of the range and normally ranks among the top four United States ski areas in terms of avalanche activity (Williams, 1989; 1993). Between 1970-71 and 1996-97, Bridger Bowl Ski area reported an average of 413 avalanches per year, through this number varies significantly from year to year (standard deviation of 216). In addition, I have observed numerous spontaneous back country avalanches in seven years of back country avalanche forecasting for the range, and over 40 skier, snowboarder and snowmobile triggered avalanches have been reported (Birkeland, 1991-1997).

## DATA COLLECTION

### Sampling teams and safety

A helicopter shuttled six two-person sampling teams (consisting of a team leader and an assistant) around the Bridgers, expediting data collection and improving safety. Team leaders chosen had several skills or attributes: 1) the ability to make route-finding decisions under adverse avalanche and/or weather conditions, 2) extensive back country and/or ski area avalanche experience, 3) familiarity with the data being collected, 4) experience collecting field data, 5) education, and 6) work and/or school schedule flexibility (Appendix A). In one case, two individuals shared team leadership since their qualifications complemented each other. Team leaders chose their assistants and sometimes changed their choices between sampling days.

Avalanches and the helicopter presented the two primary safety hazards. Selecting experienced team leaders minimized hazards posed by avalanches. In addition, I eliminated all days with a high avalanche danger from consideration for sampling. All team members carried avalanche beacons, probes, and shovels, as well as two-way radios which allowed sampling teams to communicate with one another and with the helicopter. Randy Elliot (Mountain Manager, Bridger Bowl Ski Area) served as ground coordinator, keeping track of the progress of the different teams and coordinating helicopter pick-up times. Finally, on the morning of each sampling day I briefed the teams on the current avalanche conditions. Since hazards associated with the helicopter were also significant, pilot Mike Carisch provided a pre-season helicopter orientation and training session for all project participants, and he reviewed helicopter safety at the start of each sampling day.

Using a helicopter to transport sampling teams posed both disadvantages and advantages for the study. The primary disadvantage was that the helicopter required good weather (good visibility and ridgetop winds less than about 10 m/s) to land at numerous difficult ridgetop landing zones. Given the unusually stormy 1996-97 winter, this problem severely limited the number of days available for sampling. However, advantages of helicopter use including maximizing the amount of data collected and the area covered in a day, minimizing the number of observers used, and increasing sampling team safety by allowing teams to approach slopes from the top instead of from underneath them.

**Sample site locations**

Initially, all avalanche terrain in the Bridgers provided potential sampling sites, but specific conditions eliminated many candidates. First, I eliminated slopes on the west side of the Bridgers from consideration. Located on the windward side of the range, these areas have highly variable snow depths and strengths over short distances due to wind effects. Even in the middle of a winter with above average snowfall, many of these slopes only have a thin snowcover due to wind erosion. The slopes on the west side of the Bridgers also generally had less local relief than the east side, less appropriate lower landing zones for the helicopter, and were extremely difficult access without a helicopter. Second, I eliminated slopes within Bridger Bowl Ski Area since these slopes receive heavy skier use and are avalanche controlled, both of which would affect the data collected. Third, I did not consider slopes without appropriate ridgetop and lower landing zones. Finally, I did not assess slopes that were interrupted by large cliff bands since even a small avalanche above those cliffs posed severe hazards to investigators. This initial phase of analysis resulted in the identification of 12 appropriate landing zones, and the accessible terrain associated with those landing zones, on the east side of the Bridgers. This accessible terrain comprised approximately 35% of the avalanche terrain in the Bridgers.

Within the accessible areas, I mapped the avalanche terrain to be sampled using air photos superimposed on enlarged 7.5 minute quadrangle maps. I made maps of each sampling area, and used a random sampling scheme stratified for aspect and elevation to identify sampling locations. This methodology, while scientifically sound, was logistically dangerous. Randomization resulted in sampling routes that typically crossed through the middle of several large avalanche paths. Even during stable avalanche conditions, these routes presented serious hazards to sampling teams. In addition, several nearly horizontal traverses resulted in overly time-intensive routes.

Because of these concerns, I took photographs of all slopes to be sampled early in the avalanche season. I then chose a route down the mountain that appeared to be reasonably safe from an avalanche hazard standpoint, but that allowed the team to sample a variety of aspects and elevations on slope angles typical of avalanche starting zones (generally 30 to 45 degrees (Perla, 1977)) while travelling efficiently. Field books for each sampling team included photos taken with a 200 mm telephoto lens, with markings on the photo to indicate sampling areas. Finally, sampling teams used their best judgement in regards to safety, and they sampled appropriate areas only within the realm of acceptable risk. This sampling scheme allowed for a reasonable stratification of the elevations and aspects represented by each site, and took most of the sampling location decision making out of the hands of individual team leaders, while allowing active decision making in terms of team safety. Sampling teams sampled nearly the same locations on both sampling days, though some sample sites had to be slightly relocated to avoid ski tracks or unnecessary exposure to avalanche hazards on the second sampling day. Sampling locations and helicopter landing zones are shown in Figure 6.

**Pre-season training**

In order to standardize data collection techniques, sampling team leaders and available assistants met for a data training day in November, skiing into the Bridgers just north of Bridger Bowl Ski Area. I described and demonstrated the data to be collected at each sampling point, and all the teams practiced the various tests. Instructions included special emphasis on the use of the GPS (global positioning system) units and ram penetrometers, since participants were generally unfamiliar with these instruments. Each team also conducted stability tests to assure continuity between teams.

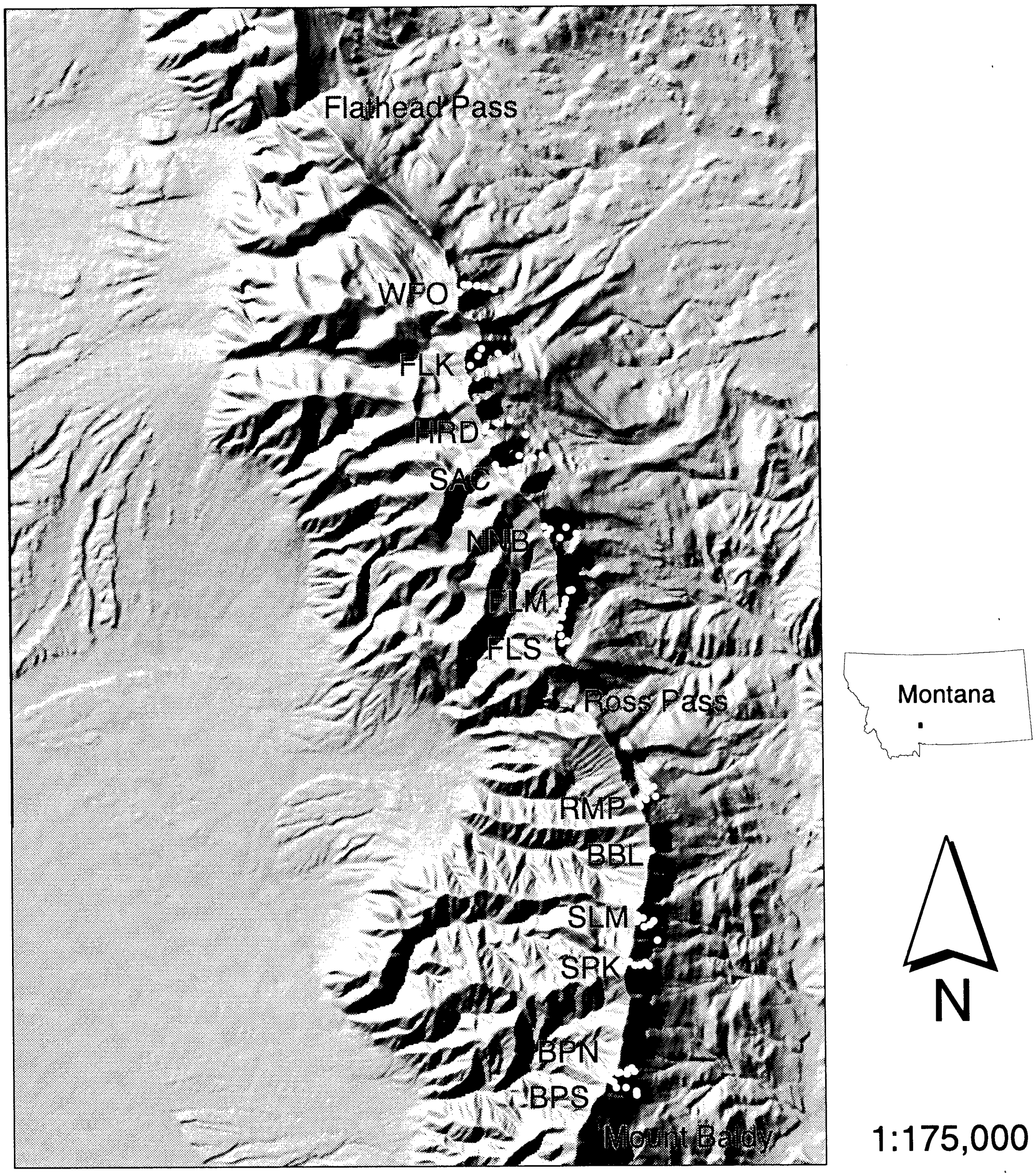


FIGURE 6: Sampling locations (represented by the yellow points) and ridgetop helicopter landing zones (in red, abbreviations from north to south: WFO = Way Far Out There, FLK = Frazier Lake, HRD = Hardscrabble, SAC = Sacajawea Saddle, NNB = Nyanuki Bowl, FLM = Flatirons Middle, FLS = Flatirons South, RMP = Ramp, BBL = Bridger Bowl, SLM = Slushman's, SPK = Saddle Peak, BPN = Bridger Peak North, BPN = Bridger Peak South).

Cold temperatures and adverse weather prohibited the collection of extensive comparative data on this training day.

**Field sampling**

Data collection was originally planned for specific snowpack conditions (somewhat unstable, but stable enough to send out sampling teams) and at specific times of the year (early-, mid-, and late-season). However, myriad logistical problems including weather, helicopter insurance, and the schedules of the helicopter pilot and other team members ultimately decided sampling dates. Flying a helicopter in the Bridgers was only possible on a handful of days during the snowy 1996-97 season, and there were no flyable days from late November (when there was finally enough snow to sample) until early February.

On February 3rd the weather finally cleared and we flew a sampling day on February 6th, safely collecting data from over 70 points. After that particular clear spell the weather deteriorated, with numerous days of high winds. The second and only additional suitable sampling day was April 2nd when we again collected data from over 70 points.

Six two-person teams collected data throughout the Bridgers, with each field team being responsible for collecting data from 10 to 12 sites. All teams met at a central staging area in the morning, flew to their first areas, and then skied down the slope, collecting data at five or six points. This first run generally took four hours. After all teams had completed one run the helicopter shuttled teams to their second area, where they completed another data collection run, again requiring approximately four hours. In addition, a team from the Bridger Bowl Ski Patrol collected data from undisturbed sites within the ski area. On the first day they collected data from four points, but by the second day all but one of their sampling locations had either been ski compacted or bombed with explosives. Thus, they sampled only one site within Bridger Bowl Ski Area on April 2nd.

## VARIABLES

At each sampling location, teams collected data which established variables describing terrain characteristics, general snowpack properties, snow strength, and snow stability (Table 2). Since this research attempted to analyze a large geographic area with a minimum of observers, emphasis was placed on measurements that were fast, consistent, and reliable. The following section describes each variable and how it was measured. Errors associated with the various measurements are discussed in Appendix B.

TABLE 2: Variable codes and descriptions for terrain, snowpack, snow strength, and snow stability variables.

| *Variable Code* | *Description* |
|---|---|
| Terrain | |
| *loc e* | Universal transverse mercator (UTM) meters east (m) |
| *loc n* | UTM meters north (m) |
| *elev* | Elevation above mean sea level (m) |
| *dis rdg* | Distance from the main ridge (m) |
| *RI* | Radiation index based on aspect (degrees away from true north) |
| *ang* | Slope angle (degrees) |
| Snowpack | |
| *dpth* | Total snow depth (m) |
| *t30* | Snow temperature 0.30 m below the snow surface (degrees C) |
| *tgrad* | Average temperature gradient ((t30)/(dpth-0.30m)) (degrees C/m) |
| Snow strength | |
| *ram drp* | Initial drop of the ram penetrometer (m) |
| *ram avg* | Average ram hardness of the top 1.50 m (N/m) |
| Snow stability | |
| *df wk sb* | Depth of failure to the weakest stuffblock failure (m) |
| *df wk rb* | Depth of failure to the weakest rutschblock failure (m) |
| *sb wk* | Stuffblock drop height (m) of the weakest stuffblock failure |
| *rb wk* | Weakest rutschblock (rutschblock number) |
| *sb wk rb* | Stuffblock drop height (m) of the stuffblock failure associated with the weakest rutschblock |
| *FI wk sb* | Failure index (FI) of the weakest stuffblock failure ((sb wk)/(df sb wk)) |
| *FI sb wk rb* | FI of the stuffblock associated with the weakest rutschblock ((sb wk rb)/(df wk rb) |
| *TFI* | Total Failure Index based on the total number of stuffblock failures, stuffblock drop heights, and depths to failure (see text for description) |

**Terrain**

Terrain variables include location within the mountain range (in UTM meters north and east), elevation, distance from the ridge, a radiation index (measured in degrees away from true north), and slope angle. Location within the range determines the unique position of the sample point, while elevation, distance from the ridge, slope aspect and slope angle are local variables that define spatial patterns on the alpine landscape. If the position of the sample point within the range is more important than local slope variables in predicting the snow and avalanche conditions found at that point, then the range would consist of more than one avalanche region. If local factors dominate, the range can be considered to be a single region. Though I consider the Bridgers to be a single avalanche region, with local factors dominating location, I have observed snowpack differences in a northerly direction that occasionally suggest that more than one avalanche region exists within this small range (Figure 7).

The northing and easting of each point is required to map their location, and both location north and location east are included as variables. Though the Bridgers are a small range, location north is still an important variable because conditions can change dramatically from north to south through the range. In seven years of avalanche forecasting for this range, I have frequently observed storms that only hit the northern part of the range,

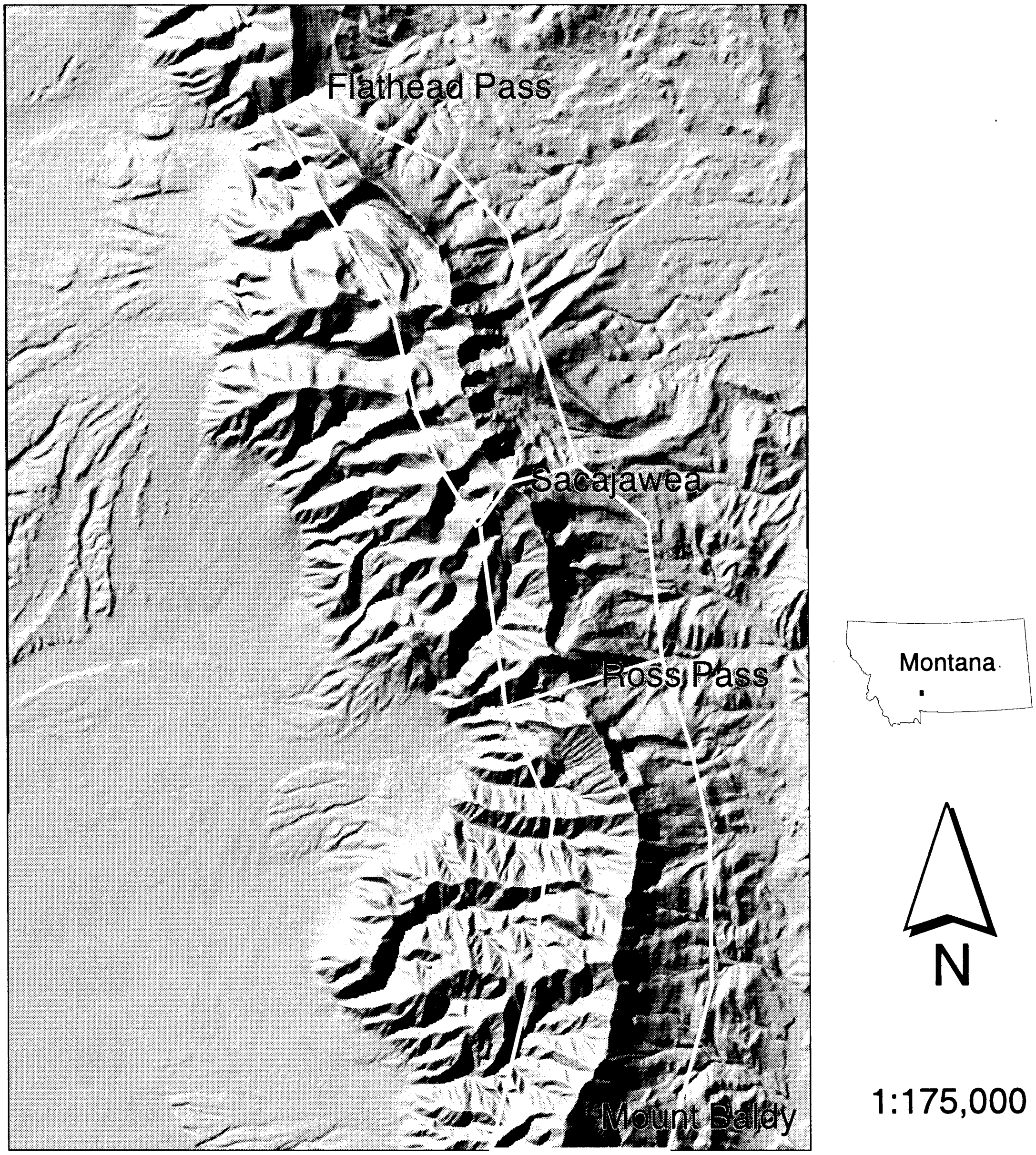


FIGURE 7: Three occasionally observed avalanche regions in the Bridgers. Though the range commonly consists of a single avalanche region, a north/south gradient of snowpack and weather conditions sometimes results in up to three separate regions, each with different avalanche conditions.

and I have noticed that the area north of Sacajawea Peak is often subjected to much stronger winds than the rest of the range, as evidenced by widespread sastrugi and wind erosion. This north/south gradient of climatic and snow conditions is largely responsible for the occasionally observed avalanche regions in Figure 7.

Location east varies less than location north in this study, but is still an important variable, describing a measure of wind exposure. The main axis of the Bridgers tends north/south, but north of Ross Pass the range tilts slightly toward the northwest (Figure 6). Thus, the sampling locations in the northern part of the range are farther west than those in the south. Since this northern area is windier, location east provides a measure of wind exposure that is independent of elevation.

Local variables measured include elevation, distance from the ridge, aspect and slope angle. I used aspect to derive a radiation index (*RI*) defined as the degrees away from north. Thus, a south aspect has a *RI* of 180 degrees, a north aspect has an *RI* of 0 degrees, and the *RI* for due east and due west aspects is 90 degrees. Elevation and aspect have been linked to various snowpack properties in a number of studies (i.e., Dexter, 1986), and distance from the ridge quantifies how far the point is from a significant wind barrier. The spatial pattern for elevation is fairly regular, uniformly increasing up the main ridge of the Bridgers (Figure 8); the pattern for distance from the ridge is similar. Spatial patterns for the radiation index

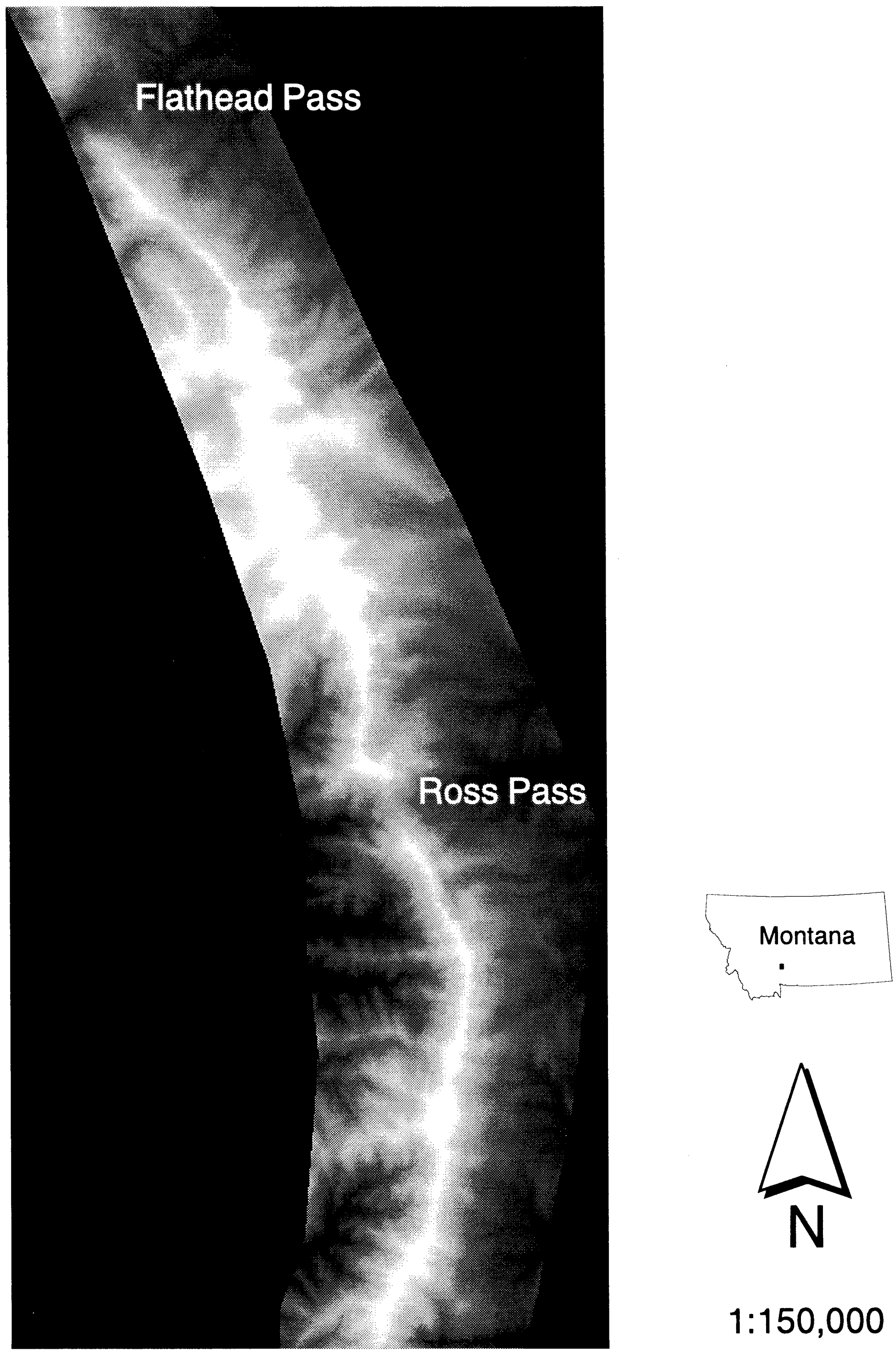


FIGURE 8: Elevation map of the core of the Bridger Range, with the highest elevations (approximately 2900 m) represented by white and the lowest elevations (approximately 1700 m) represented by black.

and slope angle are not as regular, but still create distinct spatial patterns (Figures 9 and 10).

Investigators measured slope angle and aspect with inclinometers and compasses, and ascertained elevation and location with Rockwell PLGR Global Positioning Systems (GPSs). I mapped the sample sites on a U.S. Geological Survey 30 m digital elevation model (Figure 6) and measured the distance from the main ridge using the geographic information system (GIS) software package ArcView. The GPS units used the Precise Positioning System (PPS) so there was no post-processing required to determine position. GPS accuracy, tested by the Forest Service's Missoula Technology and Development Center, is 2.5 m in average horizontal position, with a maximum error of 15 m. Elevation errors are approximately three times horizontal errors, or about 45 m.

**Snowpack**

Snow depth and snow temperature 0.30 m beneath the snow surface quantified general snowpack characteristics. Sampling teams measured depth with a folding ruler or, more frequently, with an avalanche probe due to the deep and strong snowpack. When it was impossible to extend a probe to the ground even after digging a 1 to 2 m deep snow pit, the observer assigned a minimum value to the snow depth, typically 4.0 to 4.8

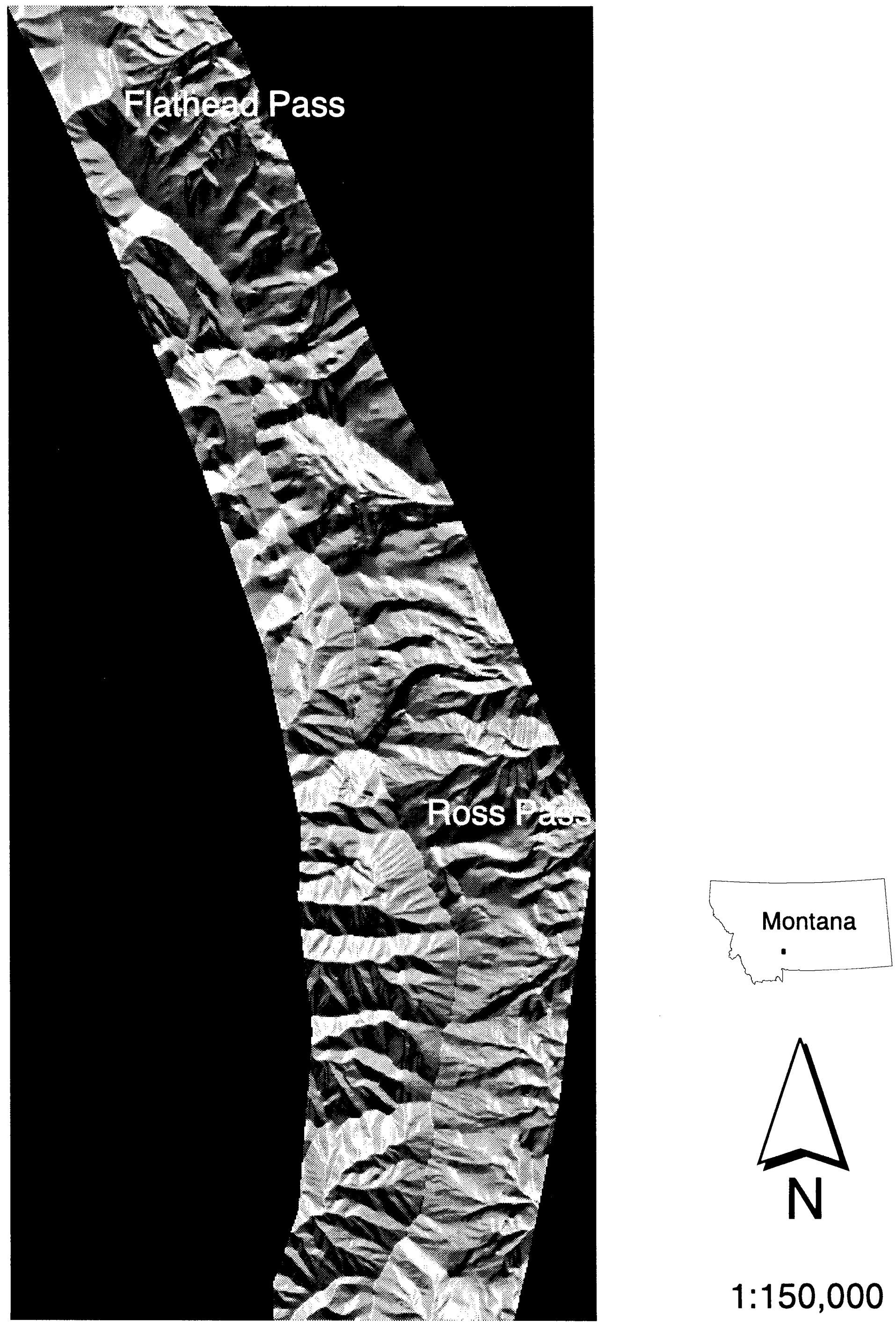


FIGURE 9: Radiation index (*RI*) map of the core of the Bridger Range, with due north (*RI* = 0 degrees) represented by white and due south (*RI* = 180 degrees) represented by black.


FIGURE 10: Slope angle map of the core of the Bridger Range, with the steepest slope angles (up to 72 degrees) represented by white and the most gentle slopes (0 degrees) represented by black.

m. Seven such sites existed on the first day and ten on the second day, for a total of about 10 to 14% of all depth measurements. I assigned those sites their minimum snow depth values for the purpose of statistical analyses. Thus, maximum depths are below the true maxima and the relationship of depth with other variables should be viewed with caution, especially in areas of deeper snowpack.

Because diurnal temperature changes in snow are typically limited to the upper 0.25 m of the snowpack (Armstrong, 1985), we measured snow temperature 0.30 m below the surface to the nearest degree using Ertco dial stem thermometers. I calibrated the thermometers the night before each sampling day in a slush bath, and teams carried them in protective aluminum cases to minimize the chances of losing their calibration. Since temperature gradients within the snowpack are largely responsible for creating the vapor pressure gradients that control snow metamorphism, and the development of weaker or stronger layers, I combined temperatures 0.30 m below the surface with total snow depth to compute the average temperature gradient through the snowpack.

**Snow strength**

Sampling teams used ram penetromers (McClung and Shaerer, 1993) to measure snow strength (Appendix C provides specifications of the various rams used in this study). Field measurements establish two strength variables: 1) surface snow strength, and 2) average snow strength of the top 1.5 meters of snow. The initial drop of the ram quantified surface snow strength, while average ram strength was computed by calculating the energy required to drive the ram through the snow. Rams have been used extensively in snow studies since their initial development in Switzerland in the 1930s, facilitating the comparison of this study with those studies (i.e., LaChapelle and Armstrong, 1977; Dexter, 1986). More detailed ram profiles take too much time and depend on operator experience, and were therefore not collected in this research.

Ram hardness is calculated using the following equation (McClung and Shaerer, 1993):

$$R = nfh/p + T + H$$

where $R$ is the ram hardness (in newtons), $n$ is the number of hammer blows, $f$ is the drop height of the hammer blows (in cm), $H$ is the weight of the hammer (in newtons), $p$ is the penetration of the ram between two readings (in cm), and $T$ is the total weight of the ram penetrometer tubes (in newtons). We only measured the top 1.50 m of snow for ram hardness because the increasingly deep and strong snowpack, in combination with the time constraints imposed by covering numerous sampling locations, precluded measurements to the ground. I divided total integrated ram hardness for the top 1.50 m by depth to arrive at the "average ram hardness" for the snow being measured.

**Snow stability**

Sampling teams used several tests to assess stability, including the widely used rutschblock test (Fohn, 1987), the more easily quantifiable stuffblock test (Birkeland and others, 1996a), the depth to failure (which represents the slab depth of a potential avalanche), and some stability indices based on stuffblock results and failure depths. These are the most replicable and accurate representations of stability available. Rutschblock tests involve isolating a large block of snow (3 $m^2$) from the snow pit wall and progressively loading it with a person on skis (Fohn, 1987). Rutchblocks have been used in previous research (Fohn, 1988; Jamieson and Johnston, 1992). For this study, sampling teams isolated the rutschblock with a snow saw attached to a ski pole. This test is useful because it is reasonably quick and reliable, and tests a relatively large sample of snow. The main drawback to the rutschblock is that it provides results based on an ordinal scale, and that the forces applied to the snow surface will undoubtedly vary somewhat between observers (Table 3). However, recent work in Switzerland (Camponovo and Schweizer, 1996) has helped to quantify rutschblock results, and suggests that each step up

Table 3: Rutschblock steps as described by Fohn (1987).

| Rutschblock Step | Load Required for Failure |
|---|---|
| 1 | Block is isolated |
| 2 | Skier gently steps on the upper 0.35 m of the block |
| 3 | Skier drops from a straight to a bent leg, pushing downwards |
| 4 | Skier jumps, clears the snow surface, and lands on the compacted spot |
| 5 | Skier jumps and lands on the same compacted spot again |
| 6 | Skier steps to the middle of the block and jumps hard at least three times |
| 7 | No failure |

the rutschblock scale between steps two and five approximately doubles the force applied to the weak layer.

It is easier to quantify results from the stuffblock test (Johnson and Birkeland, 1994; Birkeland and others, 1996a). The stuffblock involves dropping a nylon sack filled with 4.5 kg of snow onto an isolated column of snow (0.30 m square) from a known height, thereby minimizing the potential for errors between tests and between observers (Appendix B). Extensive testing during several seasons, on different snowpacks, and by different observers indicate that the stuffblock test works well in a variety of conditions (Birkeland and others, 1996a). This simple test offers the best available tool to quickly and simply quantify the surface impact energy required for failure at a given layer.

Results from rutschblock and stuffblock tests do not necessarily test avalanche danger by themselves. Another important factor is the depth to the failure plane, since that determines how much snow would be released in an avalanche. Therefore, I also included depths to failure as variables. In order to assess the combination of the depth to failure and the weak layer strength together I developed a dimensionless stuffblock failure index (*FI*) by dividing stuffblock drop height by depth to failure:

$$FI = sb/df$$

where *sb* is the stuffblock drop height (in m) and *df* is the depth to failure (in m) of a specific failure layer. Thus, smaller values of this index demonstrate more dangerous conditions.

I wanted to analyze the "most significant" failure at each location in an objective manner. Since the stuffblock test tends to pick up more discrete and subtle failure planes than the rutschblock, I took the weakest rutschblock to be the most significant failure and used the associated stuffblock drop height and depth to failure as two primary variables.

Stability data are often difficult to compare when different locations have different numbers of failure planes in the snowpack. For example, how comparable is a site with a single stuffblock failure of 0.20 m that is 0.25 m down with another site that has a stuffblock failures of 0.10 m at 0.15 m and 0.30 m at 0.45 m? To facilitate comparisons between all locations, I defined a dimensionless Total Failure Index (*TFI*). This index was developed so that changes in the following factors "pushed" the index in the appropriate direction: 1) avalanche danger increased with decreasing stuffblock drop height, 2) avalanche danger increased with increasing failure depth, and 3) avalanche danger increased with increasing number of failure planes. Avalanche danger increases with increasing numbers of failure planes because of the potential to trigger an upper snowpack layer which could overload the slope and trigger a lower layer, resulting in a much larger avalanche. Realizing that the variables do not necessarily interact in the manner specified, but also realizing the value in different indices (e.g., the widely-used Palmer Drought Index is an example of such an index), I define the *TFI* as follows:

$$TFI = [((sb_1/df_1) + (sb_2/df_2) + \dots + (sb_N/df_N))/N][1/N]$$

where $sb_1$, $sb_2$, ..., $sb_N$ are the stuffblock drop heights (in m) for the first through Nth failures, $df_1$, $df_2$, ..., $df_N$ are the depths to failure associated with each stuffblock failure (in m), and $N$ is the total number of failures. Thus, smaller values of *TFI* indicate more "dangerous" conditions because locations with lower stuffblock drop heights and increased numbers of failures will have lower *TFI* values.

**ANALYSES AND MAPPING**

Data collected allowed the construction of a space/attribute data matrix for each of the two sampling days. The rows of the matrix consists of the sample sites located throughout the Bridgers, while the columns consist of the terrain, snowpack, snow strength and snow stability variables discussed above. The end result is a three dimensional data cube, with the three dimensions representing space (the sample location), attributes (the data collected at each site), and time (the two data collection days) (Figure 11).

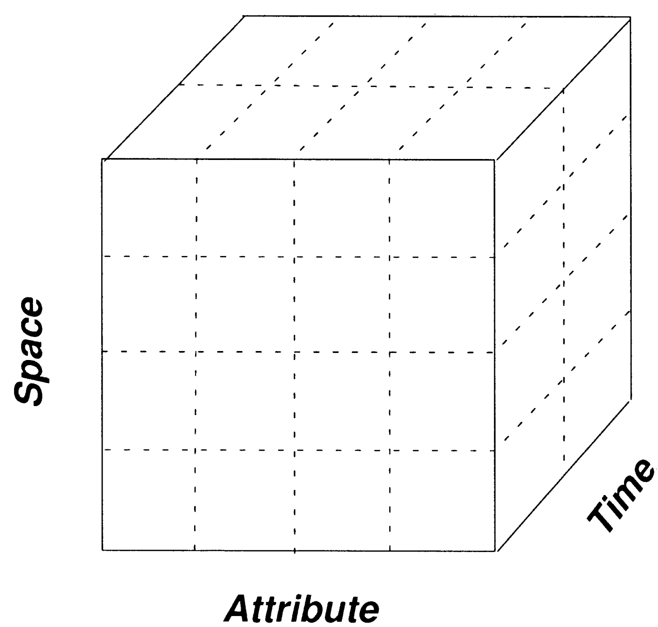


FIGURE 11: Data structure for the present research, with space represented by study site location, attributes represented by the data collected at each site, and time represented by the two sampling days.

I used a variety of statistical techniques to address the research questions, as described in more detail in the following three chapters. In short, I use descriptive statistics to describe the data and to make comparisons between the two sampling days. I tested the data for normality using the Kolmogorov-Smirnov one sample test (Massey, 1951), and attempted to transform all non-normal data. Since some of the data could not be normalized, I used non-parametric Spearman rank order correlations to quantify the relationship between each variable pair. Once the relationship between variable pairs was known, forward, stepwise least squares multiple regression analysis showed how well the dependent variables could be predicted by the multivariate interaction of the independent variables. Finally, I used canonical correlation analysis as a means of comparing the multivariate relationships between the predictor (i.e., terrain, snowpack and snow strength) and criteria (i.e., snow stability) data matrices.

I also used principal components analysis (PCA) to generate orthogonal components for multiple regression. However, in every case the resultant models explained less of the variance of the dependent variable than when the independent variables were used without PCA. Thus, I do not report those results.

I produced maps for this study using the GRID module of the GIS software program Arc/Info running on an IBM workstation. After acquiring

30 by 30 meter digital elevation models (DEMs) of the study area from the U.S. Geological Survey, I created hillshade maps, and computed grids representing elevation, radiation index, slope angle, location east and location north at each grid point. These grids allowed me to generate maps representing observed statistical relationships. I made a file of the study site coordinates and imported that file into the GIS for site location mapping. I generated final map products in ArcView.

## Chapter III

## Evolution and Characteristics of the 1996-97 Snowpack

### OVERVIEW

This chapter provides background on the history of the snowpack during the 1996-97 season. I first discuss the weather and avalanche conditions observed during the season, and their deviations from previous seasons, followed by a detailed snowpack analysis on the day after spatial data set collection. These results document the snowpack evolution and the conditions found on the sampling days, thereby facilitating my interpretation of the spatial data sets in the following three chapters.

### OVERALL WEATHER AND AVALANCHE CONDITIONS

The 1996-97 winter was unusual, with much more snow than normal. Two sites with useful climatological records are located near Bridger Bowl Ski Area: 1) Bridger Bowl's Alpine study plot, located at 2260 m on the northern side of the ski area, is where the Bridger Bowl Ski Patrol collects daily snowfall data, and 2) the Natural Resource Conservation Service's (NRCS) Bridger snow course site, located at 2210 m on the southern side of the ski area, is monitored monthly by NRCS technicians (Figure 5). A total of 8.81 m of snow fell from November 1st to April 6th at the Alpine study plot, the most snowfall since accurate records were started in the 1984-85 winter (Figure 12). In addition, the monthly NRCS data show total SWE at the Bridger snow course ranged from 154% to 188% of the 30-year historical record (1961 to 1990) between December and April (Figure 13). The excessive snowfall was often accompanied by wind, though reliable wind data are unavailable due to a variety of datalogger and anemometer difficulties.

The near record snowfall affected the snowpack conditions for this study. Heavy snowfall, with few clear periods, resulted in a nearly uniformly strong snowpack with few significant weak layers by mid-season. The deep and strong snowpack was more typical of a coastal snow climate than the Bridger's intermountain on the first sampling day, and this is reflected in the results. By the second field day more heterogenous weather conditions resulted in a layered snowpack more typical of the intermountain snow climate.

Snowfall began early, with the first major storm dropping 0.50 m of snow on October 20th. Another 0.25 m fell on the 25th, giving a settled

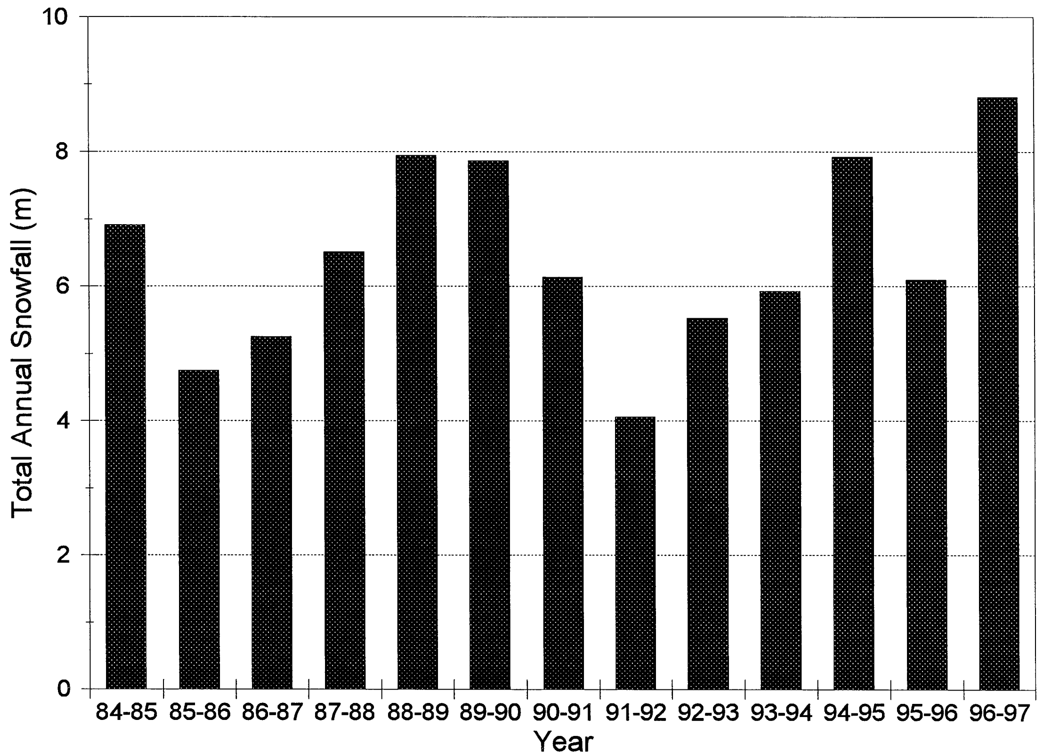


FIGURE 12: Total annual snowfall from November 1st to March 31st at Bridger Bowl's Alpine study plot.

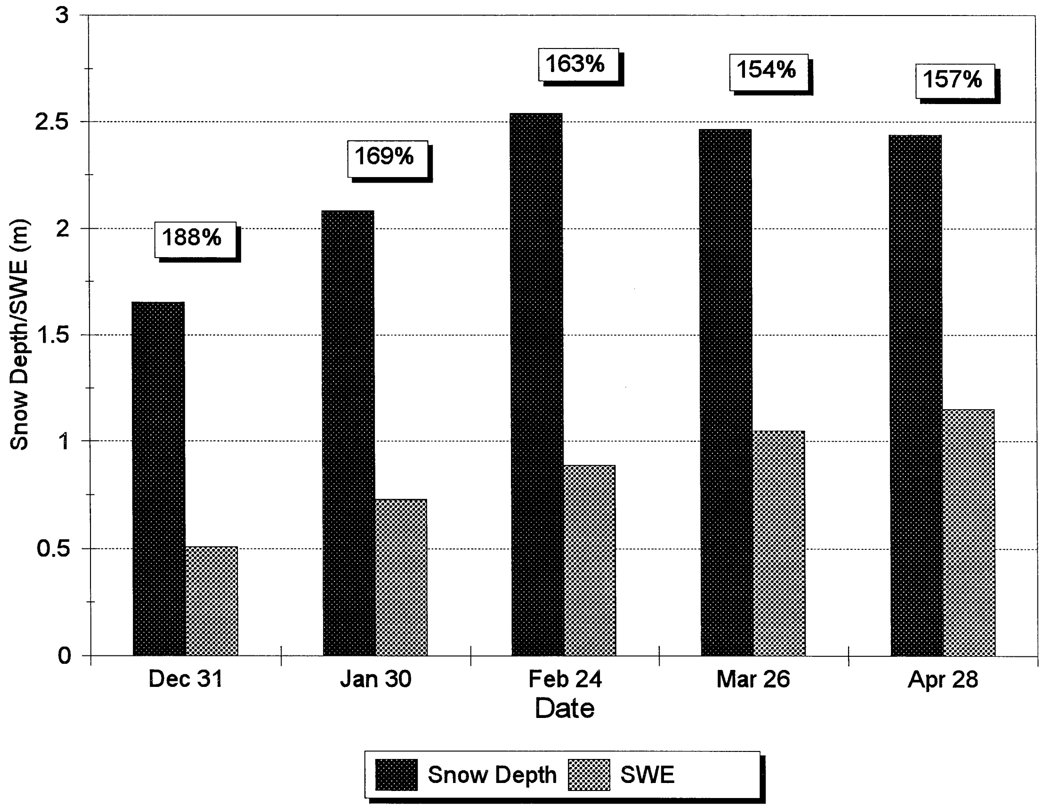


FIGURE 13: Snow depth and snow water equivalent (SWE) at the Natural Resource Conservation Service's Bridger snow course during the 1996-97 season. Percentages are the percent of the 30-year (1961-1990) average.

base depth of a little over 0.50 m on November 1st when Bridger Bowl officially began data collection for the season (Figure 14). Between November 14th and January 14th there were only 11 days without measurable snowfall at Bridger Bowl, and the base depth rose from 0.5 to 2.5 m. Highly variable temperature conditions predominated, alternating between warm weather coming in on a strong, moist, southwesterly flow, and cold temperatures that dipped as low as -30 degrees C (Figure 15). The most notable warm spell came on New Year's Day, when even the low temperatures stayed above freezing for one night and light rain fell up to 1900 m.

After mid-January snowfall decreased, though strong winds kept the helicopter for this project grounded through the month. The first prolonged period of high pressure settled in on February 3rd, allowing sampling on the 6th under clear skies, light winds, cool temperatures (high of -3 and a low of -16 degrees C) (Figure 15), and a total snow depth at the Alpine study plot of about 2.6 m (Figure 14). After that day the snow continued to accumulate, reaching 3.2 m by the April 2nd sampling day. Warm temperatures in mid-March threatened to turn the snowpack isothermal, but cool night time temperatures kept all but the southerly aspects dry, and cool weather and new snow prior to the second sampling day insured winter-like conditions that day.

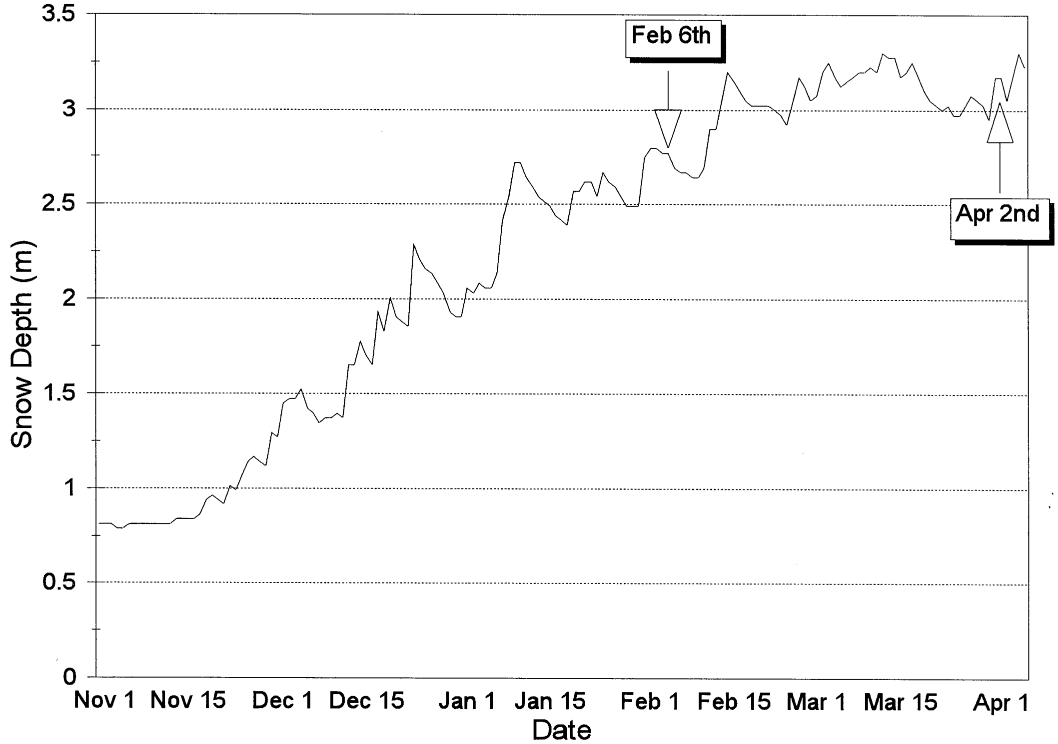


FIGURE 14: Total snow depth measured by the Bridger Bowl Ski Patrol at the Alpine study plot during the 1996-97 season.

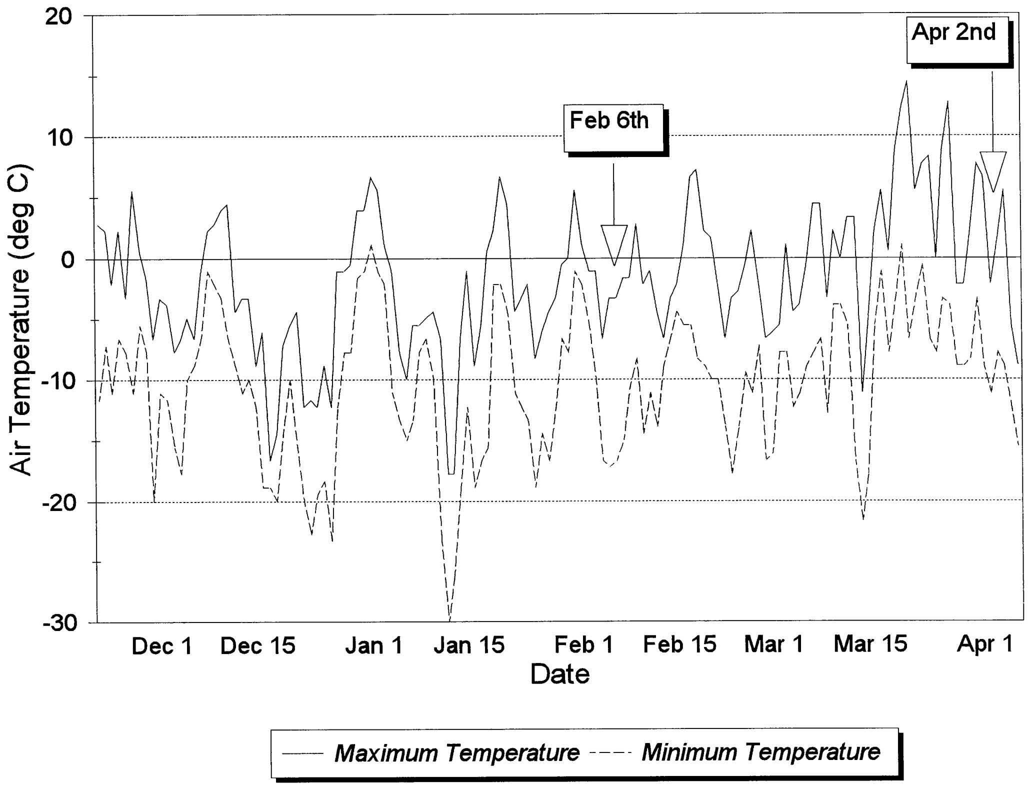


FIGURE 15: Daily maximum and minimum air temperatures measured by the Bridger Bowl Ski Patrol at the Alpine study plot during the 1996-97 season.

The Bridger Bowl Ski Patrol reported 776 avalanches for the season, the largest number since 1975-76 (Figure 16). Approximately 95% of these slides were class 2, while about 5% were class 3 or larger, demonstrating that most of the avalanche activity within the ski area consisted of small to medium-sized avalanches (Table 4). Nearly all of these avalanches were direct action avalanches, involving only the snow from the most recent snow and not deeper buried weak layers. This is a typical pattern during seasons with relatively continuous, heavy snowfall.

The new snow also resulted in a numerous spontaneous back country avalanches, as well as at least seven human-triggered slides involving back country skiers and snowmobilers. Though no one was killed, two skiers were badly injured after taking long rides in two separate avalanches. In early November an avalanche carried a victim 250 vertical meters over cliffs

Table 4: Avalanche size classification (after Perla and Martinelli (1978)).

| | Description |
|---|---|
| 1 | Sluff (any slide running less than 50 m slope distance regardless of other dimensions) |
| 2 | Small (relative to the path) |
| 3 | Medium (relative to the path) |
| 4 | Large (relative to the path) |
| 5 | Major or maximum (relative to the path) |

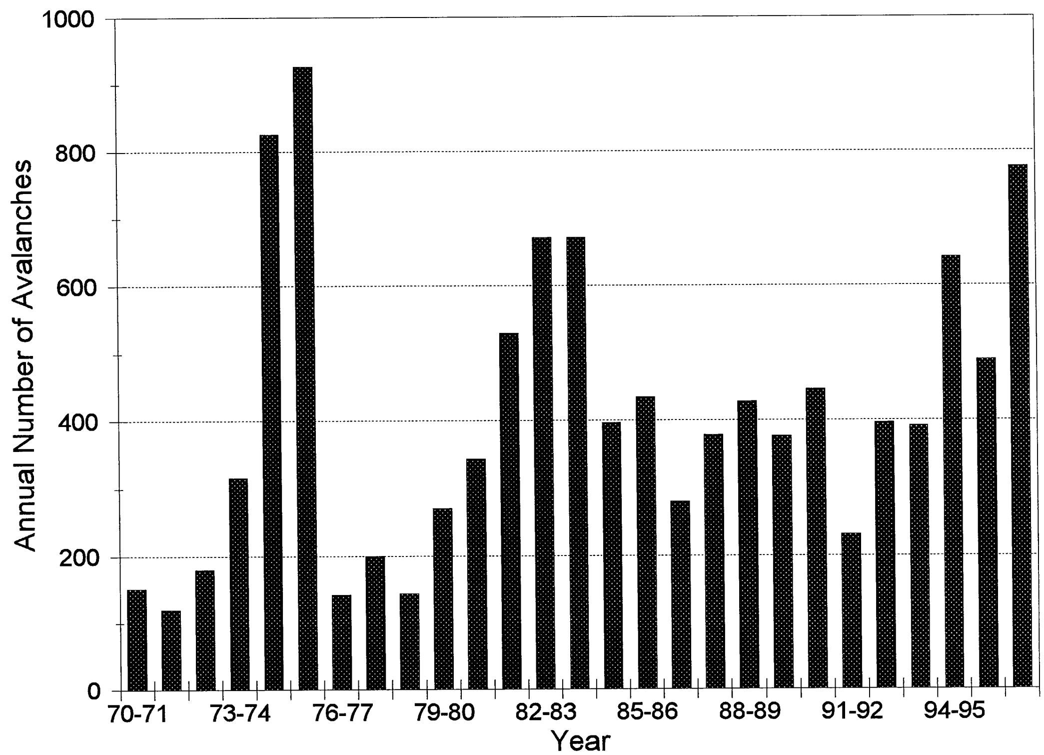


FIGURE 16: Total annual number of avalanches at Bridger Bowl Ski Area, as compiled by the Bridger Bowl Ski Patrol, 1970-71 to 1996-97.

and trees at speeds over 30 meters per second; the injured skier was evacuated by helicopter.

## SNOWPACK CONDITIONS ON THE SAMPLING DAYS

Comprehensive snow pit analyses on the day after sampling documented snowpack conditions. I collected snow pit data typical of many U.S. ski areas at an easily accessible study plot within the Bridger Bowl Ski Area. The site, which was roped off at the beginning of the season to insure that it remained undisturbed, was on a 33 degree east-southeast facing slope at 2490 m in elevation. In addition to the data collected for the spatial data set, I measured snow temperatures every 0.10 m, identified significant snowpack layers, and classified the crystal type and size, measured the hand hardness and measured the density from each layer. Colbeck and others (1990) outline crystal identification and snow pit techniques. Careful analysis of the top 1 m of the snow sufficiently characterized the entire deep and homogenous snowpack. Comparisons between the detailed snowpack data that follow and the spatial data sets in Appendix D show these snow pits reasonably represented the data collected on the sampling days.

**Snowpack conditions on February 6th**

Snow pit analyses on February 7th approximated snowpack conditions on the first sampling day. The snowpack reflected the snowy season's history with a total depth of over three meters (Figure 17). Due to the depth of the snowpack and the continuity of the storm systems, the lower snowpack layers consolidated and strengthened into a relatively homogenous layer with pencil hardness and few weak layers. The deep snowpack also minimized the temperature gradient at depth. Assuming a ground/snow interface temperature of 0 degrees C (Perla and Martinelli, 1978), the temperature gradient in the top 2.7 m was less than 2 degrees C/m, far below the accepted threshold of 10 degrees C/m for faceted crystal growth (Armstrong, 1985).

In contrast to the relatively homogenous lower snowpack, the upper 0.40 m had several distinct layers created by recent weather conditions. A graupel layer at 2.80 m was deposited at the beginning of a storm on January 31st and February 1st which dropped over 0.30 m of snow; this graupel layer created a distinctive failure layer in our snow pits on February 6th. In fact, two back country skiers triggered an avalanche on this layer in an area immediately south of the Ramp (RMP on Figure 6) on February 2nd. Another failure layer occurred at 2.95 m, where the snow changed during the storm. This change may have been due to a change in temperature,

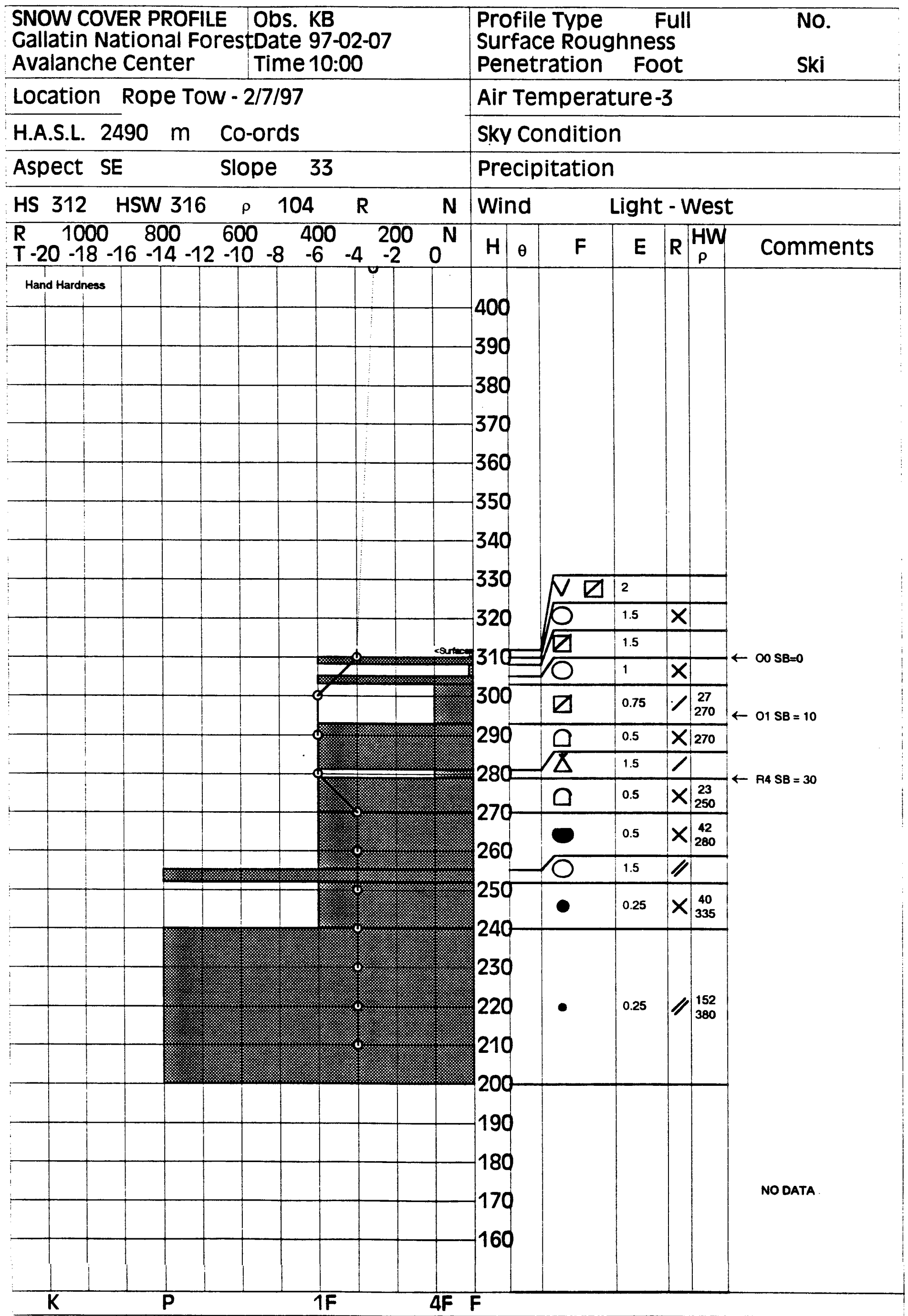


FIGURE 17: Snow pit profile collected at the rope tow site within Bridger Bowl Ski Area on February 7th, 1997.

snow type, or wind, and this failure layer prevailed through much of the Bridgers on the sampling day.

Between 2.95 m and the snow surface the snowpack structure became more complicated due to processes of near-surface faceting (Birkeland, under review). The warm, sunny days, and cold, clear nights that predominated after February 3rd created ideal conditions for diurnal recrystallization by causing large snow surface temperature swings, leading to temperature gradients that can exceed 200 degrees C/m (Birkeland and others, under review). These intense temperature gradients quickly formed the near-surface faceted crystals observed between 2.95 and 3.03 m, and between 3.05 and 3.08 m. In addition, radiation recrystallization (LaChappelle and Armstrong, 1977; Armstrong, 1985; Birkeland, under review) probably played a part in the formation of the layers from 3.05 to 3.08 m and from 3.10 to 3.12 m on this southerly facing slope. In radiation recrystallization the insolation is absorbed right below the snow surface, while longwave radiation losses keep the snow surface cool, and the resulting near-surface temperature gradient creates faceted crystals. The layer from 3.10 to 3.12 m also had surface hoar crystals, which were deposited on the snow surface during the previous cold, clear nights with intense longwave radiation losses.

Investigators observed near-surface faceted snow throughout the Bridgers on the February 6th; this snow was not associated with any crusts on easterly and northerly aspects, but was associated with some surface crusts on southerly aspects. Such layers of near-surface faceted snow are critical for future stability considerations after they are buried by subsequent snowfall, since nearly 60% of all back country avalanches in southwest Montana fail on these layers (Birkeland and others, 1996b). However, because no significant slab existed on top of them at the time of sampling, they did not affect the stability on the February 6th sampling day.

**Snowpack conditions on April 2nd**

Total snow depth at the study plot remained about the same between the two sampling days, which is surprising given the increase of 0.70 m at the Alpine study plot (Figure 18). The slight southerly aspect of the snow pit site (aspect of 118 degrees) may be the reason for this discrepancy, since the warm temperatures and sunshine in mid- to late-March probably accelerated the densification of the snowpack. Indeed, the lower layers of the snowpack were moist (below 2.7 m the snow consisted of melt-freeze crystals at 0 degrees C), showing the effects of those warmer March temperatures (Figure 15). Further, a comparison of the densities measured shows the a much denser snowpack on April 2nd (maximum density of 525 kg/m$^2$ (Figure 18)) existed than on February 6th (maximum density of 380 kg/m$^2$ (Figure 17)).

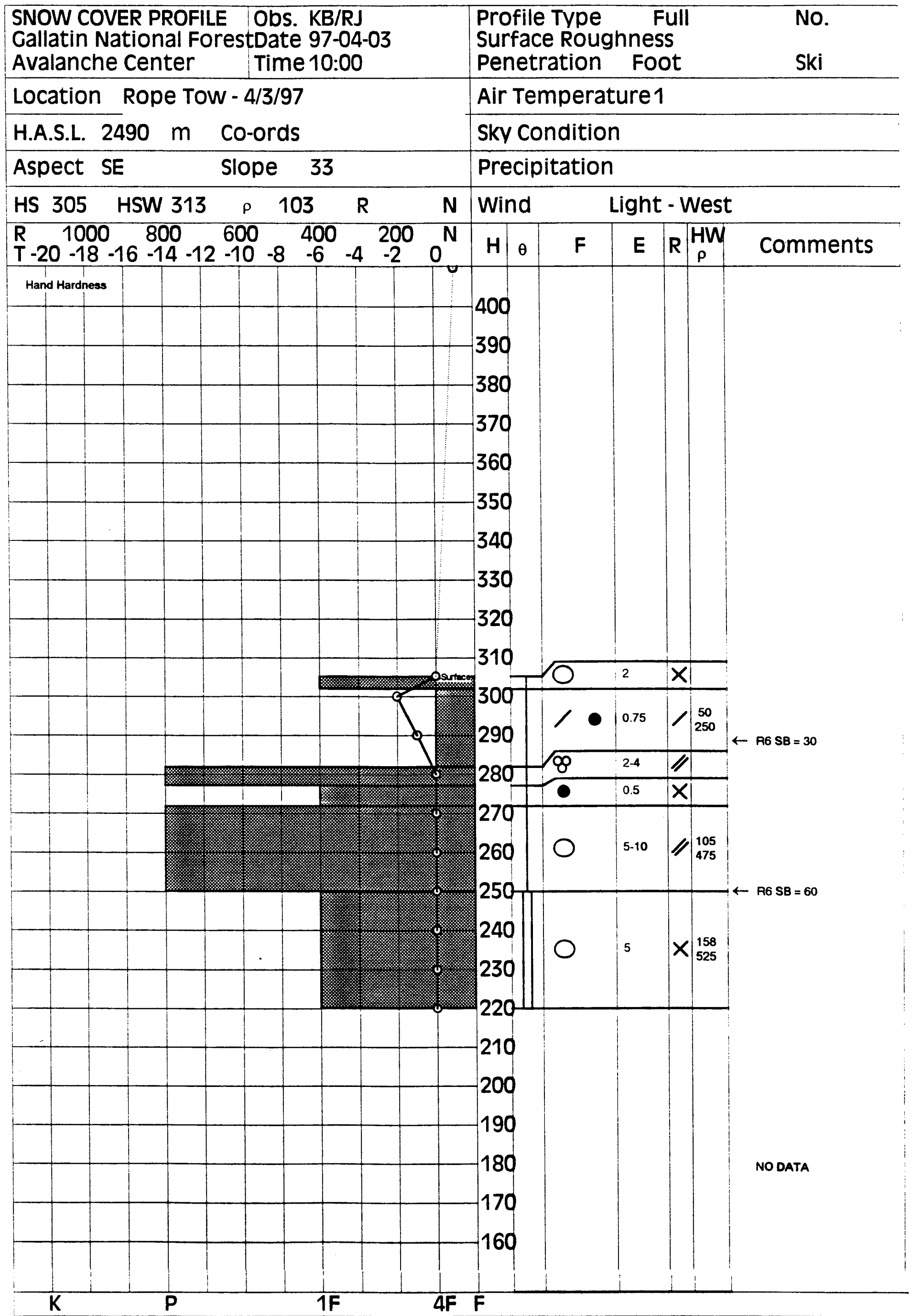


FIGURE 18: Snow pit profile collected at the rope tow site within Bridger Bowl Ski Area on April 3rd, 1997.

The composition of the upper 0.35 m of snowpack was the most critical for snow stability on April 3rd (Figure 18). A layer of snow above 2.7 m was capped by a thin, strong melt-freeze crust up to 2.82 m. A storm that dropped 0.35 m of snow at the Alpine study plot from the night of March 31st to the early morning of April 2nd deposited the snow above 2.82 m. Cool temperatures, partial cloud cover, and some light winds kept this layer largely dry during sampling, though some areas (like this snow pit site) received enough sun to create a surface melt-freeze crust by April 3rd. A slight density change within the new snow at about 2.87 m created the most significant failure. Though I could not measure this density change, I easily observed it in the snow pit wall, and investigators consistently noted failures at that level throughout the Bridgers on April 2nd.

# Chapter IV

## Spatial and Temporal Variations in Snow Stability

### OVERVIEW

The purpose of this results and discussion chapter is to report the evaluation of the spatial patterns and temporal changes of snow stability for the two sampling days. A series of statistical analyses assess linkages between snow stability with terrain, snowpack and snow strength variables, starting on the simplest level (data distribution and descriptive statistics) and proceeding to more complex techniques (multiple regression and canonical correlation analysis). Within the various statistical tests, the analysis starts by relating snow stability to terrain (path 1 in Figure 3). This has broad utility since terrain parameters can be easily modelled, thereby allowing relationships between snow stability and terrain to be extrapolated over an area of interest. However, predicting snow stability given only terrain variables is difficult since even the relationship between snowpack and terrain has proven to be hard to quantify (Dexter, 1986; Elder, 1995). Thus, the second level of analysis compares snow stability variables with a combination of terrain and snowpack variables (paths 1 and 2 in Figure 3). The snowpack variables used are quick, repeatable measures, and may improve the predictability of snow stability. The third and final level of analysis uses snow strength variables in conjunction with terrain and snowpack to predict snow stability (paths 1, 2 and 3 in Figure 3). In all of the analyses I first discuss the spatial variations, followed by the temporal changes.

## THE DATA

I generated a two-dimensional space/attribute data matrix for each sampling day, with the rows representing the sampling locations and the columns representing the terrain, snowpack, snow strength, and snow stability variables described in the Methods chapter (Table 2). All variables were tested for normality using the Kolmogorov-Smirnov one sample test (Massey, 1951). Most variables do not significantly deviate from normality at $p < 0.05$ (Table 5). However, on the first sampling day location east (*loc e*), average ram strength (*ram avg*), weakest stuffblock failure (*sb wk*), failure index associated with the weakest stuffblock (*FI wk sb*), the depth to failure of the weakest rutschblock (*df wk rb*), weakest rutschblock (*rb wk*), stuffblock associated with the weakest rutschblock (*sb wk rb*), and total

TABLE 5: Variable codes, normalized variable codes, and transformations for variables that deviated significantly from normality ($p < 0.05$ using the Kolmogorov-Smirnov one sample test). Successfully transformed variables did not deviate from normality at $p < 0.05$.

| *Variable Code* | *Normalized Code* | *Transformation* |
|---|---|---|
| February 6th | | |
| loc e | | Unable to normalize. However, *loc e* does not deviate from normality at $p < 0.04$. |
| ram avg | *ram avg sqrt* | Transformed with a square root transformation |
| df wk rb | *df wk rb sqrt* | Transformed with a square root transformation |
| sb wk | | Unable to transform |
| rb wk | *rb wk sq* | Transformed by squaring |
| sb wk rb | | Unable to transform |
| Fl wk sb | *Fl wk sb tf* | Transformed by raising *Fl wk sb* to the two thirds power |
| TFl | *TFl sqrt* | Transformed with a square root transformation |
| April 2nd | | |
| t30 | *t30 tf* | Transformed by raising *t30* to the two thirds power. |
| tgrad | *tgrad tf* | Transformed by raising *tgrad* to the two thirds power. |
| df wk rb | *df wk rb sqrt* | Transformed with a square root transformation |
| sb wk | | Unable to transform |
| sb wk rb | | Unable to transform |
| Fl wk sb | | Unable to transform |
| TFl | *TFl sqrt* | Transformed with a square root transformation |

failure index (*TFI*) do deviate from normality at p = 0.05, and on the second day temperature 0.30 m below the surface (*t30*), temperature gradient (*tgrad*), depth to failure of the weakest rutschblock (*df wk rb*), *sb wk, sb wk rb, FI wk sb*, and *TFI* are not normally distributed. I transformed *ram avg*, *df wk rb*, and *TFI* by taking the square root of each variable, *rb wk* was transformed by squaring it, and *FI wk sb, t30*, and *tgrad* were transformed by raising them to the two thirds power. Once transformed, none of these variables significantly deviated from normality. I was unable to transform included *loc e, sb wk, sb wk rb*, and *FI wk sb*, though *loc e* was normally distributed at $p < 0.04$. An excessive number of zero values made normalizing the other variables difficult.

Values for the weakest rutschblock (*rb wk*) are problematic because they are ordered data from 1 to 7 (Table 3). Some research has shown that, through the middle range of values (rutschblock degrees 2 to 5) this scale is exponential, with each level resulting in about twice the force applied to the weak layer as the previous level (Camponovo and Schweizer, 1996). The stuffblock test also results in ordered data, but since stuffblock results relate to a linear scale of the surface impact energy necessary to cause failure (Birkeland and others, 1996a), the stuffblock is better suited to parametric statistical tests than the rutschblock. Thus, care must be used when interpreting parametric statistical results related to stuffblock drop heights, and special care must be used when interpreting rutschblock results.

Because my data set included variables I was unable to normalize, I took a conservative approach with my analyses and used non-parametric tests that did not rely on assumptions of normality when possible. While conducting non-parametric tests I used all non-transformed data, and I used the normalized data and applied more stringent significance testing with variables that were non-normal when performing parametric tests. For example, with multiple regression I used a significance level of $p < 0.025$ with those variables that were non-normal or ordered. Finally, the parametric statistical analyses I used are considered to be robust with respect to deviations from normality, especially as sample sizes approach one hundred (StatSoft, 1994). Since my sample size was fairly large (N of approximately 70), the use of these tests is appropriate.

## QUANTIFYING EXISTING CONDITIONS AND TEMPORAL CHANGES USING DESCRIPTIVE STATISTICS

Descriptive statistics from both sampling days for snowpack, snow strength and snow stability variables show how the two days differed (Table 6). I report mean values for consistency, though median values are more appropriate for ordered data like the weakest rutschblock (*rb wk*). I tested for a significant difference in a variable between the days using a t-test for

TABLE 6: Descriptive statistics for snowpack, snow strength, and snow stability variables on both sampling days. Variables marked with an asterisk are significantly ($p < 0.05$) different between the sampling days (SD = standard deviation, SEM = standard error of the mean).

| | Descriptive Statistics | | | | | |
|---|---|---|---|---|---|---|
| | February 6th | | | April 2nd | | |
| | Mean | SD | SEM | Mean | SD | SEM |
| Snowpack | | | | | | |
| *dpth (m)** | 2.59 | .81 | .095 | 3.06 | .87 | .104 |
| *t30 (deg C)** | -6.5 | 2.3 | .27 | -2.7 | 2.4 | .29 |
| *tgrad (deg C/m)** | -2.6 | 1.3 | .16 | -1.1 | 1.6 | .20 |
| Snow strength | | | | | | |
| *ram drp (m)* | 0.35 | 0.13 | .016 | 0.37 | 0.19 | .022 |
| *ram avg (N/m)** | 0.148 | 0.097 | .0118 | 0.209 | 0.099 | .0119 |
| Snow Stability | | | | | | |
| *df wk sb (m)* | .22 | .11 | .014 | .24 | .19 | .022 |
| *df wk rb (m)** | .30 | .17 | .021 | .36 | .16 | .019 |
| *sb wk (m)** | .12 | .11 | .013 | .18 | .16 | .019 |
| *rb wk* | 4.9 | 1.7 | .20 | 4.8 | 1.7 | .21 |
| *sb wk rb (m)** | .21 | .18 | .022 | .29 | .16 | .019 |
| *FI wk sb* | .567 | .525 | .062 | .825 | 1.07 | .126 |
| *FI sb wk rb* | .660 | .476 | .058 | .835 | .424 | .051 |
| *TFI** | .450 | .354 | .042 | .498 | .434 | .052 |

*Means are significantly different ($p < 0.05$) between the sampling days. Difference of means were tested using the t-test for variables that were normally distributed, and the Wilcoxson matched pairs test for non-normal data.

normally distributed data, and a Wilcoxson matched pairs test for ordered and non-normal data.

Snow depth (*dpth*) increased significantly between the two days, with an average depth of just over 2.5 m on February 6th increasing to over 3 m on April 2nd. Sub-surface temperature (*t30*) increased, and the average temperature gradient (*tgrad*) decreased, indicating that increases in temperature dominated depth increases between the two sampling days. The initial ram drop (*ram drp*) was quite similar between the two sampling days at just over 0.3 m. Though the surface snow was soft on both sampling days, observations indicate the surface snow structure differed. In February much of the surface snow consisted of near-surface faceted snow formed through diurnal recrystallization (Birkeland, under review), while in April the surface snow consisted of new snow from the previous day and night. Average ram hardness (*ram avg*) increased between the sampling days due to densification of the snowpack through settlement and equilibrium metamorphic processes.

Slab depth increased slightly between the two days. Though the increase in depth to failure for the weakest stuffblock (*df wk sb*) was insignificant, the depth to failure of the weakest rutschblock (*df wk rb*) did significantly increase. Results from the weakest rutschblock (*rb wk*) were virtually unchanged between the sampling days, but both the weakest stuffblock (*sb wk*) and the stuffblock associated with the weakest rutschblock (*sb wk rb*) increased significantly. As a result the failure indices associated with the specific stuffblock results did not differ between sampling days, though total failure index (*TFI*) increased significantly.

The snowpack on the second sampling day was deeper, warmer, and stronger than on the first day. Such trends are commonly observed from mid- to late-season in the mountain snowpack, and have been documented previously (i.e., Armstrong and Ives, 1977; Dexter, 1986). Interestingly, although snowpack and snow strength properties changed dramatically between the two days, snow stability is similar, with four of the eight stability variables showing no difference, one variable indicating decreased stability (*df wk rb*), and the other three showing slightly more stable conditions. The significant changes in snowpack and snow strength, without dramatic changes in stability, illustrates the dynamic nature of stability changes in comparison to the more slowly changing snowpack and strength variables.

## ASSESSING RELATIONSHIPS BETWEEN VARIABLE PAIRS USING CORRELATION ANALYSIS

Since some variables were ordered or not normally distributed, I used non-parametric Spearman rank order correlations to quantify the relationships between variable pairs.

### February 6th

*The relationship between stability and terrain variables*

There are several significant correlations between slab depth and terrain, but only limited relationships between terrain and weak layer stability and stability indices (Table 7, Figure 19). Slab depths are significantly correlated to a number of terrain variables on the first sampling day, with *df wk sb* and *df wk rb* being positively correlated to *loc e* and *ang*, and negatively correlated to *loc n*, *elev*, and *dis rdg* (significant correlations are indicated in the table). Thus, areas farther north and west, and at higher elevations, had shallower slab depths.

There is only limited evidence of significant relationships between terrain and weak layer stability and the stability indices. The weakest rutschblock is not significantly correlated to any terrain variables, though *sb wk* is negatively correlated to *dis rdg* and *sb wk rb* is negatively correlated to

TABLE 7: Spearman rank order correlations between snow stability and terrain, snowpack and snow strength on February 6th, 1997.

| Stability Variables | | Terrain Variables | | | | | | Snowpack Variables | | | Snow Strength Variables | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | *dpth* | *t30* | *tgrad* | *ram drp* | *ram avg* |
| Slab Depth | *df wk sb* | ***.44*** | ***-.44*** | -.19 | ***-.28*** | .06 | ***.29*** | ***-.28*** | ***.30*** | .17 | ***.59*** | ***-.36*** |
| | *df wk rb* | .15 | ***-.24*** | ***-.28*** | .00 | -.15 | .20 | -.22 | ***.34*** | .21 | ***.30*** | -.14 |
| Stability of Weak Layer | *sb wk* | .16 | -.14 | -.17 | ***-.24*** | .13 | .17 | -.19 | .20 | .12 | ***.34*** | -.14 |
| | *rb wk* | -.12 | -.05 | -.15 | -.04 | .19 | -.13 | -.14 | .23 | .15 | -.10 | -.02 |
| | *sb wk rb* | .02 | -.10 | ***-.31*** | .08 | .23 | .14 | -.17 | ***.31*** | .17 | .14 | -.04 |
| Stability indecies | *FI wk sb* | .11 | .10 | -.05 | -.14 | .10 | -.07 | -.05 | .03 | .03 | -.02 | .11 |
| | *FI sb wk rb* | -.09 | .07 | ***-.26*** | .11 | .20 | -.09 | -.12 | .15 | .03 | -.04 | .11 |
| | *TFI* | -.08 | .15 | -.13 | -.05 | .17 | .03 | -.14 | .02 | .02 | -.04 | -.09 |

Note: correlations in ***bold/italics*** are significant at $p < 0.05$.

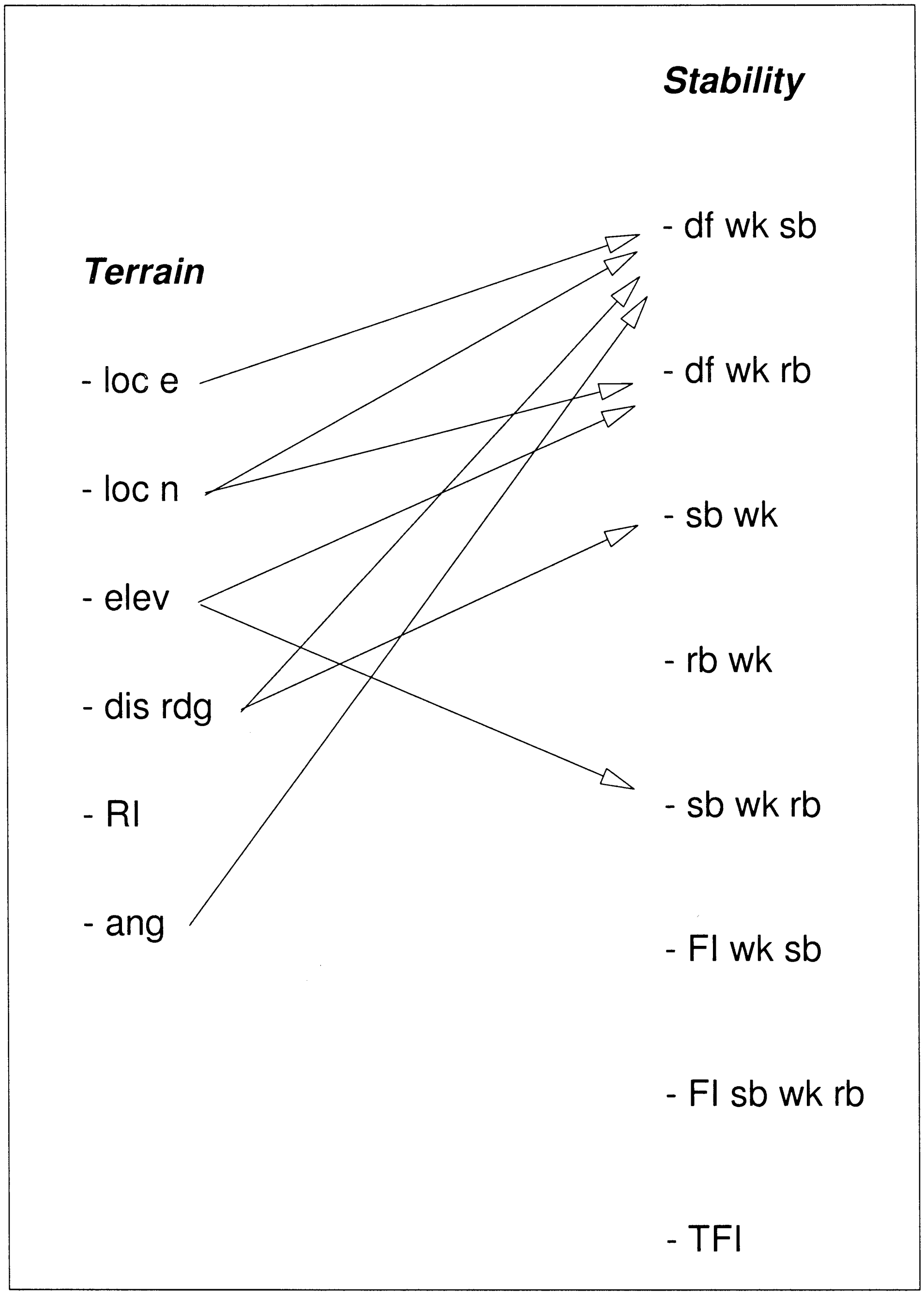


FIGURE 19: Visual representation of Table 7 showing the significant ($p < 0.05$) correlations between terrain and stability variables on February 6th.

*elev*. Neither *FI wk sb* nor *TFI* are significantly correlated to any terrain variables. *FI sb wk rb* is significantly negatively correlated to elevation, again emphasizing more unstable conditions at the higher elevations. Even though slab depths are lower at upper elevations, weak layer stability is decreasing more quickly, thereby lowering the failure indices.

Wind exposure may explain the spatial patterns of slab depth and stability. A wind event might have created a shallower, more sensitive slab that was not evident in more wind-protected areas. Over the past 10 years I have observed that the Bridgers north of Sacajawea Peak (Figure 7) are consistently windier than the rest of the range, as are the upper elevations. These observations are based on numerous trips into the Bridgers, as well as common observations of wind sculpted sastrugi in the northern part of the range. This might explain both the thinner slab depths in the northern part of the range and at higher elevations, as well as the evidence for slightly more unstable conditions at higher elevations. The positive correlation between slab depth and slope angle is more puzzling since I would expect steeper slopes to sluff more regularly, thereby decreasing slab depths. Perhaps many of the steeper slopes sampled are underneath even steeper cliffs and rock bands, though this was not tested.

*The relationship between stability and snowpack variables*

As with the relationship to terrain, there are significant correlations between slab depth and snowpack variables, but there are no significant correlations between the failure indices and snowpack variables, and only one significant correlation between weak layer stability and snowpack variables (Table 7, Figure 20). Slab depth is negatively correlated to *dpth*, and positively correlated to *t30*. The only significant correlation between weak layer stability and snowpack is the positive correlation between *sb wk rb* and *t30*. Thus, areas with warmer temperatures appear to be slightly more stable than colder areas.

Although it is initially surprising that slab depth decreases in areas with a deeper snowpack, those deeper areas are likely to be in the upper elevation areas that are receiving the winds discussed above. Warmer subsurface snow temperatures are also correlated to deeper slabs, which could also be a product of higher elevation, colder areas which had thinner slabs. Alternately, stability tests in areas with warmer temperatures may be affecting deeper layers since recent research indicates that warmer temperatures in the weak layer decreases snow stiffness, failure toughness, and strength (McClung and Schweizer, 1996). The evidence that warmer areas are more stable may be due to increased slab depths, or the warmer temperatures in the weak layer might be increasing the intensity of

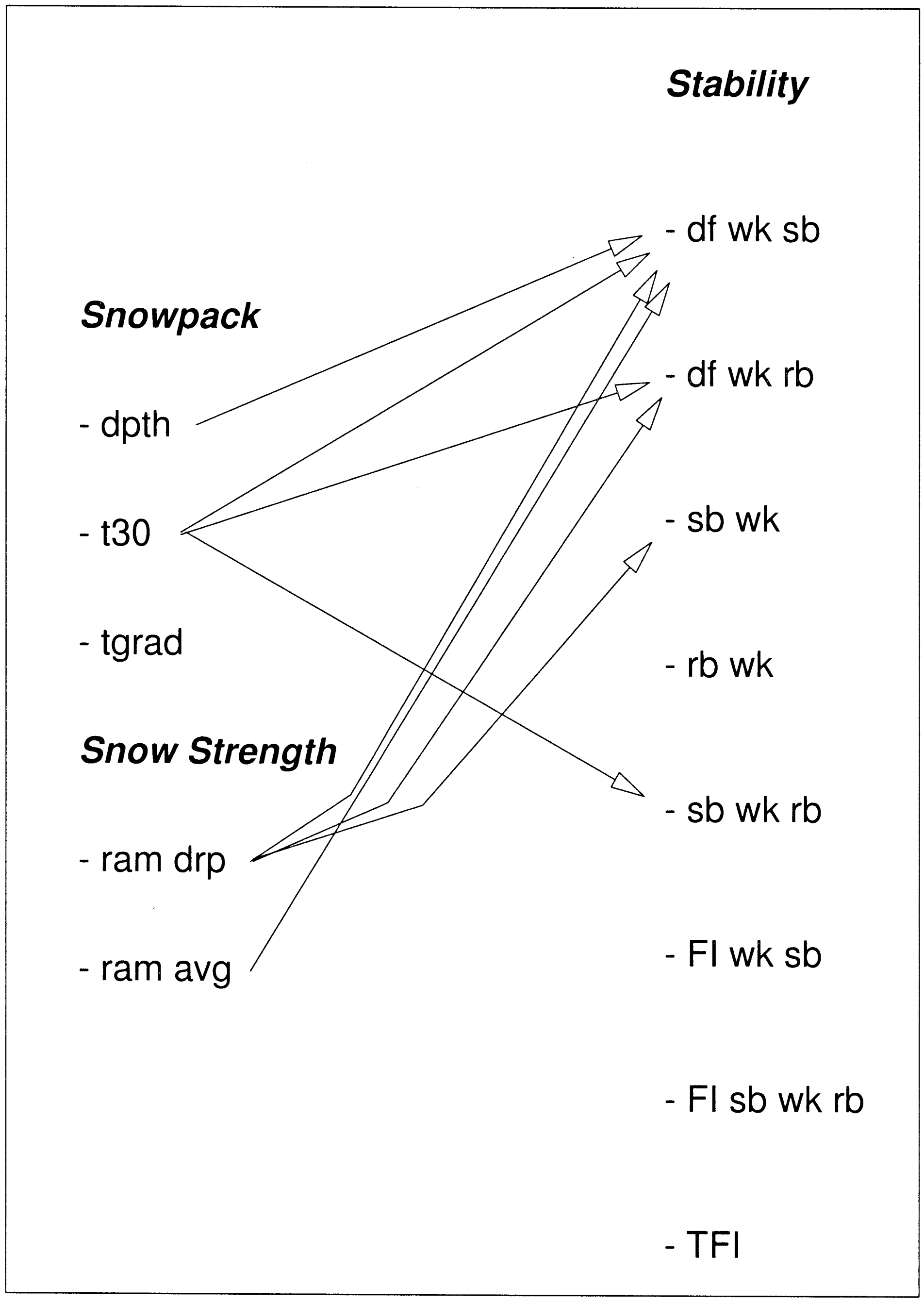


FIGURE 20: Visual representation of Table 7 showing the significant ($p < 0.05$) correlations between snowpack, snow strength, and stability variables on February 6th.

equilibrium metamorphic processes which hastens the strengthening of the weak layer.

*The relationship between stability and snow strength variables*

As with terrain and snowpack, the strongest linkages between snow strength and stability variables are with slab depth (Table 7, Figure 20). Slab depths are positively correlated to *ram drp* and negatively correlated with *ram avg*. Areas with softer surface snow may have had deeper slab depths because there was more new snow there, while areas with harder surface layers may have had that layer blown away. Areas with stronger snowpacks had shallower slab depths, probably because of the relationships between slab depths, elevation, and wind exposed areas discussed previously.

In terms of weak layer stability, only *sb wk* is positively correlated with *ram drp*, indicating that stuffblock drop height for the first stuffblock failure increases as the softness of the surface snow increases. Since the stuffblock involves transmitting energy from the snow surface through the snowpack and into the weak layer (Birkeland and others, 1996a), this relationship makes sense. When the surface snow is hard, the snow will transmit the energy provided by the stuffblock more effectively, but if the surface snow is soft it will cushion the stuffblock and not as much energy will make it through the snowpack to the weak layer.

*Summary*

Though a number of variables are significantly correlated to slab depth, only limited relationships can be quantified between the other stability variables and terrain, snowpack and snow strength (Table 7, Figures 19 and 20). Correlation analysis demonstrates some linkages between stability and other variables, but many of these linkages are weak. This result is initially puzzling, since avalanche forecasters who predict snow stability typically rely on known variation in terrain and snowpack to infer changes in stability over a region of interest. However, the 1996-97 winter was unusual, with heavy snowfall and little time between storms for weak layers to form. Since the sun almost never shone between late-November and early-February, snowpack conditions were similar on southerly and northerly slopes. In addition, many of the storms deposited surprisingly uniform quantities of snow throughout the Bridgers at various elevations, thereby muting elevational differences in the snowpack. I have rarely observed such a uniform distribution of snowfall in the Bridgers in my seven years of avalanche forecasting for the range. Investigators observed that snow stability conditions on the sampling day were also remarkably uniform throughout the range, and this is demonstrated in the data.

**April 2nd**

*The relationship between stability and terrain variables*

A glance at the correlation matrix for the second sampling day shows that terrain, and specifically *elev*, is much more closely linked to stability than on the first day (Table 8, Figure 21). In fact, *elev* is significantly negatively correlated to every stability variable except *df wk sb*. Thus, slab depth is decreasing at higher elevations, as is the weak layer stability. Weak layer stability is decreasing faster than slab depth, however, resulting in decreasing failure indices with increasing elevation. Distance to the ridge (*dis rdg*) is negatively correlated with *df wk sb* and positively correlated to *sb wk rb*, *FI wk sb* and *FI sb wk rb*, indicating increasingly unstable conditions closer to the main Bridger ridge. Another interesting relationship is the significant positive correlation between the failure indices *FI sb wk rb* and *TFI* and the terrain variable *RI*, demonstrating more stable conditions on southerly aspects. Thus, a recognizable spatial pattern in the instability is appearing on this particular sampling day, where higher elevation, northerly-facing slopes have the most unstable conditions.

This pattern of instability is common, prompting avalanche forecasters to often rely on a "rule of thumb" that upper elevation shady slopes are more unstable and slower to stabilize. This is due to two main reasons. First, these upper elevation areas are exposed to wind, and wind is a major

TABLE 8: Spearman rank order correlations between snow stability and terrain, snowpack and snow strength on April 2nd, 1997.

| Stability Variables | | Terrain Variables | | | | | | Snowpack Variables | | | Snow Strength Variables | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | *dpth* | *t30* | *tgrad* | *ram drp* | *ram avg* |
| Slab Depth | *df wk sb* | .21 | ***-.28*** | -.18 | ***-.31*** | .07 | .17 | ***-.24*** | ***.29*** | .23 | ***.24*** | ***-.30*** |
| | *df wk rb* | .18 | -.19 | ***-.28*** | .05 | -.00 | .09 | -.14 | .07 | .07 | ***.35*** | ***-.42*** |
| Stability of Weak Layer | *sb wk* | .14 | -.13 | ***-.32*** | -.01 | .18 | .09 | ***-.41*** | ***.47*** | ***.34*** | ***-.27*** | -.11 |
| | *rb wk* | -.12 | .11 | ***-.39*** | .22 | .22 | -.15 | ***-.31*** | ***.36*** | ***.29*** | ***-.43*** | .04 |
| | *sb wk rb* | -.09 | .00 | ***-.49*** | ***.29*** | .17 | -.10 | ***-.31*** | ***.33*** | ***.24*** | ***-.24*** | -.15 |
| Stability indecies | *FI wk sb* | .04 | -.01 | ***-.34*** | ***.30*** | .21 | -.08 | ***-.30*** | ***.44*** | ***.34*** | ***-.62*** | .09 |
| | *FI sb wk rb* | .01 | .12 | ***-.38*** | ***.35*** | ***.28*** | -.23 | -.20 | ***.37*** | ***.30*** | ***-.57*** | .08 |
| | *TFI* | .10 | -.12 | ***-.41*** | .11 | ***.31*** | -.04 | ***-.40*** | ***.56*** | ***.45*** | ***-.54*** | -.07 |

Note: correlations in ***bold/italics*** are significant at $p < 0.05$.

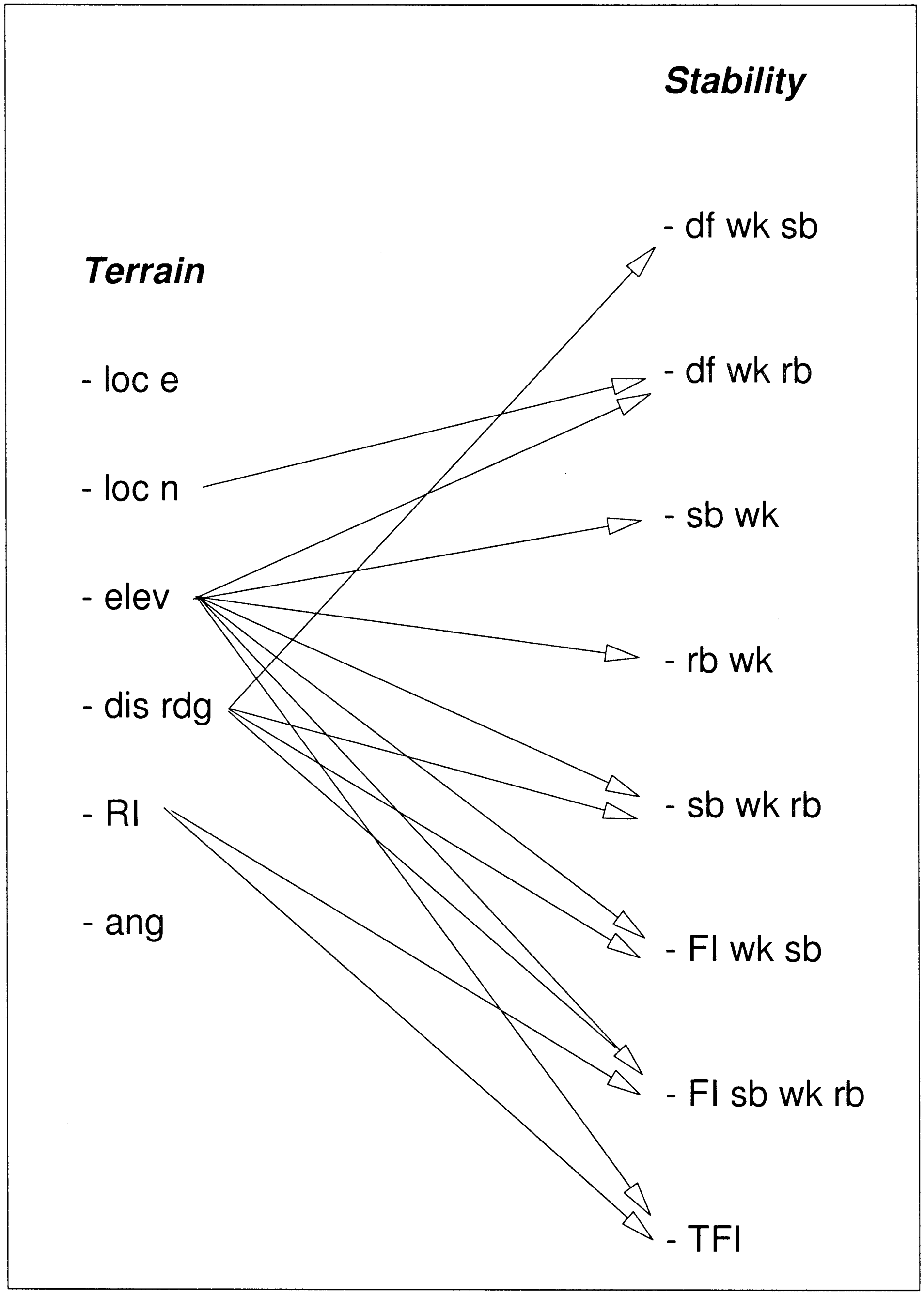


FIGURE 21: Visual representation of Table 8 showing the significant ($p < 0.05$) correlations between terrain and stability variables on April 2nd.

contributor to instability. Second, high elevation northerly-facing slopes are the coldest areas, and this is where changes in the snowpack occur the most slowly. Weak layers that form throughout an area will therefore persist in these colder locations long after they have stabilized in other areas.

*The relationship between stability and snowpack variables*

On April 2nd there is a strong relationship between snowpack and stability variables (Table 8, Figure 22). Only *df wk rb* is not significantly correlated to at least two of the variables. In general, weak layer strength decreases with increasing depth and increasingly cold temperatures, a result that is mirrored in the relationship of the failure indices to the snowpack variables. The correlation between stability and *tgrad* is positive, indicating that areas with larger (more negative) temperature gradients are more unstable. As with the comparisons with terrain, the relationship of stability variables to snowpack variables results in a fairly clearly defined pattern. On April 2nd, areas with deeper and colder snowpacks have more unstable conditions. Since these snowpack conditions are commonly associated with upper elevation, northerly facing slopes, this result is not unexpected, and the reasons for these patterns were discussed above.

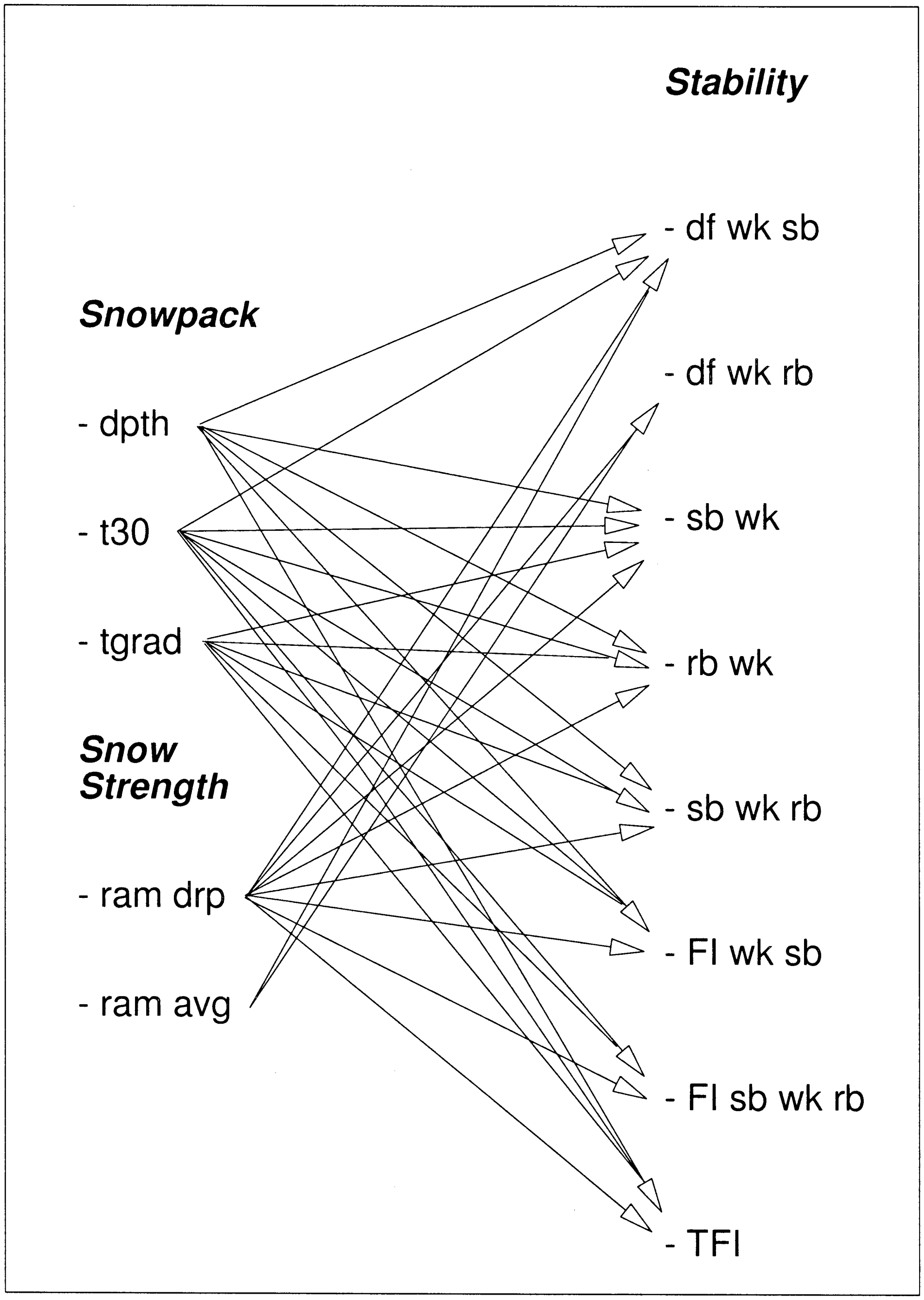


FIGURE 22: Visual representation of Table 8 showing the significant ($p < 0.05$) correlations between snowpack, snow strength, and stability variables on April 2nd.

*The relationship between stability and strength variables*

On this sampling day there is a significant relationship between *ram drp* and all of the stability variables, while *ram avg* is only significantly related to slab depth, with areas of stronger snow showing thinner slab depths (Table 8, Figure 22). The initial ram drop is positively correlated to slab depth and negatively correlated to both weak layer stability and the failure indices. Areas with harder snow have shallower slab depths, possibly due to denser, shallower wind slabs at those locations. *Ram drp* is consistently negatively correlated with weak layer stability, meaning that, on this particular day, areas with softer surface snow had weaker stability results. Since this sampling day commenced immediately after a snow storm, areas with largest *ram drp* probably had the most new snow, and therefore the most stress applied to the weak layer, resulting in more unstable conditions. Since *ram drp* increased with increasing slab depth and decreasing weak layer stability, it is not surprising that increasingly soft surface snow is also significantly correlated to decreasing failure indices. Thus, areas with softer snow had deeper slabs and more unstable weaknesses, clearly resulting in more unstable conditions.

*Summary*

On April 2nd, spatial patterns of instability begin to emerge. Stability is related to *elev* and *RI*, with the end result being more unstable conditions on higher elevation, northerly aspects. Further, stability decreases with increasing depth and increasingly cold temperatures. Finally, stability decreases with increasingly soft surface snow. The end result is that statistically significant linkages between many of the variable pairs can be established (Table 8, Figures 21 and 22).

**Temporal changes between February 6th and April 2nd**

A comparison of the two sampling days reveals that the relationships between the variables are complex, and those relationships change over time. Few significant links existed between stability variables and terrain, snowpack and snow strength variables on February 6th (Table 7, Figures 19 and 20). This situation differed dramatically on April 2nd, with the terrain variables *elev* and *RI*, the snowpack variables *dpth, t30*, and *tgrad*, and the strength variable *ram drp* all being significantly correlated with snow stability (Table 8, Figures 21 and 22). Thus, on the second sampling day numerous linkages between the variables exist that did not exist on the first sampling day.

The weather leading up to the sampling days largely explains the lack of significant linkages on February 6th. Up until that point the season had been a blitz of consistent snowfall and wind. Few significant weak layers existed in the snowpack, and differences between north and south aspects were minimal since the sun rarely shone. The weather conditions in the early season mimicked a more coastal avalanche climate (Mock and Kay, 1992), with more snow, less sun, and fewer weak layers than are typical for the Bridgers. Though the rest of the season was also stormy, there were more sunny periods and more storms that dropped increased snowfall at upper elevations. Further, the sun affected southerly-facing slopes more dramatically by April because of increased insolation compared to earlier in the season. Thus, the homogenous weather conditions up until February resulted in few connections between stability and the other variables, while increasingly heterogenous weather conditions later in the year allowed the establishment of numerous statistically significant links between the variables in April.

## PREDICTIVE MODELLING USING MULTIPLE REGRESSION ANALYSIS

I investigated the potential of predicting snow stability given terrain, snowpack and snow strength variables using forward, stepwise, least squares multiple regression. Initially, I attempted to predict the various stability variables using terrain as the independent variables. To determine if adding snowpack variables improved the predictability of the models, I then ran model again with both terrain and snowpack variables used as the independent variables. Finally, I ran the model allowing snow strength variables, as well as terrain and snowpack variables, to be considered independent variables.

Before beginning the analyses, I set criteria to determine model "validity". Though I chose the level of explained variance of the dependent variable, the other criteria simply assured the models met the basic assumptions of regression. These criteria included the following: 1) the model must be significant ($p < 0.05$, or $p < 0.025$ for dependent variables that are either ordered or not normally distributed), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two independent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) significant autocorrelation does not exist (Durbin-Watson statistics generally > 1.5), and 6) and the residuals must be normally distributed. I quantified the shared variance of each variable pair using Pearson product moment correlations. Results indicated that *loc n* and *loc e* were strongly correlated, with $R = 0.92$, and *elev* and *dis rdg* shared just under 50% of their variance with an $R = 0.68$. On the second sampling day the transformed variables *t30 tf* and *tgrad tf* were also highly correlated ($R = 0.78$). Thus, on both days I ran models first with *loc n* and then with *loc e*, and chose the model that explained more the variance of the dependent variable. Likewise, I only used either *elev* or *dis rdg* in each model, choosing the superior model. Finally, on the second day only *t30* or *tgrad* was used as an independent variable.

I tried not to eliminate any data. However, on April 2nd one data point repeatedly arose as a significant outlier with inordinate leverage (as measured by Cook's distance (Statsoft, 1994)) on the regression models. At the third snow pit from Sacajawea (SAC in Figure 6) the weakest (and only) failure occurred at a slab depth of 0.05 m and a stuffblock drop height of 0.40 m. This resulted in a *TFI* of 8, with the next nearest *TFI* being 2.5 and most *TFIs* being less than 1. This result is highly questionable, since normally by the time the stuffblock has been dropped from 0.40 m it has compressed the snowpack far below 0.05 m. The sampling team could not recall this particular site. As a result of the leverage this point had on the resultant models, and the questionable result reported, the April 2nd data set for regression and canonical correlation analyses did not include this case.

**February 6th**

*Modelling snow stability using terrain variables*

There were no valid models of stability when terrain variables were chosen as the independent variables for the February 6th data.

*Modelling snow stability using terrain and snowpack variables*

When snowpack was combined with terrain as the independent variables, and the stability variables were each chosen as the dependent variables, one valid model was produced (Table 9). This model explained just over 20% of the variance in *FI sb wk rb* using the variables *loc e, elev*, and *t30*. Comparing the standardized partial regression coefficients shows the relative importance of the independent variables in predicting *FI sb wk rb*. *Loc e* is the most important (beta = -.53), followed by *elev* (beta = -.43) and *t30* (beta = .35). Thus, stability is decreasing at higher elevations, colder subsurface snow temperatures, and more easterly locations within the Bridgers. Interestingly, there were no valid models for any other stability variables, emphasizing that the links between stability and terrain and snowpack are fairly weak on this particular day.

*Modelling snow stability using terrain, snowpack and snow strength variables*

Adding snow strength to the suite of independent variables did not change the regression model for *FI sb wk rb*, but it did result in a valid model for the transformed variable *TFI sqrt* (Table 10). This model explained 15% of the variance of the dependent variable, but was based on entirely different variables than those used to predict *FI sb wk rb*, with *loc n, RI*, and *ram drp* brought into the equation. The standardized partial regression

TABLE 9: Standardized partial regression coefficients and coefficients of determination (adjusted $R^2$) on February 6th, 1997 for multiple regression models run with dependent stability variables and independent terrain and snowpack variables.

| Stability Variables | | Terrain Variables | | | | | | Snowpack Variables | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | *dpth* | *t30* | *tgrad* | ***Adj. $R^2$*** |
| Slab Depth | *df wk sb* | | | | | | | | | | - |
| | *df wk rb sqrt* | | | | | | | | | | - |
| Stability of Weak Layer | *sb wk* | | | | | | | | | | - |
| | *rb wk sq* | | | | | | | | | | - |
| | *sb wk rb* | | | | | | | | | | - |
| Stability indecies | *FI wk sb tf* | | | | | | | | | | - |
| | *FI sb wk rb* | -.53 | | -.43 | | | | | .35 | | .23 |
| | *TFI sqrt* | | | | | | | | | | - |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$; $p < 0.025$ for ordered or non-normal data), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

TABLE 10: Standardized partial regression coefficients and coefficients of determination (adjusted $R^2$) on February 6th, 1997 for multiple regression models run with dependent stability variables and independent terrain, snowpack, and snow strength variables.

| Stability Variables | | Terrain Variables | | | | | | Snowpack Variables | | | Strength Variables | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | *dpth* | *t30* | *tgrad* | *ram drp* | *ram avg sqrt* | ***Adj. $R^2$*** |
| Slab Depth | *df wk sb* | | | | | | | | | | | | - |
| | *df wk rb sqrt* | | | | | | | | | | | | - |
| Stability of Weak Layer | *sb wk* | | | | | | | | | | | | - |
| | *rb wk sq* | | | | | | | | | | | | - |
| | *sb wk rb* | | | | | | | | | | | | - |
| Stability indecies | *FI wk sb tf* | | | | | | | | | | | | - |
| | *FI sb wk rb* | -.53 | | -.43 | | | | | .35 | | | | .23 |
| | *TFI sqrt* | | .40 | | | .35 | | | | | .40 | | .15 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$; $p < 0.025$ for ordered or non-normal data), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

coefficients show that all three variables are similar in their relative importance in predicting *TFI sqrt*. This result implies that stability increases in a northerly direction, on more southerly facing slopes, and in areas with softer surface snow. However, lack of other valid models and the low $R^2$ value indicates that the links between stability and the independent variables are still relatively weak.

*Summary*

Regression models generated with forward, stepwise multiple regression emphasize earlier conclusions that stability on February 6th is only weakly linked to terrain, snowpack and snow strength variables. Valid regression models were possible for only two stability variables, and both of those explained less than 25% of the variance of the dependent variables. The valid models imply that stability is decreasing at higher elevations, on more northerly aspects, in areas with cooler snowpacks, and in areas with harder snow surfaces. In addition, the more unstable areas appear to be in the southern and eastern parts of the Bridgers.

**April 2nd**

*Modelling snow stability using terrain variables*

In contrast to February 6th, I successfully modelled several stability variables using only terrain as the independent variables on April 2nd (Table 11). Valid models were generated for *rb wk, sb wk rb, FI sb wk rb*, and *TFI*, though none of them explained more than 30% of the variance of the dependent variable. *Elev* appeared in three of the four models and was the most important variable each model for predicting stability; the model which did not include *elev* used *dis rdg*, which is highly correlated to *elev*. In all cases the standardized regression coefficients for *elev* are negative, again demonstrating decreasing stability at higher elevations. The model for *sb wk rb* used only elevation, while the other three models used *RI* to explain the variance in the stability variables. Positive partial regression coefficients for *RI* demonstrate more stable conditions on sunnier slopes. Finally, one model used *loc e* in addition to *elev* and *RI* to predict *rb wk*, showing more unstable conditions in areas farther east in the study area. In short, the regression models all emphasize that, on this particular day, stability decreased at higher elevations and on more northerly aspects.

Of the models produced, the model predicting *rb wk* is especially interesting because this study represents the first time that the spatial distribution of this popular measure of snow stability has been quantified at

TABLE 11: Standardized partial regression coefficients and coefficients of determination (adjusted $R^2$) on April 2nd, 1997 for multiple regression models run with dependent stability variables and independent terrain variables.

| Stability Variables | | Terrain Variables | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | ***Adj. $R^2$*** |
| Slab Depth | *df wk sb* | | | | | | | - |
| | *df wk rb sqrt* | | | | | | | - |
| Stability of Weak Layer | *sb wk* | | | | | | | - |
| | *rb wk* | -.41 | | -.54 | | .23 | | .28 |
| | *sb wk rb* | | | -.46 | | | | .21 |
| Stability indecies | *FI wk sb* | | | | | | | - |
| | *FI sb wk rb* | | | | .36 | .35 | | .20 |
| | *TFI sqrt* | | | -.32 | | .30 | | .20 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$; $p < 0.025$ for ordered or non-normal data), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

the regional scale. Though results should be viewed with caution due to the ordered nature of rutschblock data, a closer look at this model is warranted. The terrain-based equation, which explains 28% of the variance of *rb wk* is:

$$rb\ wk = 271 - (4.95 \times 10^{-4})loc\ e - (6.83 \times 10^{-3})elev$$
$$+ (9.14 \times 10^{-3})RI$$

where *rb wk* is the weakest rutschblock in rutschblock degrees, *loc e* is the location in UTM meters east, *elev* is the elevation in meters, and *RI* is a radiation index based on aspect (where *RI* = the degrees away from north). Since this model is terrain-based, a visual representation can be mapped over the Bridgers using a digital elevation model (Figure 23). A limitation of this map is that it includes more terrain than was actually sampled, and therefore the statistical relationship may not hold for all the terrain mapped. Still, the obvious effect of elevation is apparent since the most unstable conditions (represented in black) are found close to the main ridge.

The terrain-based model for *TFI* is also interesting, since *TFI* is a measure of the overall stability of a particular location, and this study represents the first quantification of such a measure at the regional scale. The equation, which explains 20% of the variance of the transformed *TFI* is:

$$TFI\ sqrt = 2.14 - (6.44 \times 10^{-4})elev + (1.89 \times 10^{-3})RI$$

where *TFI sqrt* is the square root of the total failure index, *elev* is the elevation in meters, and *RI* is a radiation index based on aspect (where *RI* = degrees away from north). Similar to the representation for *rb wk*, a map of

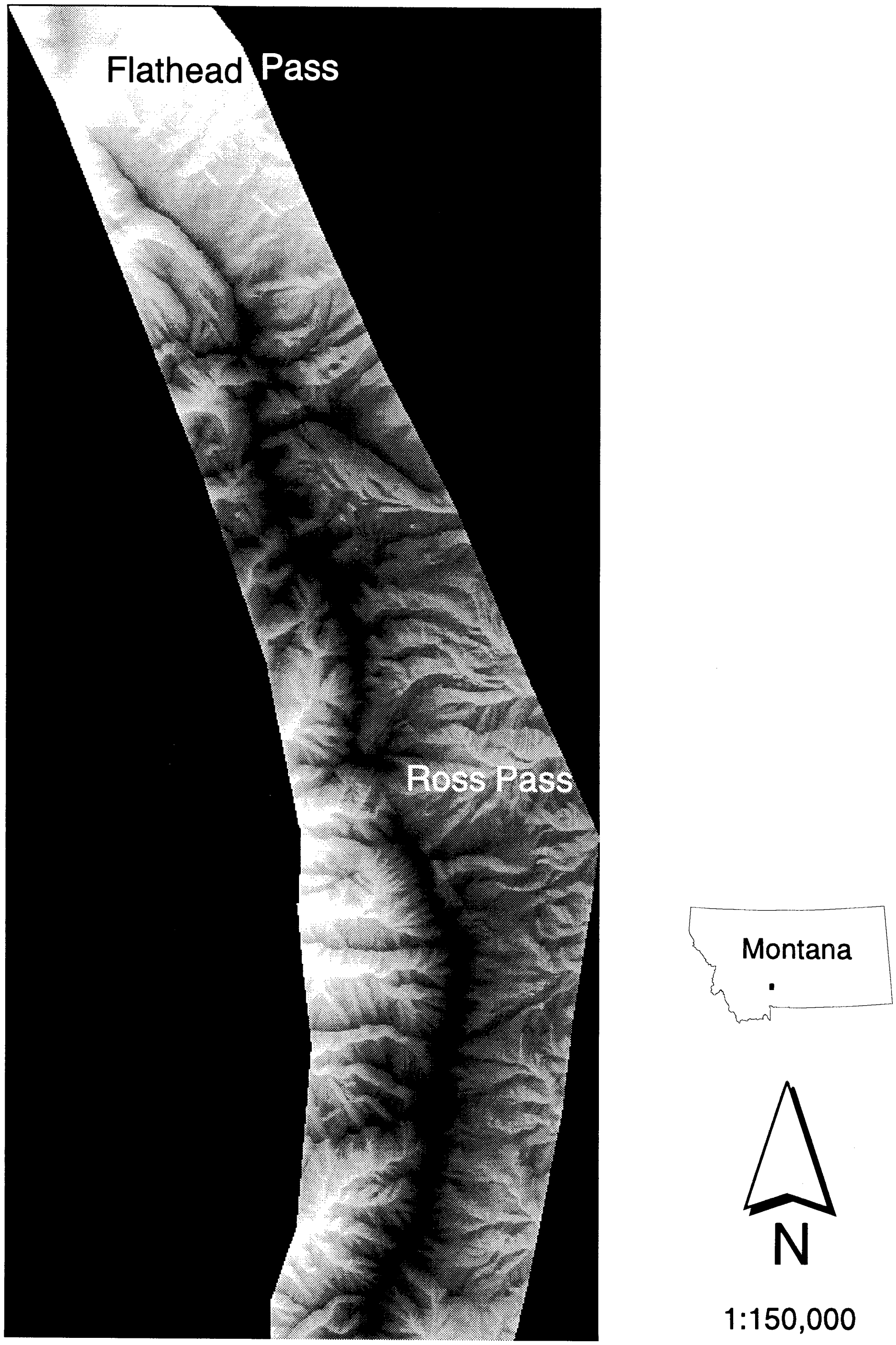


FIGURE 23: Map of the statistical relationship between weakest rutschblock failure (*rb wk*) and terrain. The darkest areas on the map represent the smallest rutschblock numbers (and most unstable conditions), while the whitest areas represent the largest rutschblock numbers (and most stable conditions).

*TFI sqrt* is dominated by the effects of elevation, with the highest elevations along the main Bridger ridge demonstrating the most unstable (represented by black) conditions (Figure 24). This map, however, shows the effects of aspect more clearly than the map for *rb wk*, in which aspect and location east share secondary importance in predicting stability.

*Modelling snow stability using terrain and snowpack variables*

Including snowpack as independent variables results in valid regression models for all stability variables except slab depths, with 20 to 33% of the variance of the dependent variables explained (Table 12). With snowpack added, four of the six models brought in the variable *loc n*. Though less important than other variables in the model, the positive standardized regression coefficients for *loc n* indicate that the areas farther north had increasingly stable conditions. Three of the six models (for *sb wk, FI sb wk*, and *FI sb wk rb*) included the transformed variable *t30 tf*, and in every case this was the most important variable in the model. Negative standardized regression coefficients again emphasize more unstable conditions in areas with colder snowpacks. Two models (for *sb wk* and *sb wk rb*) used *dpth* as a predictor of stability. In both cases stability decreased with increasing depth, perhaps because deeper snowpacks are typically found on colder, upper elevation slopes.

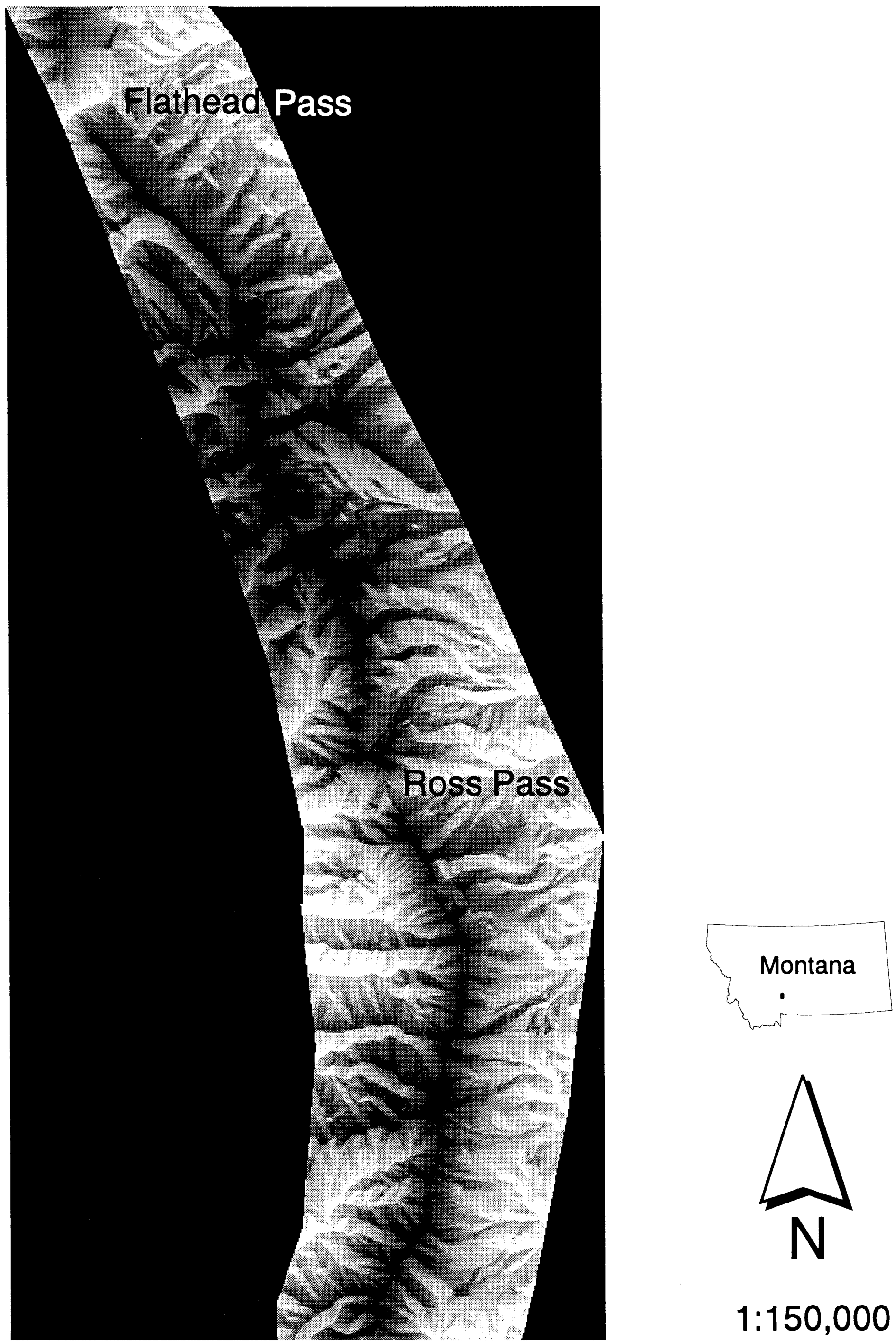


FIGURE 24: Map of the statistical relationship between the transformed total failure index (*TFI sqrt*) and terrain. The darkest areas on the map represent the smallest values of *TFI sqrt* (and most unstable conditions), while the whitest areas represent the largest values of *TFI sqrt* (and most stable conditions).

TABLE 12: Standardized partial regression coefficients and coefficients of determination (adjusted $R^2$) on April 2nd, 1997 for multiple regression models run with dependent stability and independent terrain and snowpack variables.

| Stability Variables | | Terrain Variables | | | | | | Snowpack Variables | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | *dpth* | *t30 tf* | *tgrad tf* | ***Adj. $R^2$*** |
| Slab Depth | *df wk sb* | | | | | | | | | | - |
| | *df wk rb sqrt* | | | | | | | | | | - |
| Stability of Weak Layer | *sb wk* | | .26 | | | | | -.36 | -.44 | | .33 |
| | *rb wk* | -.41 | | -.54 | | .23 | | | | | .28 |
| | *sb wk rb* | | .24 | -.47 | | | | -.30 | | | .29 |
| Stability indecies | *FI wk sb* | | .27 | | | | | | -.60 | | .24 |
| | *FI sb wk rb* | | .38 | | | | | | -.55 | | .22 |
| | *TFI sqrt* | | | -.32 | | .31 | | | | | .20 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$, $p < 0.025$ for data that are ordered or non-normal), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

Forward, stepwise, least squares regression resulted in several valid models for stability when terrain and snowpack were chosen as the dependent variables. The inclusion of snowpack variables increased the number of valid models produced from four to six, as well as increasing the amount of variance of *sb wk rb* and *Fl sb wk rb* explained by the models.

*Modelling snow stability using terrain, snowpack and snow stability variables*

Adding snow strength variables into the regression models resulted in valid models for every stability variable, with models explaining anywhere from 20% to almost 50% of the variance of the dependent variable (Table 13). Five of the eight models used *ram drp* as an independent variable, and in every case *ram drp* was the most important variable for predicting the variance of the dependent variable. It is interesting that no two models used the same independent variables, and the only *dis rdg, ang*, and *ram avg* were not used in any model. The usage of the various independent variables was remarkably even. Of the eight models, *ram drp* was brought into five of them, *t30 tf* and *dpth* were each brought into four models, *elev* and *loc n* were each brought into three models, while *loc e*, *RI*, and *tgrad tf* were each used in one model.

TABLE 13: Standardized partial regression coefficients and coefficients of determination (adjusted $R^2$) on April 2nd, 1997 for multiple regression models run with dependent stability variables and independent terrain, snowpack, and snow strength variables.

| Stability Variables | | Terrain Variables | | | | | | Snowpack Variables | | | Strength Variables | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | *dpth* | *t30 tf* | *tgrad tf* | *ram drp* | *ram avg* | ***Adj. $R^2$*** |
| Slab Depth | *df wk sb* | | | | | | | -.36 | -.33 | | .38 | | .22 |
| | *df wk rb sqrt* | | | -.46 | | | | | | | .52 | | .33 |
| Stability of Weak Layer | *sb wk* | | .26 | | | | | -.36 | -.44 | | | | .33 |
| | *rb wk* | -.41 | | -.54 | | .23 | | | | | | | .28 |
| | *sb wk rb* | | .24 | -.47 | | | | -.30 | | | | | .29 |
| Stability indecies | *FI wk sb* | | | | | | | | -.23 | | -.54 | | .43 |
| | *FI sb wk rb* | | .28 | | | | | | -.34 | | -.39 | | .33 |
| | *TFI sqrt* | | | | | | | -.31 | | -.25 | -.41 | | .47 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$; $p < 0.025$ for ordered or non-normal data), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

The best model, in terms of the amount of variance of the dependent variable that was explained, was for *TFI sqrt*. The following model explains 47% of the variance of *TFI sqrt*:

$$TFI\ sqrt = 1.29 - (6.06 \times 10^{-3})ram\ drp - (1.01 \times 10^{-3})dpth - (1.02 \times 10^{-1})tgrad$$

where *TFI sqrt* is the square root of the total failure index, *ram drp* is the initial ram drop in m, *dpth* is the total snow depth in m, and *tgrad* is the average temperature gradient in degrees C per m. This is the first quantitative representation of a stability index over a area the size of the present study.

### *Summary*

For the April 2nd data a number of strong statistical relationships allow the construction of valid regressions for every stability variable. Regression results strengthen previous conclusions that the most unstable conditions on the second sampling day could be found on high elevation, northerly facing slopes with deep, cold snowpacks that had weaker surface snow. There is also evidence that conditions were more unstable in the eastern and southern parts of the Bridgers. The April 2nd data yield two especially interesting results. First, the easily measured *ram drp* is a good predictor of stability on this day, implying that *ram drp* or some equivalent may be a fast and useful addition to a field stability test. Second, the numerous regression models, none of which use the same variables to predict stability, demonstrate quantitatively that there may be more than one way to predict snow stability.

**Temporal changes between February 6th and April 2nd**

The predictability of the spatial patterns of snow stability were significantly different between February 6th and April 2nd, though many of the underlying patterns appear to be similar. Some relationships between stability and terrain existed on February 6th, but those weak linkages prevented the generation of valid regression models (Table 14). On the other hand, four valid models linked stability to terrain on April 2nd. Even when including all snowpack and snow strength variables, there were only valid models for two of eight dependent variables on the February 6th. Meanwhile, adding those same variables allowed the successful modelling of all eight dependent variables on April 2nd.

Regression analyses confirm previous conclusions about the two sampling days. The fairly homogenous (and stormy) weather conditions in the months before the February 6th sampling day established a similarly homogenous snowpack. Thus, finding differences in snow stability between aspects, elevations, and locations was difficult. In other words, the spatial variability on that particular day was not so "variable". Increased weather

TABLE 14: Coefficients of determination (adjusted $R^2$) for forward, stepwise, multiple regressions run on data from both sampling days with stability variables chosen as the dependent variables, and terrain, terrain and snowpack, and terrain, snowpack and snow strength chosen as the independent variables.

| Stability Variables | | Terrain Variables | | Terrain, Snowpack Variables | | Terrain, Snowpack, Snow Strength Variables | |
|---|---|---|---|---|---|---|---|
| | | Feb. 6th | Apr. 2nd | Feb. 6th | Apr. 2nd | Feb. 6th | Apr. 2nd |
| Slab Depth | *df wk sb* | - | - | - | - | - | .22 |
| | *df wk rb sqrt* | - | - | - | .24 | - | .33 |
| Stability of Weak Layer | *sb wk* | - | - | - | .33 | - | .33 |
| | *rb wk sq* | - | .28 | - | .28 | - | .28 |
| | *sb wk rb* | - | .21 | - | .29 | - | .29 |
| Stability indecies | *FI wk sb tf* | - | - | - | .24 | - | .43 |
| | *FI sb wk rb* | - | .20 | .23 | .22 | .23 | .33 |
| | *TFI sqrt* | - | .20 | - | .20 | .15 | .47 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$; $p < 0.025$ for ordered or non-normal data), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

variability resulted in more snowpack variability on April 2nd, thereby facilitating the prediction of stability based on the independent variables.

The "valid" regression models generated for all eight dependent stability variables on April 2nd still only explained 20 to 50% of the variance of any one variable. A large amount of variance remains unexplained, and may be due to a number of factors. First, small scale terrain variability undoubtedly introduced unexplained variance into the data. Several researchers have demonstrated that small scale terrain variability due to rocks, trees, and wind that are not readily apparent to field observers can affect the snowpack properties of adjacent areas (Conway and Abrahamson, 1984; Fohn, 1988; Birkeland, 1990; Birkeland and others, 1995; Jamieson and Johnston, 1992). Secondly, though I made every effort to limit differences between sampling teams, unavoidable inconsistencies undoubtedly added to the inexact nature of the models. Finally, some of the data relationships may not be strictly linear. While scatterplots show the data relationships to be generally linear, problems with some variables may exist. For example, though depth typically increases with elevation, high elevation wind exposed areas (that are also prone to avalanching) may have either extremely shallow snowpacks (areas of wind scour) or excessively deep snowpacks (areas of wind deposition). In spite of the limitations, the generation of valid regression models for snow stability on a particular day is encouraging given such a large and diverse area.

## QUANTIFYING MULTIVARIATE INTERACTIONS USING CANONICAL CORRELATION ANALYSIS

The purpose of canonical correlation (CCA) analysis is to explore the multi-variate relationship between the variance of two different matrices. In essence, CCA involves running simultaneous principal components analyses on the two matrices, and then correlating those PCAs to identify a canonical vector pair. The canonical correlation, or canonical R, is simply the Pearson product moment correlation between the two vectors of the canonical pair. Canonical vector pairs are interpreted through canonical loadings, which are analogous to component loadings in principal components analysis. Loadings represent the proportion of variance in a variable shared with a matrix through a canonical vector.

For this study, the rows of the predictor and criteria matrices consisted of sample locations. In the first part of the analysis, the columns of the predictor matrix consisted of the terrain variables, and the criteria matrix consisted of the snow stability variables so that the relationship between terrain and stability could be discerned. Successive analyses added snowpack and then snow strength variables to the predictor matrix.

In order to discern the subtle patterns in the data, I carefully chose the variables to be included in each matrix. When I first ran CCA, results were difficult to interpret. The terrain matrix consists of two locational variables (*loc e* and *loc n*), and four variables that quantify local slope characteristics (*elev, dis rdg, RI*, and *slp ang*), and I was interested in whether location or local slope factors would be more strongly related to stability. In the local slope variables, the strong correlation between *elev* and *dis rdg* allowed these two variables to dominate the terrain matrix at the expense of the other terrain variables, specifically aspect (*RI*). Since *elev* consistently predicted stability better than *dis rdg* in previous analyses, I took *dis rdg* out of the terrain matrix, thereby greatly improving the interpretability of subsequent analyses. In addition, I wanted to emphasize the importance of the stability of the weak layer in the stability matrix, while still retaining some information about weak layer depth. I decided not to include the variable *df wk sb* because it is the least important of all the stability variables, and using it hindered the generation of significant canonical variates. Significance of specific canonical variates was determined by using the chi-square test with successive roots removed (Statsoft, 1994).

**February 6th**

*The relationship between snow stability and terrain*

On the first sampling day, CCA indicates that 13% of the variance of the terrain matrix is shared with 17% of the variance of the stability matrix

(Table 15). The canonical R for the relationship is 0.61. A chi-squared test with successive roots removed shows that while the first canonical pair is significant ($p = 0.06$), subsequent pairs are not ($p > 0.41$). The redundancies of each canonical pair shows that, through the first (and only significant) canonical pair, 6% of the variance of the terrain matrix is shared with 14% of the variance of the stability matrix.

Analyzing of the canonical loadings allows the interpretation of the first canonical variate (Table 16). Terrain variables that load most heavily on the first canonical variate are *elev*, which has the highest absolute loading at 0.66, and *RI*, which loads nearly as heavily at -0.56. All other variables load at levels less than 0.14. All snow stability variables loaded heavily (absolute loadings greater than 0.60) except for variables associated with the weakest stuffblock failure (*sb wk* and *FI sb wk*). These loadings indicate that this canonical variate explains the relationship between terrain and stability on February 6th, and that stability decreases with increasing elevation and increasingly northerly aspect. Thus, these results show a weak, but discernable, relationship exists between terrain and snowpack on the first sampling day, and that increasingly unstable conditions could be found on upper elevation, northerly facing slopes.

TABLE 15: Results of canonical correlation analysis with snow stability variables chosen as the criteria set, and terrain, terrain and snowpack, and terrain, snowpack and snow strength variables chosen as the predictor sets.

| | Predictor Set | | |
|---|---|---|---|
| | Terrain | Terrain, Snowpack | Terrain, Snowpack, Strength |
| ***February 6th, 1997*** | | | |
| Total variance extracted (criteria set) | 68% | 100% | 100% |
| Total variance extracted (predictor set) | 100% | 89% | 73% |
| Total redundancy (criteria set) | 17% | 21% | 26% |
| Total redundancy (predictor set) | 13% | 12% | 11% |
| Canonical R | 0.61 | 0.65 | 0.68 |
| Number of significant canonical roots* | 1 | 0 | 0 |
| p-value of root(s) | 0.06 | > 0.29 | > 0.21 |
| ***April 2nd, 1997*** | | | |
| Total variance extracted (criteria set) | 83% | 100% | 100% |
| Total variance extracted (predictor set) | 100% | 94% | 78% |
| Total redundancy (criteria set) | 22% | 35% | 45% |
| Total redundancy (predictor set) | 23% | 26% | 29% |
| Canonical R | 0.63 | 0.73 | 0.80 |
| Number of significant canonical roots* | 2 | 2 | 2 |
| p-value of root(s) | 0.00, 0.03 | 0.00, 0.02 | 0.00, 0.00 |

* significance of roots tested with a chi-squared test with successive roots removed.

TABLE 16: Canonical weights on each pair of significant canonical variates for a canonical correlation analysis run for data from February 6th, 1997 with stability variables chosen as the criteria set and terrain variables chosen as the predictor set.

| | 1st Canonical Variate (p = 0.06) |
|---|---|
| Terrain | |
| *loc e* | .05 |
| *loc n* | .00 |
| *elev* | .66 |
| *RI* | -.56 |
| *ang* | -.14 |
| Stability | |
| *df wk rb sqrt* | -.62 |
| *sb wk* | -.38 |
| *rb wk sq* | -.69 |
| *sb wk rb* | -.82 |
| *FI wk sb tf* | -.32 |
| *FI sb wk rb* | -.63 |
| *TFI sqrt* | -.62 |

*The relationship between snow stability and terrain and snowpack variables*

The addition of snowpack variables to the predictor matrix resulted in no significant canonical pairs ($p > 0.29$) (Table 15). The weak relationships between stability and snowpack variables on this sampling day meant that adding snowpack variables did not allow the generation of any significant canonical variates.

*The relationship between stability and terrain, snowpack and strength variables*

As with the relationship discussed above, the addition of strength variables to the predictor matrix resulted in no significant canonical variates ($p > 0.21$) (Table 15).

*Summary*

CCA successfully established a relationship between terrain and stability on February 6th, with more unstable conditions at higher elevations and on more northerly aspects. Although the relationship is not strong, CCA provides solid evidence of the underlying spatial distribution of instability over the alpine landscape on this sampling day.

**April 2nd**

*The relationship between stability and terrain*

CCA successfully established linkages between stability and terrain on the second sampling day. When I chose stability as the criteria matrix and terrain as the predictor matrix, CCA indicated that 22% of the total variance of the stability matrix is shared with 23% of variance of the terrain matrix (Table 15). This analysis resulted in two significant canonical variates ($p < 0.03$).

An analysis of the redundancies associated with the first canonical variate indicate that 17% of the variance of the stability matrix is shared with 7% of the terrain matrix through this variate. Canonical loadings on the terrain variables indicates that *elev* loads the most heavily at -0.77, with *RI* the next most important variable at 0.40 (Table 17). The absolute loadings of all other variables are less than 0.24. Of the stability variables, only *df wk rb sqrt* loads less than 0.50, and all the other variables except *sb wk* load more heavily than 0.60. The most dominant variable is *rb wk* with a loading of 0.91. These results provide further evidence for increasingly unstable conditions at higher elevations and on more northerly aspects, and also indicate that the primary control on instability at the scale of this investigation may be local factors such as elevation and aspect rather than location within the mountain range, as measured by *loc e* and *loc n*.

TABLE 17: Canonical weights on each pair of significant canonical variates for a canonical correlation analysis run for data from April 2nd, 1997 with stability variables chosen as the criteria set and terrain variables chosen as the predictor set.

| | 1st Canonical Variate ($p < 0.00$) | 2nd Canonical Variate ($p = 0.03$) |
|---|---|---|
| Terrain | | |
| *loc e* | -.09 | -.93 |
| *loc n* | .16 | .80 |
| *elev* | -.77 | .52 |
| *RI* | .40 | -.11 |
| *ang* | -.24 | -.56 |
| Stability | | |
| *df wk rb sqrt* | .21 | -.47 |
| *sb wk* | .51 | -.41 |
| *rb wk* | .91 | -.10 |
| *sb wk rb* | .79 | -.30 |
| *FI wk sb* | .61 | -.24 |
| *FI sb wk rb* | .66 | -.04 |
| *TFI sqrt* | .64 | -.34 |

A total of 14% of the variance of the terrain matrix is shared with about 3% of the variance of the stability matrix through the second canonical variate. This second variate better represents location. Terrain variables that load most heavily on this variate include *loc e* and *loc n*, as well as lesser loadings on *elev* and *ang* (Table 17). However, none of the stability variables load at absolute levels heavier than 0.50, further emphasizing that, at the scale of this study, local factors may be more important than location when determining instability. The two stability variables *df wk rb sqrt* and *sb wk* load the most heavily on this canonical variable. Thus, this second canonical variate only establishes a weak relationship between location and some of the stability variables.

*The relationship between stability and terrain and snowpack variables*

When snowpack variables are added to the predictor matrix, CCA results in 35% of the stability matrix being shared with 26% of the terrain/snowpack matrix (Table 15). Adding snowpack variables increases the canonical R from 0.63 to 0.73, and results in two significant ($p < 0.02$) canonical variates.

Redundancies associated with the first canonical variate indicate that 26% of the variance of the stability matrix is shared with 13% of the terrain/snowpack matrix through the first canonical variate. The loadings on this variate indicate that, in the terrain/snowpack matrix, *elev* and all the snowpack variables load the most heavily, with absolute loadings greater than 0.62 (Table 18). A number of stability variables load heavily on the variate, with *sb wk, rb wk, sb wk rb*, and *TFI sqrt* all loading more heavily than 0.7 and *FI wk sb* and *FI sb wk rb* loading at levels greater than 0.57. This canonical variate shows that elevation and snowpack variables relate strongly to snow stability on this particular day, with more unstable conditions at higher elevations with deeper, colder snowpacks that have stronger temperature gradients.

Only 7% of the terrain matrix is shared with 3% of the stability matrix through the second canonical variate, though this variate is also significant (Table 18). Terrain/snowpack variables that load heavily on this variate include *loc e, loc n*, and, to a lesser extent *ang*. The only stability variate that loads greater than 0.5 on this variate is *df wk rb sqrt*. This second variate only establishes a weak link between slab depth and location.

*The relationship between stability and terrain, snowpack and strength*

A final CCA added strength variables to terrain and snowpack variables to create the predictor matrix. This analysis again resulted in two significant canonical variates ($p < 0.00$) (Table 15). The total redundancies for the relationship show that 45% of the variance of the stability matrix is shared with 30% of the terrain/snowpack/strength matrix through seven canonical pairs, and the canonical R increased to 0.80.

TABLE 18: Canonical weights on each pair of significant canonical variates for a canonical correlation analysis run for data from April 2nd, 1997 with stability variables chosen as the criteria set and terrain and snowpack variables chosen as the predictor set.

| | 1st Canonical Variate ($p < 0.00$) | 2nd Canonical Variate ($p = 0.02$) |
|---|---|---|
| Terrain and Snowpack | | |
| *loc e* | .17 | -.79 |
| *loc n* | -.09 | .74 |
| *elev* | -.71 | .24 |
| *RI* | .37 | .12 |
| *ang* | -.02 | -.54 |
| *dpth* | -.66 | .31 |
| *t30 tf* | -.67 | .11 |
| *tgrad tf* | -.62 | .05 |
| Stability | | |
| *df wk rb sqrt* | .36 | -.56 |
| *sb wk* | .75 | -.06 |
| *rb wk* | .87 | .36 |
| *sb wk rb* | .79 | -.07 |
| *FI wk sb* | .58 | .21 |
| *FI sb wk rb* | .57 | .36 |
| *TFI sqrt* | .79 | .08 |

Loadings on the first canonical variate indicate that *ram drp* is the most important variable from the terrain/snowpack/strength matrix in explaining the canonical variate, though *t30 tf* and *tgrad tf* also load at absolute levels greater than 0.50 (Table 19). Stability variables that load most heavily on this variate (loadings greater than 0.75) include *rb wk* and the three failure indices. About 12% of the variance of the terrain/snowpack/strength matrix is shared with 28% of the variance of the stability matrix through this first canonical pair. This CCA shows a strong connection between stability and surface snow strength, subsurface temperature, and temperature gradient existed on April 2nd.

The second canonical variate loads most heavily (absolute loadings greater than 0.5) on the terrain/snowpack/strength variables *elev*, *dpth*, and *loc e* (Table 19). Stability variables loading heavily on this vector pair are *df wk rb sqrt* and *sb wk rb*. An analysis of the redundancies indicates that about 10% of the variance of the terrain/snowpack/strength matrix is shared with 10% of the stability matrix though this canonical variate.

*Summary*

CCA confirmed the conclusions of the previous analyses for the April 2nd data. Strong and significant statistical linkages are established between stability and the other variables. Stability is closely tied to the terrain variables elevation and aspect, with increasing elevations and increasingly

TABLE 19: Canonical weights on each pair of significant canonical variates for a canonical correlation analysis run for data from April 2nd, 1997 with stability variables chosen as the criteria set and terrain, snowpack, and snow strength variables chosen as the predictor set.

| | 1st Canonical Variate ($p < 0.00$) | 2nd Canonical Variate ($p < 0.00$) |
|---|---|---|
| Terrain, Snowpack, and Strength | | |
| *loc e* | -.11 | .53 |
| *loc n* | .15 | -.46 |
| *elev* | -.40 | -.65 |
| *RI* | .38 | .12 |
| *ang* | -.19 | .27 |
| *dpth* | -.36 | -.60 |
| *t30 tf* | -.55 | -.41 |
| *tgrad tf* | -.52 | -.35 |
| *ram drp* | -.86 | .09 |
| *ram avg* | .19 | -.62 |
| Stability | | |
| *df wk rb sqrt* | -.29 | .81 |
| *sb wk* | .55 | .45 |
| *rb wk* | .75 | .37 |
| *sb wk rb* | .41 | .65 |
| *FI wk sb* | .81 | .05 |
| *FI sb wk rb* | .75 | .02 |
| *TFI sqrt* | .84 | .30 |

northerly aspects having the most unstable conditions. When snowpack variables are considered, stability is related to all snowpack variables, demonstrating that deeper, colder snowpacks had more unstable conditions on this particular day. Finally, surface snow strength is again demonstrated to be a significant contributor to the explanation of stability patterns observed, with areas that had the softest surface conditions also having the most unstable conditions.

**Temporal changes between February 6th and April 2nd**

CCA confirmed the results of the previous analyses. A much stronger relationship between terrain, snowpack, strength and snow stability existed on April 2nd than on February 6th. However, CCA quantified a weak relationship between elevation, aspect and stability on the first sampling day. On the second day a similar pattern emerges, although the relationship is much more pronounced. Thus, similar spatial patterns existed for the two days, though the magnitude of the relationships differs markedly.

The CCA provides additional valuable information. In all cases local terrain variables such as elevation and aspect are more closely associated with stability than location (as measured by *loc e* and *loc n*) within the mountain range. This implies that local slope factors are more important than location within the range at the scale of this particular study, suggesting that the Bridgers comprised a single avalanche region during the present research.

## TESTING FOR AVALANCHE REGIONS USING CLUSTER ANALYSIS AND ANOVA

CCA suggests the Bridger comprise a single avalanche region, with differences in aspect and elevation dominating changes in location. However, I hypothesized that up to three different avalanche regions occasionally exist in this small range based on my experience (Figure 7). To quantitatively test for the presence of distinct regions, I used principal components analysis (PCA) on the snowpack and stability data to generate orthogonal components for use in cluster analysis. The resultant clusters showed no discernable spatial patterns, strengthening the conclusion that local factors are dominating locational factors in determining stability.

Since I was unable to arrive at distinct regions through cluster analysis, I used my hypothesized avalanche regions (Figure 7), and tested for differences in stability variables using analysis of variance (ANOVA). I divided the range up three different ways: 1) the area north and south of Sacajawea (two regions), 2) the area north of Sacajawea, the area from Ross Pass to Sacajawea, and the area south of Ross Pass (three regions), and 3) the areas north and south of Ross Peak (two regions). Applying these three divisions for separate ANOVAs using all the April 2nd stability variables resulted in a significant difference for only one of the eight stability variables (Table 20), thereby providing further evidence that the Bridgers consisted of a single avalanche region on this particular day.

TABLE 20: P-values for a Kruskal-Wallis analysis of variance (ANOVA) test for April 2nd, 1997 for hypothetical "avalanche regions" (as shown in Figure 7) within the Bridgers.

| | Hypothetical Avalanche Regions | | |
|---|---|---|---|
| Stability variable | N. of Sacajawea, S. of Sacajawea (2 regions) | N. of Sacajawea, Sacajawea to Ross Pass, S. of Ross Pass (3 regions) | N. of Ross Pass, S. of Ross Pass (2 regions) |
| df wk sb | ***0.02*** | ***0.04*** | ***0.03*** |
| df wk rb | 0.10 | 0.21 | 0.11 |
| sb wk | 0.22 | 0.46 | 0.54 |
| rb wk | 0.16 | 0.27 | 0.12 |
| sb wk rb | 0.77 | 0.94 | 0.97 |
| FI wk sb | 0.59 | 0.83 | 0.90 |
| FI sb wk rb | 0.20 | 0.44 | 0.39 |
| TFI | 0.42 | 0.62 | 0.94 |

Relationships significant at $p < 0.05$ in ***bold/italics***.

The highly dynamic nature of snow stability makes generalizations about specific avalanche regions difficult. Results reported above change on a seasonal, monthly or even daily time scale depending on the weather factors affecting snow stability. However, evidence that the Bridgers are a single avalanche region is convincing since forecasters have largely considered this to be the case during the majority of the seven winters that forecasts have been issued for the range.

## CONCLUSIONS

On the February 6th only a subtle relationship exists between snow stability and terrain, snowpack and strength variables. There are few significant correlations between variable pairs (Table 7, Figures 19 and 20), few valid regression models (Tables 9 and 10), and only one significant canonical variate produced through canonical correlation analysis (Table 15). The nature of the relationships can largely be explained by the weather leading up to the sampling day. Prolonged storms with little sunshine and remarkably uniform snowfall led to similarly uniform stability conditions. In spite of the subtle relationships, some patterns do emerge from the data, with more unstable conditions on high elevation, northerly-facing, colder slopes. There less evidence that stability decreases with decreasing snow surface hardness, and in the more southerly and easterly parts of the Bridgers.

By the April 2nd more heterogenous weather conditions created increasingly discernable differences in the snowpack, and this is reflected in the data. There are statistically significant correlations between many variable pairs (Table 8, Figures 21 and 22), numerous valid regression models (Tables 11, 12 and 13), and three different canonical correlation analyses each produced two significant canonical variates (Table 15). All of the results confirm that increasingly unstable conditions existed at higher elevations, on more northerly aspects, in areas with deeper, colder snow, and in areas with softer surface snow on April 2nd. In addition, there is some evidence that more unstable conditions existed in the southerly and easterly areas of the Bridgers.

Though the statistical strength of snow stability's relationship with terrain, snowpack and strength variables varies between the sampling days, the relationships observed are surprisingly similar. On both days more unstable conditions existed in the southerly and easterly parts of the mountain range, and on upper elevation, northerly facing slopes. The quantification of this latter relationship is interesting, since avalanche forecasters have long suspected and observed more unstable conditions on shady, high elevation slopes. Not only are higher elevation areas exposed to more wind, which implies that there is more wind loading, deeper slabs, and more load on the weak layer, but they are also colder. Snow changes form quickly in the mountain snowpack, but the rate of change is highly temperature dependent. Colder areas change more slowly, so weaker layers tend to persist longer in these locations.

The data support the conclusion that the Bridgers comprise a single avalanche region, with local slope factors such as aspect and elevation dominating location within the range in affecting snow stability. Indeed, the idea of aspect and elevation dominating location is used by avalanche forecasters to define avalanche regions. To better visualize the Bridger Range avalanche region, I created a map based on elevation and aspect that defines the spatial patterns of stability observed in this research (Figure 25). On this map I combine elevation (which is given a value from 0 to 50, where 50 is the highest elevation and zero is the lowest) and aspect (*RI*, with due north aspects receiving a value of 50 and due south receiving zero) to arrive at a number between 0 and 100. The map weights elevation and aspect the same, which may be somewhat misleading since elevation dominated aspect in predicting stability in this research. Still, the statistical analyses consistently show instability increasing with increasing elevation and northerly aspect. Thus, this map represents the instability space for the Bridgers, with higher values (represented by black on the map) generally associated with more unstable conditions on the two sampling days.

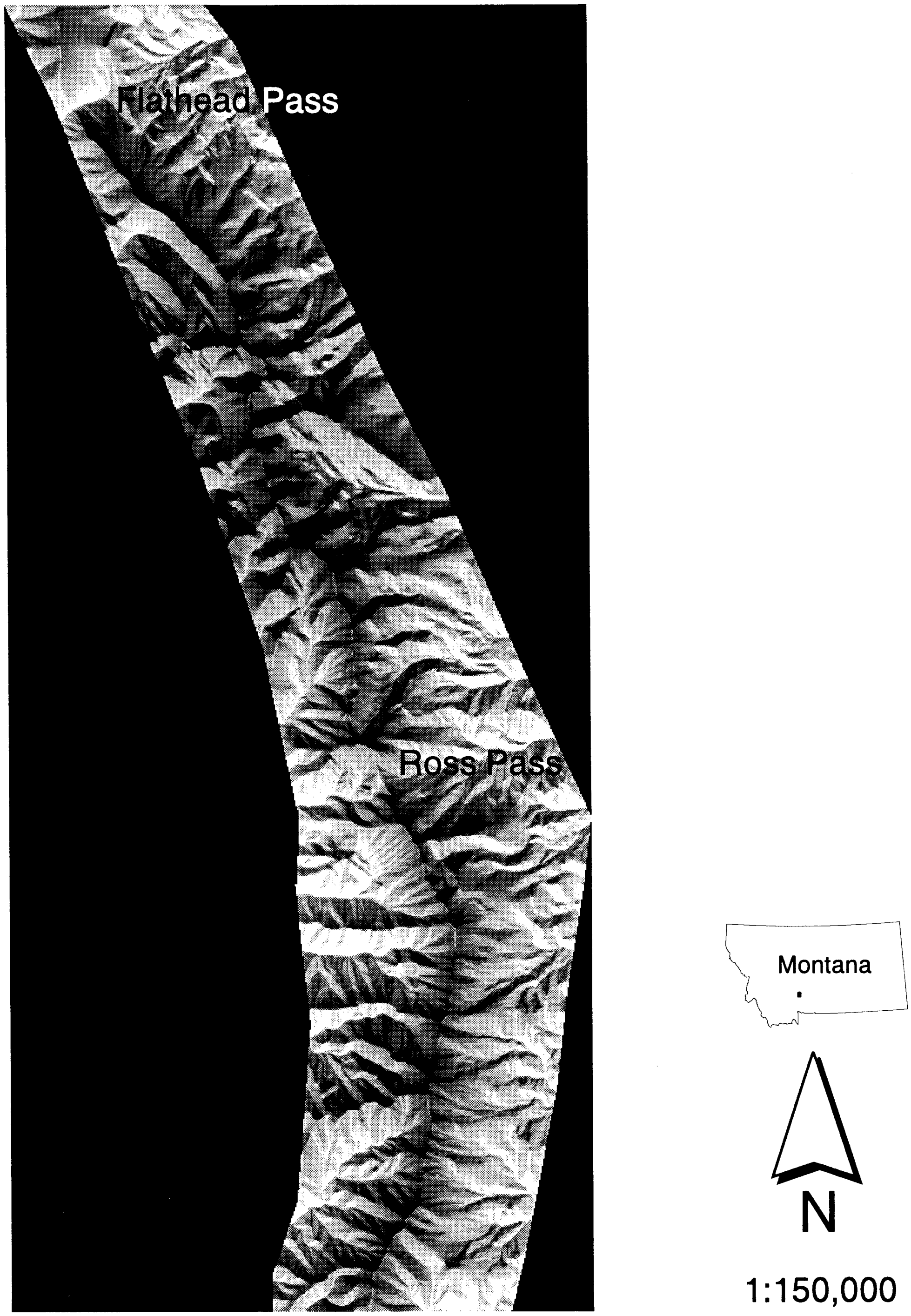


FIGURE 25: Combined aspect and elevation map of the core of the Bridger Range. Higher elevation north aspects are shown in black and lower elevation south aspects are shown in white. This research consistently demonstrated increasing instability on higher elevation, northerly aspects.

It is emphasized that this research merely provides two quick snapshots of an extremely dynamic system. Though more unstable conditions are often observed at higher elevations and on more northerly aspects, this is only the roughest of guidelines for avalanche forecasters during what might be considered "typical" conditions. However, avalanche forecasters often face atypical conditions where such guidelines do not apply. For example, Schweizer and others (1996) documented a layer of surface hoar which formed only within a specific elevational range, thereby creating dangerous instabilities at mid-elevations and more stable snowpacks at higher elevations. Likewise, during the 1995-96 season the Bridgers had a much thinner early season snowpack at low elevations. This thinner snowpack led to increased temperature gradients, weaker snowpacks, and more unstable conditions than upper elevation areas by mid-season. I have also observed a number of examples where increasingly unstable conditions have been found on southerly facing slopes due to the formation of dangerous weak layers on those aspects.

The only relationship that differs markedly between the two sampling days is the relationship between *ram drp* and stability. On the first day, surface snow strength is positively correlated with *sb wk*, and there was also a positive relationship between *ram drp* and *TFI sqrt* when a regression model was generated. This relationship may be just due to chance, since no clear conclusions can be drawn with the other stability variables.

Alternately, it may be because the soft surface snow, which largely consisted of small grained faceted snow formed by diurnal recrystallization (Birkeland, under review), cushioned the stuffblock and reduced the amount of energy transmitted to the weak layer. On the second day correlation, regression, and canonical correlation analyses all provide evidence that increasing *ram drp* values are associated with more unstable conditions. On this day the instability was largely due to a storm the night before, and the ram often dropped through the depth of the new, soft snow. New snow is better bonded than faceted crystals and therefore transmits energy from the stuffblock to the weak layer more effectively. In addition, areas with more new snow have greater stresses on the weak layer, further decreasing stability and accounting for the relationship between *ram drp* and stability.

One interesting result from this research is that the numerous regression models generated for the April 2nd data each used different inputs to predict stability when given the same array of independent variables (Table 13). The stability variables are similar, and one would expect that the models generated to predict them would be similar. The differences between the models emphasize the underlying data complexity, and some of the difficulties that avalanche scientists face when trying to understand and predict avalanches. When LaChapelle (1980) asked various avalanche forecasters with similar forecasting success rates to identify the data they used for avalanche forecasting, and which data were the most important, they chose different variables and weighed them differently. He concluded that "there is more than one way to predict avalanches given conventional means." The data from this research suggest that, quantitatively, there is more than one way to predict snow stability. The low coefficients of determination also indicate that many more complicating factors than the ones measured in this research might have to be considered by avalanche forecasters to arrive at accurate forecasts, and that additional variables or combinations of variables have to be considered by snow scientists to better understand patterns of stability.

# Chapter V

## Spatial and Temporal Variations in Snow Strength

### OVERVIEW

This results and discussion chapter evaluates the spatial patterns and temporal changes of snow strength on the two sampling days. As with the analysis of snow stability, I establish linkages between snow strength and terrain and snowpack variables. Since just two strength variables exist, rather than the eight stability variables analyzed in the previous chapter, and since these two variables are quite different from each other, this chapter is organized by variable.

I first discuss surface snow strength, as measured by the initial ram drop, and its relationship to the terrain variables (path 1 in Figure 4) before analyzing the relationship of ram drop to both terrain and snowpack (paths 1 and 2 in Figure 4). Then I do the same set of analyses for average ram strength. Descriptive statistics, correlations, and regression are used to interpret the data.

## THE DATA

As with the stability data, I generated two dimensional space/attribute data matrices for each sampling day, with the rows representing the sampling locations and the columns representing the terrain, snowpack and snow strength variables (Table 2). Though most data were normally distributed, *ram avg* on the first day and *t30* and *tgrad* on the second day were not. Once transformed, these variables did not deviate from normality as tested by the Kolmogorov-Smirnov one sample test (Massey, 1950) at $p < 0.05$ (Table 5).

Since *loc e* and *loc n* shared more than 50% of their variance and *elev* and *dis rdg* shared close to 50% of their variance on both sampling days, and *t30 tf* and *tgrad tf* were highly correlated on the second sampling day, I used only one or the other of each of these variable pairs with regression analysis to insure that the independent variables were truly independent, thereby obviating problems associated with multicollinearity.

## DESCRIPTIVE STATISTICS

Descriptive statistics, which I discussed in the previous chapter, but are briefly reviewed. Between the two sampling days *dpth, t30, tgrad,* and *ram avg* all increased significantly (Table 6). There was no significant change in *ram drp* between the two days. Thus, the snowpack became deeper, warmer, and stronger, all common temporal changes in the seasonal snowpack. Though the snow surface strength was similar, the surface snow structure differed. On February 6th the snow surface consisted of small grained faceted crystals formed through diurnal recrystallization (Birkeland, under review), while on April 2nd the soft surface snow was composed of new stellar crystals deposited by snowfall within the previous 36 hours.

## SURFACE SNOW STRENGTH

### February 6th

#### *The relationship between initial ram drop and terrain variables*

Significant correlations existed between ram drop and every terrain variable except for *dis rdg* and *RI* on the first sampling day (Table 21, Figure 26). *Ram drp* was positively correlated to *loc e* and *ang*, and negatively correlated to both *loc n* and *elev*, indicating stronger surface snow in upper elevation, northerly and westerly locations. Forward, stepwise, least squares multiple regression showed *ram drp* could be predicted given the

TABLE 21: Spearman rank order correlations between snow strength and terrain and snowpack variables.

| Snow Strength Variables | | Terrain Variables | | | | | | Snowpack Variables | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | *dpth* | *t30* | *tgrad* |
| February 6th | *ram drp* | ***.62*** | ***-.55*** | ***-.30*** | -.04 | -.13 | ***.25*** | -.15 | .23 | .13 |
| | *ram avg* | ***-.64*** | ***.52*** | ***.30*** | .01 | .00 | -.15 | ***.37*** | ***-.48*** | .17 |
| April 2nd | *ram drp* | -.11 | .04 | ***.35*** | ***-.43*** | ***-.37*** | .13 | ***.26*** | ***-.42*** | ***-.39*** |
| | *ram avg* | ***-.48*** | ***.41*** | ***.40*** | .03 | .00 | -.23 | .18 | ***-.45*** | ***-.44*** |

Note: correlations in ***bold/italics*** are significant at $p < 0.05$.

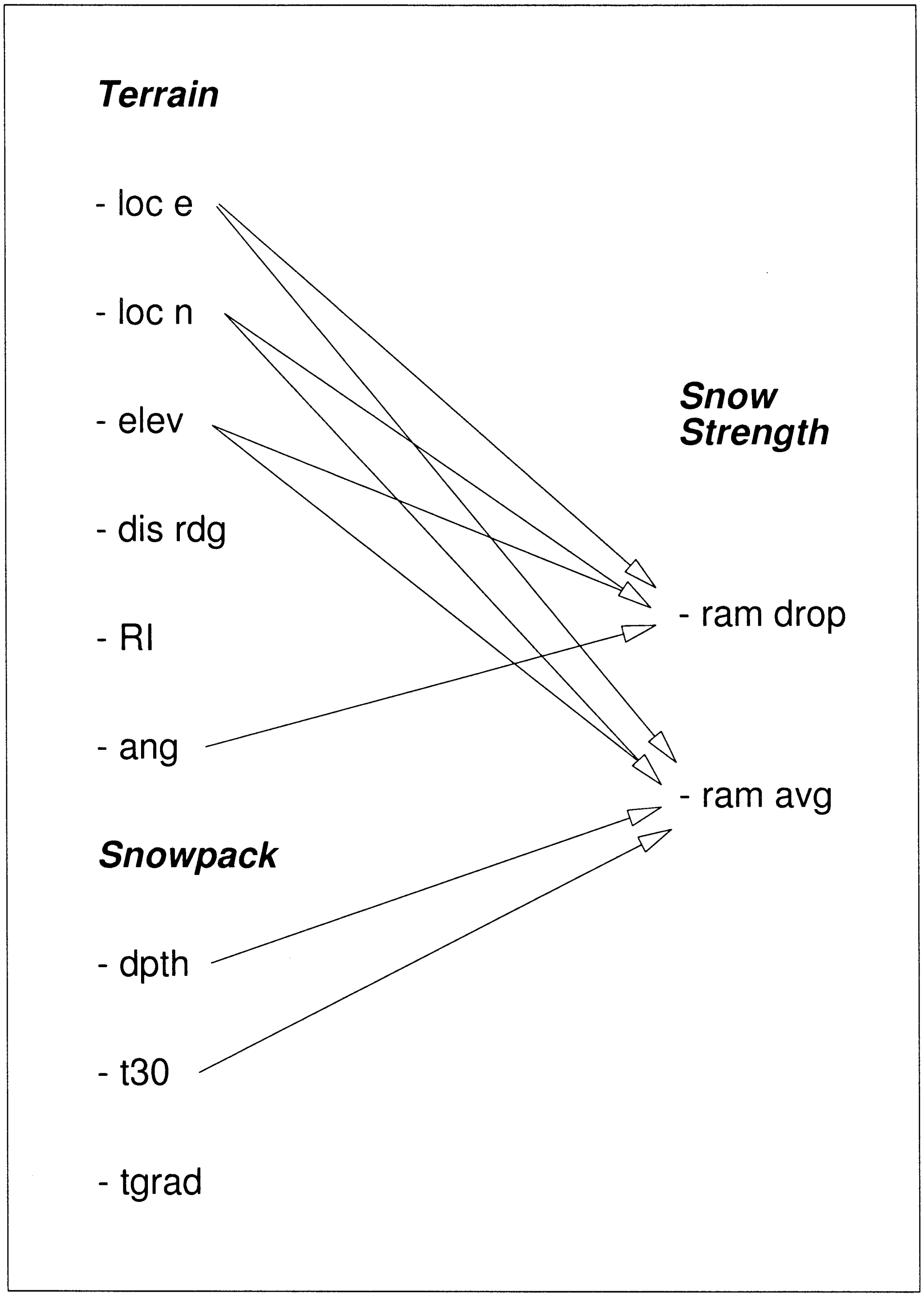


FIGURE 26: Visual representation of Table 21 showing the significant ($p < 0.05$) correlations between terrain, snowpack, and snow strength variables on February 6th.

terrain variables *loc e* and *RI*, with the following model explaining nearly 50% of the variance of *ram drp* (Table 22):

$$ram\ drp = (5.62 \times 10^{-1})loc\ e - (6.3)RI - 279223$$

where *ram drp* is the initial ram drop in m, *loc e* is the location of the site in UTM meters east, and *RI* is the radiation index in degrees away from north. The standard error for the model is 0.09 m. A comparison of the standardized regression coefficients shows that *loc e* is about three times more important than *RI* in explaining the variance of *ram drp*. The standardized partial regression coefficient of *RI* is negative, demonstrating increased surface hardness on southerly facing slopes.

There is a clear spatial pattern of *ram drp* on February 6th, with surface snow strength increasing at higher elevations, on more southerly aspects, and in areas that are farther north and west. The effects of elevation and location are probably due to wind exposure, since higher elevations and the northern Bridgers are windier. Further, as discussed in the methods chapter, the areas farthest west are also in the northern Bridgers due to the slight westerly tilt of the range north of Ross Pass (Figure 6), and I have observed these areas to be consistently windier than the southern part of the range. Increased wind exposure creates harder surfaces in those locations. Surface snow strength also increased on southerly aspects because a few days of sunshine prior to the sampling day created a surface melt-freeze crust on many southerly aspects, thereby

TABLE 22: Standardized partial regression coefficients and coefficients of determination (adjusted $R^2$) for forward, stepwise, least squares regression models run with strength variables chosen as the dependent variables, and terrain variables chosen as the independent variables.

| Snow Strength Variables | | Terrain Variables | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | ***Adj. $R^2$*** |
| February 6th | *ram drp* | .70 | | | | -.22 | | .48 |
| | *ram avg sqrt* | -.68 | | | | | | .46 |
| April 2nd | *ram drp* | | | | | | | - |
| | *ram avg* | -.54 | | | | | | .28 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

decreasing *ram drp*. In addition, protected and colder locations are more favorable for forming the deep layers of soft, diurnally recrystallized near-surface faceted crystals (Birkeland, under review) that made up the snow surface on this sampling day.

*The relationship between initial ram drop and terrain and snowpack variables*

On February 6th, *ram drp* is not significantly correlated to any snowpack variables (Table 21, Figure 26). Not surprisingly, adding these variables to terrain as the independent variables in regression analysis does not change the regression model (Tables 23 and 24).

*Summary*

On the first sampling day several statistically significant relationships between *ram drp* and terrain variables exist, and a regression model explained almost 50% of the variance of *ram drp*. However, *ram drp* is not significantly correlated with the snowpack variables, and the addition of these variables does not improve the predictability of the regression model.

TABLE 23: Standardized partial regression coefficients and coefficients of determination (adjusted $R^2$) for forward, stepwise, least squares regression models run with strength variables chosen as the dependent variables, and terrain and snowpack variables chosen as the independent variables.

| Snow Strength Variables | | Terrain Variables | | | | | | Snowpack Variables | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | *dpth* | *t30* | *tgrad* | ***Adj. $R^2$*** |
| February 6th | *ram drp* | .70 | | | | -.22 | | | | | .48 |
| | *ram avg sqrt* | -.59 | | | | | | .22 | | | .49 |
| April 2nd | *ram drp* | .31 | | | | | | | .57 | | .22 |
| | *ram avg* | -.29 | | | | .40 | | .23 | | .58 | .49 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

TABLE 24: Coefficients of determination (adjusted $R^2$) for forward, stepwise, multiple regressions run on data from February 6th and April 2nd, 1997 with snow strength variables chosen as the dependent variables, and terrain, terrain and snowpack, and terrain and snowpack chosen as the independent variables.

| Strength Variables | | Terrain Variables | Terrain, Snowpack Variables |
|---|---|---|---|
| February 6th | *ram drp* | .48 | .48 |
| | *ram avg sqrt* | .46 | .49 |
| April 2nd | *ram drp* | - | .23 |
| | *ram avg* | .28 | .49 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

**April 2nd**

*The relationship between initial ram drop and terrain variables*

On the second sampling day *ram drp* was significantly positively correlated with *elev*, and negatively correlated with *dis rdg* and *RI* (Table 21, Figure 27). Using terrain as the dependent variables in multiple regression analysis results in no valid model (Table 22). On April 2nd the linkages

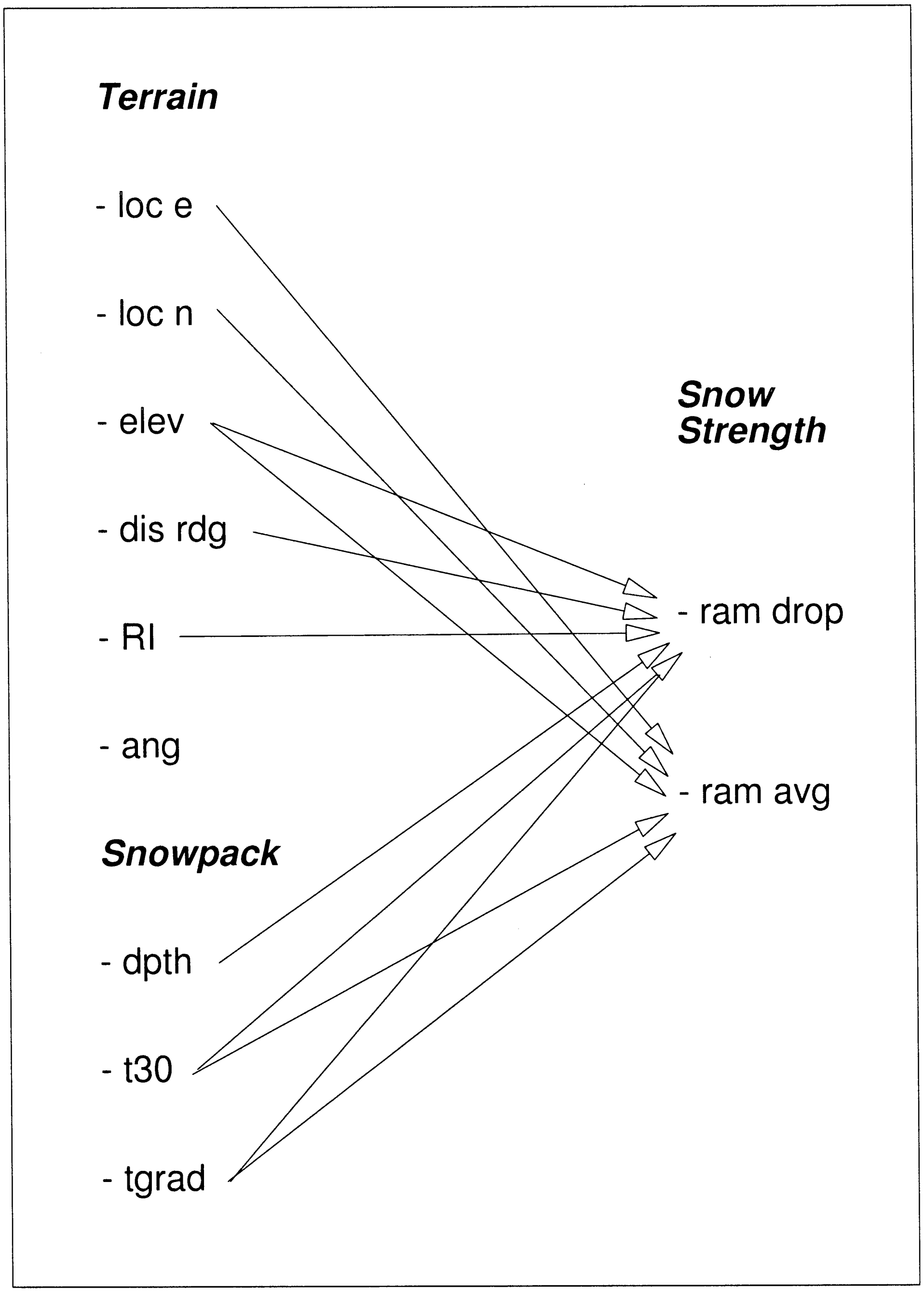


FIGURE 27: Visual representation of Table 21 showing the significant ($p < 0.05$) correlations between terrain, snowpack, and snow strength variables on April 2nd.

between *ram drp* and terrain are weaker than on the first day, and the relationship with elevation is reversed.

*The relationship between initial ram drp and terrain and snowpack variables*

Unlike the first sampling day, *ram drp* is significantly correlated with all of the snowpack variables on April 2nd (Table 21, Figure 27). Initial ram drop is positively correlated with *dpth*, and negatively correlated with *t30* and *tgrad*, demonstrating greater values of *ram drp* in areas with deeper, colder snowpacks.

Adding snowpack to terrain as the independent variables in a multiple regression analysis resulted in a valid model that explained 22% of the variance of *ram drp* based on *loc e* and *t30 tf* (Tables 23 and 24). The standardized partial regression coefficients indicate that *t30 tf* is about twice as important in explaining the variance of *ram drp* as *loc e*. This again demonstrates the dominance of local slope variables over locational variables when assessing snow properties at the scale of this investigation.

*Summary*

On the second sampling day *ram drp* was statistically linked to *elev, RI*, and all the snowpack variables. Though no valid regression models used only terrain as the independent variables, adding snowpack variables resulted in a regression model that explained 22% of the variance in *ram drp* using *loc e* and *t30 tf*. The statistical evidence indicates that *ram drp* was highest on this particular day on high elevation, northerly aspects with deep, cold snowpacks in the western part of the area sampled.

**Temporal changes between February 6th and April 2nd**

A comparison of the spatial distribution of *ram drp* on the two sampling days reveals similarities and differences. On both days surface snow softness decreased with increasingly southerly aspect, an observation that was likely due to surface melt-freeze crusts that formed on those aspects. The relationship between *ram drp* and *elev* differed between the days, however. On the first sampling day *ram drp* decreased with increasing elevation, while on the second day it increased. This is because of the nature of the weak surface snow on the two days. On the first day there had not been new snow for several days and most of the soft surface snow consisted of near-surface faceted crystals. Winds at the upper elevations had blown some of the snow around, creating harder snow surfaces in those areas. On the second day the surface snow consisted of new snow that had fallen in the previous 36 hours. Since more snow was deposited at higher elevations, there was a deeper soft surface layer and higher values of *ram drp* in those areas. Furthermore, winds were light during the storm that deposited the new snow and had not started blowing before sampling occurred. Thus, wind exposure did not play a significant role in determining the spatial distribution of *ram drp* on the second sampling day.

Initial ram drop is a dynamic variable that changes quickly in response to wind, new snow, changes in temperature, and metamorphic processes in the upper snowpack. Snow stability is also dynamic and interacts with many of the same variables, although the nature of those interactions can be quite different. Still, the use of such dynamic variables, in contrast to more stable variables such as average snow strength, may helpful in quantifying patterns of instability. On the second sampling day *ram drp* was significantly correlated to all the weak layer stability and stability index variables, though this may because it was so closely linked to all the snowpack variables. A better understanding of the relationship between ram drop and stability might result in the use of some measure of surface snow softness in stability evaluations.

## AVERAGE SNOW STRENGTH

### February 6th

*The relationship between average ram strength and terrain*

Average ram strength was significantly correlated to several terrain variables on the first sampling day, with a positive correlation with both *loc n* and *elev* and a negative correlation with *loc e* (Table 21, Figure 26). A forward, stepwise, least squares regression model used only the variable *loc e* to explain 46% of the variance of *ram avg* (Table 22). Wind exposure largely explains these relationships since higher elevations and more northerly locations are subjected to more wind. Further, *loc e* is a variable that provides a measure of wind exposure that is independent of elevation since the calmer southern part of the range is farther east than the windier northern part of the range. Wind mechanically breaks up the snow, depositing it in denser, harder drifts with higher *ram avg*.

*The relationship between average ram strength and terrain and snowpack*

When snowpack variables are considered, *ram avg* is positively correlated to *dpth* and negatively correlated to *t30* (Table 22, Figure 26). A regression model with snowpack and terrain variables chosen as the independent variables used *loc e* and *dpth* to explain 49% of the variance of *ram avg sqrt* (Tables 23 and 24). Thus, average ram strength is greatest in areas with deeper, colder snowpacks. The relationship between average strength and depth is expected since deeper snowpacks are often more dense due to overburden pressures, and deeper snowpacks are less likely to be affected by faceted crystal formation from large temperature gradients. Warmer snowpacks are also less likely to be affected by faceted crystal growth, but this is apparently not as dominant as depth since *ram avg* is higher in areas with colder snowpacks.

*Summary*

Average ram strength is statistically linked to several snowpack and terrain variables, though adding snowpack variables only marginally increases the explanation of the variance of *ram avg*. On February 6th the spatial distribution of *ram avg* was primarily controlled by wind, with greater *ram avg* at higher elevations, and more northerly and westerly locations. Areas with the deepest, coldest snowpacks also had the strongest snow.

**April 2nd**

*The relationship between average ram strength and terrain*

The spatial patterns of snow strength on April 2nd were similar to February 6th. *Ram avg* was positively correlated to both *loc n* and *elev* and negatively correlated to *loc e* (Table 21, Figure 27). Regression analysis using terrain as the independent variables again resulted in a valid model that explained 28% of *ram avg* using only *loc e* (Table 22). Like the first day, the wind exposure of the different locations explains these spatial patterns. I have commonly observed soft snow in the Bridgers south of Ross Pass on the same day that the wind affected snow near Sacajawea Peak, Hardscrabble Peak, and Frazier Lake in the northern Bridgers (SAC, HRD, and FLK in Figure 6) is extremely hard.

*The relationship between average ram strength and terrain and snowpack*

On the second sampling day *ram avg* is negatively correlated to both *t30* and *tgrad*, and no significant correlation exists between *ram avg* and *dpth* (Table 21, Figure 27). Adding snowpack to terrain as independent variables increased the amount of the variance of *ram avg* explained with multiple regression (Table 24). Regression resulted in a valid model that uses *tgrad tf, RI, loc e* and *dpth* to explain 49% of the variance of *ram avg* (Table 23):

$$\mathit{ram\ avg} = (6.94)\mathit{tgrad\ tf} + (8.90 \times 10^{-2})\mathit{RI} - (1.90 \times 10^{-3})\mathit{loc\ e} + (2.60)\mathit{dpth} + 980$$

where *ram avg* is the average ram strength of the upper 1.50 m in N/m, *tgrad tf* is the transformed (raised to the two thirds) average temperature gradient, *RI* is the radiation index in degrees away from north, *loc e* is the location of the site in UTM meters east, and *dpth* is the total snow depth in m. The standard error of estimate is 7.2 m. A comparison of the standardized regression coefficients reveals that *tgrad tf* is the most important variable for explaining the variance of *ram avg*, followed by *RI, loc e*, and *dpth* (Table 23).

The standardized partial regression coefficients associated with the equation indicate that areas that were farther west, faced more to the south, had deeper snowpacks, and smaller absolute (less negative) temperature gradients had stronger snowpacks. Stronger snowpacks would be expected on the southerly aspects due to increased numbers of ice crusts in the upper part of the snowpack.

### *Summary*

Several statistically significant links exist between snow strength and terrain and snowpack on April 2nd. Unlike the first sampling day, adding snowpack variables leads to a large improvement in the multiple regression model (Table 24). However, the two days are similar in that the relationship between *ram avg* and terrain appears to be primarily controlled by wind exposure. However, the relationship is much more complex than on the second day, with several variables interacting in the regression equation to explain *ram avg*.

**Temporal changes between February 6th and April 2nd**

Though the direction of the relationship between various terrain and snowpack variables and snow strength is similar between the two sampling days, on April 2nd the underlying relationships were more complex and were more closely tied to the snowpack variables than on February 6th. Regression equations for each day explained nearly 50% of the variance of *ram avg*, but on the first day that equation only used two variables, while on the second day it required the interaction of four variables. Changes in the weather conditions affecting the snowpack in the latter part of the season account for this increase in complexity. Early in the year there was little sun and nothing more than a thin surface crust on the snowpack, so there was little interaction between *ram avg* and aspect. However, there was more sun and numerous ice crusts could be found in the top 1.5 m of the snowpack, especially in sunny, low elevation areas.

## CONCLUSIONS

Discernable relationships between snow strength and terrain and snowpack variables existed on both sampling days. Though valid regression models for surface snow strength could be generated for each day, the relationship between *ram drp* and the various terrain and snowpack variables differed markedly. On February 6th, surface snow strength was closely linked to terrain, but was not strongly related to snowpack variables. The opposite was true on April 2nd, with a much more subtle relationship between *ram drp* and terrain and a strong relationship between *ram drp* and the snowpack variables. The differences observed are due to the differing surfaces on the two sampling days. On the first day the snow surface consisted of near-surface faceted crystals, and the distribution of that layer was closely tied to terrain. This result is of interest to avalanche scientists and forecasters since this layer was later buried and created a weak layer responsible for numerous avalanches. The ability to predict the distribution of such layers as a function of terrain could potentially improve avalanche prediction once those layers were buried. On the second day the snow surface consisted of recently fallen new snow, and surface snow strength was much more closely related to snowpack variables.

Similar patterns of average snow strength emerged for both days, with *ram avg* increasing at higher elevations, and in the northern and western parts of the Bridgers. This result is likely due to the increased amount of wind in these areas which mechanically break up the snow crystals and deposits them in strong wind deposits. Not only do those wind deposits start out strong, but the increased densities observed inhibit the formation of weaker, faceted crystals later in the year. Average snow strength also increased in areas where the snowpack was deeper and warmer, though no correlation existed between aspect and average strength. Deeper, warmer snowpacks are subjected to lower temperature gradients. Since those gradients drive the formation of faceted crystals, areas with lower temperature gradients are less likely to be weakened by faceted crystal growth.

The present research reinforces Dexter's (1986) results, who also showed that average snow strength increased with elevation and had an indeterminant relationship with aspect in a smaller spatial area in the Colorado Front Range. The results of this research suggest that these results still apply at a larger scale, in a different climatological region, and in a sample set that included wind affected areas.

# Chapter VI

## Spatial and Temporal Variations in Snowpack

### OVERVIEW

This results and discussion chapter evaluates the spatial patterns and temporal changes of the various snowpack variables on the two sampling days. This chapter links snowpack properties to terrain (path 3 in Figure 4). As with the chapter on snow strength, each variable is individually presented. The first variable is snow depth, followed by the subsurface temperature, and average temperature gradient, which is a function of the first two variables. Descriptive statistics, correlations, and regressions are used to interpret the data.

### THE DATA

Similar to the previous two chapters, I generated a two-dimensional space/attribute data matrix for each of sampling day with the rows represented by the sampling locations and the columns represented by snowpack and terrain variables (Table 2). Though most of the data were normally distributed, *t30* and *tgrad* on the second day were not. Once normalized, the transformed variables *t30 tf* and *tgrad tf* no longer deviated from normality at $p < 0.05$ as tested by the Kolmogorov-Smirnov one sample test (Table 5). Since *loc e* and *loc n* shared more than 50% of their variance, and *dis rdg* and *elev* shared close to 50% of their variance on both sampling days, only one or the other was used in regression analyses.

## DESCRIPTIVE STATISTICS

I discussed descriptive statistics for all variables in the two previous chapters: between the two sampling days *dpth, t30*, and *tgrad* all increased significantly (Table 6). Thus, the snowpack became deeper and warmer as the season progressed, a common pattern observed in the seasonal snowcover. In addition, warmer temperatures and increased depth increased the value of the temperature gradient. Since temperature gradients are negative, the absolute value of the temperature gradient decreased between the two sampling days.

## THE RELATIONSHIP BETWEEN SNOWPACK AND TERRAIN

### Snow depth

On the February 6th snow depth significantly correlates to every terrain variable except distance to the ridge and slope angle, with positive relationships with *loc n* and *elev*, and negative relationships with *loc e* and *RI* (Table 25, Figure 28). Thus, the deepest snow was found on high elevation, northerly facing slopes, in the northern and western (higher elevation and more northerly) parts of the Bridgers. In spite of the significant correlations,

TABLE 25: Spearman rank order correlations between snowpack and terrain variables.

| Snowpack Variables | | Terrain Variables | | | | | |
|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* |
| February 6th | *dpth* | ***-.38*** | ***.38*** | ***.24*** | .08 | ***-.26*** | -.02 |
| | *t30* | ***.53*** | ***-.53*** | ***-.38*** | -.04 | ***.58*** | .14 |
| | *tgrad* | .21 | -.22 | -.16 | -.01 | ***.36*** | .07 |
| April 2nd | *dpth* | ***-.37*** | ***.40*** | ***.26*** | .10 | ***-.48*** | -.10 |
| | *t30* | ***.55*** | ***-.53*** | ***-.64*** | .21 | ***.55*** | .16 |
| | *tgrad* | ***.51*** | ***-.46*** | ***-.66*** | ***.27*** | ***.48*** | .15 |

Note: correlations in ***bold/italics*** are significant at $p < 0.05$.

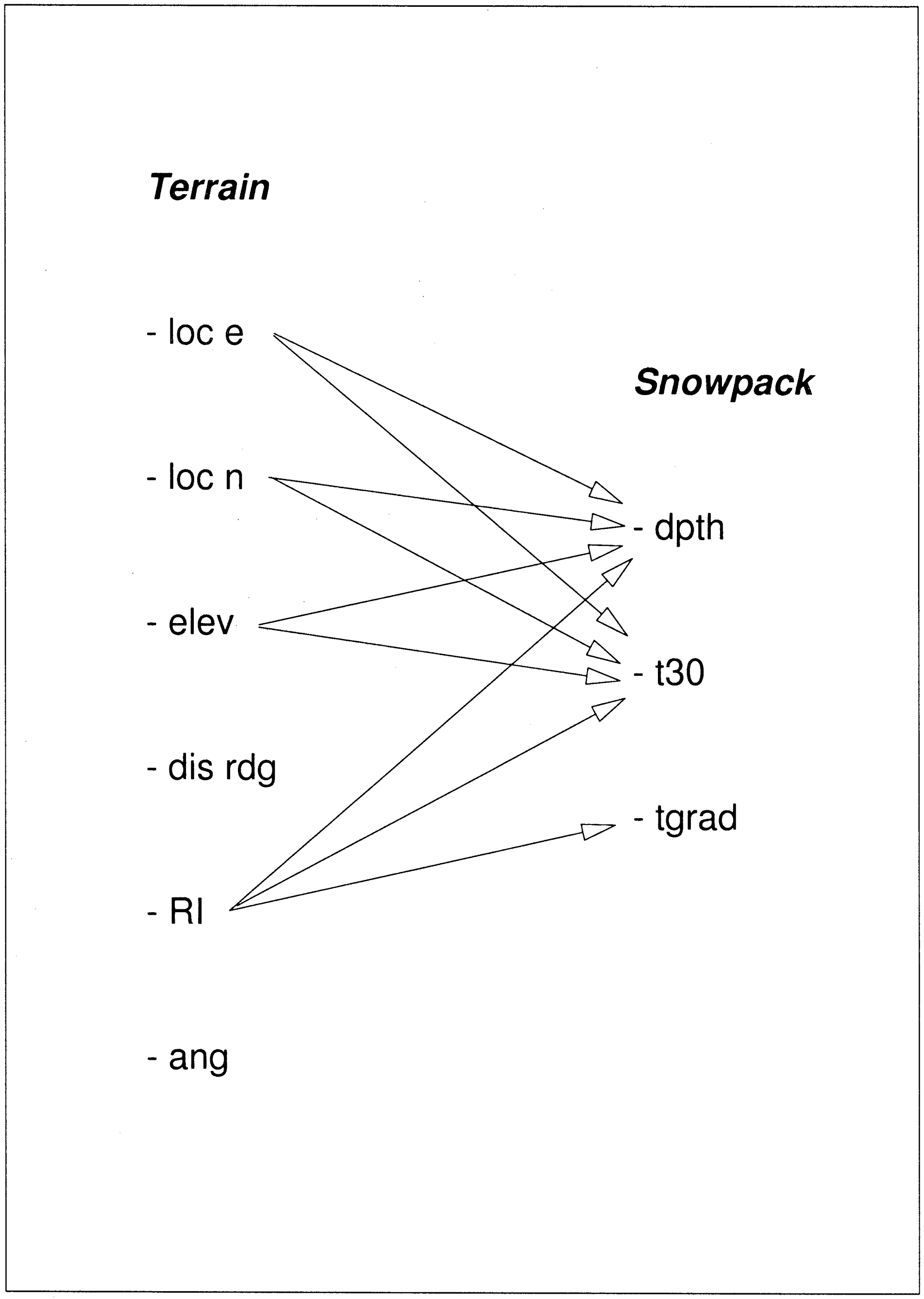


FIGURE 28: Visual representation of Table 25 showing the significant ($p < 0.05$) correlations between terrain and snowpack variables on February 6th.

the interactions between depth and terrain are complex. A forward, stepwise, least squares multiple regression using terrain as the dependent variables explained only 15% of the variance of *dpth* through *loc e*, which was the only variable pulled into the equation (Table 26).

TABLE 26: Standardized partial regression coefficients and coefficients of determination (adjusted $R^2$) for forward, stepwise, least squares regression models run with snowpack variables chosen as the dependent variables, and terrain variables chosen as the independent variables.

| Snowpack Variables | | Terrain Variables | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *loc e* | *loc n* | *elev* | *dis rdg* | *RI* | *ang* | ***Adj. $R^2$*** |
| February 6th | *dpth* | -.41 | | | | | | .15 |
| | *t30* | .50 | | | | .47 | | .55 |
| | *tgrad* | | | | | | | - |
| April 2nd | *dpth* | | | | | -.43 | | .17 |
| | *t30 tf* | -.26 | | .48 | | -.40 | | .65 |
| | *tgrad tf* | | | .52 | | -.30 | | .38 |

Coefficients of determination marked with a "-" indicate that there was no valid model. A valid model must meet the following criteria: 1) the model must be significant ($p < 0.05$), 2) the model must explain at least 15% of the variance of the dependent variable ($R^2 > 0.15$), 3) all partial regression coefficients must be significant ($p < 0.05$), 4) the shared variance of any two dependent variables must be less than 50%, thereby insuring that the independent variables are independent and obviating problems associated with multicollinearity, 5) no significant autocorrelation (Durbin-Watson statistic > 1.50), and 6) normally distributed residuals.

Snow depth patterns observed on April 2nd are similar to February 6th. Depth again significantly correlates positively with *loc n* and *elev*, and negatively with *loc e* and *RI* (Table 25, Figure 29). Multiple regression explained 17% of the variance in *dpth* through a single variable, *RI*. The increased influence of *RI* on the snowpack on this second sampling day is because the Bridgers received little sunshine prior to the first sampling day, but received more insolation before the second day.

Patterns of snow depth are similar on the two sampling days, with snow depth increasing at higher elevations and on more northerly aspects. Depth also increases in a northerly direction both days. Finally, Depth increases in a westerly direction, probably due to the increased elevation and northerly locations in a westerly direction amongst the sampling locations. Interestingly, regression models based on terrain have limited predictive value, explaining less than 20% of the variance of snow depth (Table 26). A number of local factors dramatically affecting snow depth probably explains this lack of regression strength. The most important factor is the deposition and scouring of the snowpack by wind, whereby small topographic features or changes in wind exposure may dramatically impact snow depth. Other factors affecting snow depth include local shading, sluffing from cliffs or steeper slopes above the site, or avalanching, which may decrease (if the sample site is located in a starting zone) or increase (if the sample site is in a runout area) depth.

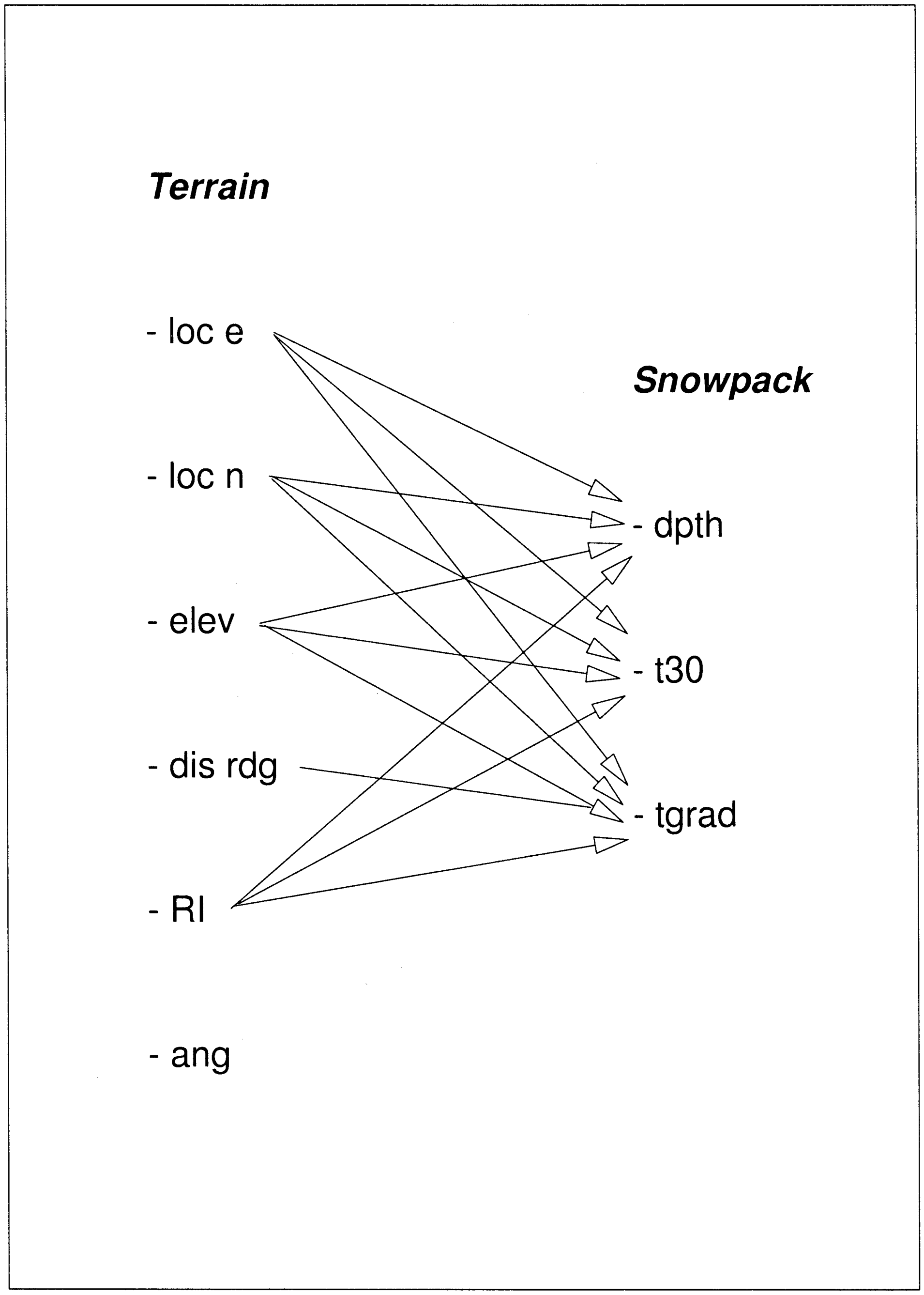


FIGURE 29: Visual representation of Table 25 showing the significant ($p < 0.05$) correlations between terrain and snowpack variables on April 2nd.

**Sub-surface snow temperature**

On the February 6th, snowpack temperatures at 0.30 m in depth significantly correlate to a number of terrain variables, with positive relationships between temperature and *loc e* and *RI*, and negative relationships between temperature and *loc n* and *elev* (Table 25, Figure 28). Forward, stepwise, least squares multiple regression run with terrain as the independent variables resulted in the explanation of 55% of the variance of *t30* using *loc e* and *RI* (Table 26). Thus, warmer temperatures existed at lower elevations, more southerly aspects, and areas farther to the east and south.

Similar spatial patterns of *t30* existed on April 2nd. *T30* again correlated positively with *loc e* and *RI*, and negatively with *loc n* and *elev* (Table 25, Figure 29). A valid multiple regression model for the transformed variable *t30 tf* explained 65% its variance:

$$t30\ tf = (4.5 \times 10^{-3})elev - (1.14 \times 10^{-2})RI - (2.22 \times 10^{-4})loc\ e + 103$$

where *t30 tf* is the transformed (raised to the 2/3 power) subsurface snow temperature, *elev* is the elevation in meters, *RI* is a radiation index measured in degrees away from north, and *loc e* is the location of the site in UTM meters east. The standardized regression coefficients indicate that *elev* is the most important variable for explaining the variance of *t30 tf*, followed by *RI* and *loc e* (Table 26).

On both February 6th and April 2nd the coolest snowpack temperatures existed at higher elevations and on more northerly aspects. Temperature increased in a southerly and easterly direction in the Bridgers. Warmer snow temperatures have a number of implications for the snowpack. Areas with warmer snowpack change more quickly, and therefore instabilities are not be as persistent. Warmer temperatures also reduce temperature gradients, thereby resulting in equilibrium metamorphism and a stronger snowpack.

**Temperature gradient**

An analysis of temperature gradient, which is a function of both *t30* and *dpth*, shows which variable changes more quickly as terrain changes. On February 6th, the only significant correlation between *tgrad* and terrain is the positive correlation with *RI* (Table 25, Figure 28); no valid regression model is generated with *tgrad* chosen as the dependent variable and the terrain chosen as the independent variables (Table 26). Thus, the only clear relationship on this day is that the temperature gradient increases with increasingly southerly aspect. Since *tgrad* is negative, this means the absolute *tgrad* decreases on warmer southerly aspects. Thus, though *dpth* is decreasing and *t30* is increasing on these aspects, *t30* is increasing more quickly, resulting the observed relationship on the first sampling day.

In contrast to February 6th, on April 2nd a number of significant statistical correlations exist between *tgrad* and terrain, with positive relationships with *loc e, dis rdg*, and *RI*, and negative relationships with *loc n* and *elev* (Table 25, Figure 29), indicating that the absolute value of the temperature gradient is greatest on northerly aspects and at higher elevations. Thus, *t30* changes over terrain more quickly than *dpth*, resulting in a similar pattern for *tgrad* as for *t30*. Unlike the first day, when no valid regression model could be generated for *tgrad*, on the second day regression explained 38% of the variance of the transformed variable *tgrad tf* using *elev* and *RI* (Table 26).

Though the spatial patterns of *tgrad* discerned are similar between the two sampling days, the second day shows much stronger linkages between terrain and *tgrad*. Changes in *dpth* and *t30* with terrain on the February 6th apparently cancel each other out, resulting in few recognizable spatial patterns for *tgrad*. However, on April 2nd changes in temperature dominate changes in *dpth*, resulting in easily observable patterns of *tgrad*.

Patterns of temperature gradient are important in the mountain snowpack. Temperature gradients drive vapor pressure gradients which, in turn, result in the formation of weak faceted crystals which form significant weak layers and result in avalanches. Therefore, the ability to predict spatial patterns of temperature gradients is useful for locating areas with potentially weaker snowpacks.

## CONCLUSIONS

Snowpack characteristics like depth, subsurface temperature, and temperature gradient are statistically correlated with terrain features such as elevation, aspect and location. Snow depth increased with elevation and decreased with southerly aspect. Several previous studies found that depth increased with elevation (e.g., McPartland, 1971; Dexter, 1986; Birkeland, 1996; Pipp, 1977), though none of those studies examined as large a spatial area as the present study. Further, most of the previous research did not account for wind affected areas. Research that compares depth with aspect is less common. In contrast to the present research, Dexter (1986) did not find that depth significantly changed with aspect. However, Elder (1995) did find a strong relationship between SWE (which is strongly correlated to depth) and his radiation index (which is strongly correlated to aspect).

Snow temperatures decreased with increasing elevation and increasingly northerly aspect. Comparisons with other research is difficult since spatial investigations of snow temperature are rare. Dexter (1986) found that temperature decreased with elevation in the early and mid-season, and were equal in the late season, results consistent with the present research. Though the second sampling day of this study was in April, winter-like temperatures insured snowpack temperature conditions similar to mid-season. When the relationship between temperature and aspect is explored, temperatures increased with increasing southerly aspect. Dexter (1986) found the same result in early-season, but did not find that relationship for mid- or late-season measurements. This discrepancy results from differences between the sampling days. Sampling days following periods of sunshine might exhibit clear spatial patterns of sub-surface temperature with respect to aspect, while such patterns might not exist following cloudy days.

The absolute value of the temperature gradient increased at higher elevations and on northerly aspects in this study, indicating temperatures cooled more quickly than depths increased. In other words, temperature changes occurred more rapidly than depth changes in relationship to terrain. Dexter (1986) did not observe this relationship, instead concluding that temperature gradients either decreased or remained the same with elevation. When compared to aspect, he found the absolute temperature gradient increased with increasingly southerly aspect in the early-season, decreased in mid-season, and remain about the same late-season. Thus, Dexter's (1986) work suggests the interplay between depth and temperature over terrain is more complex than this study. Further, in contrast to this research, his results suggest depth changed more rapidly than temperature over terrain.

While depth correlates significantly to almost all the terrain variables, regression models still explain less than 20% of its variance, emphasizing the numerous processes which affect snow depth. The most obvious variable not taken into account was wind drifting. Micro-topographical features result in large changes in depth over short distances due to snow drifting, undoubtedly making the effective explanation of snow depth difficult. In contrast to depth, I could more effectively explain patterns of subsurface temperature, with regression models explaining over 50% of the variance in *t30*. Dexter (1986) also found subsurface snow temperatures to be the most stable variable he measured.

The only terrain variable not related to any snowpack variables was slope angle, perhaps because of the relatively narrow range of slope angles sampled. I only considered slopes from 28 to 44 degrees, terrain typical of avalanche starting zones (Perla, 1977). Though slope angle may not be related to the snowpack variables in the range of slope angles sampled, this result does not minimize the its importance, since slope angle determines the gravitational force acting on the snowpack and is therefore the single most important terrain variable in stability decisions (Figure 1).

# Chapter VII

## Summary

### OVERVIEW

Previous spatial studies of snow stability investigated patterns of stability at the scale of a single slope of $10^2$ to $10^3$ $m^2$ (Conway and Abrahamson, 1984; Fohn, 1988; Jamieson, 1995), but no work addresses larger scale patterns (on the order of hundreds of square kilometers) of interest to avalanche scientists and forecasters. Further, though researchers have studied snowpack properties at a larger scale (e.g., Caine, 1975; Dexter, 1986; Elder, 1995; Pipp, 1997), most investigators avoided wind exposed areas and heretofore no field-based studies sampled areas larger than ten square kilometers. This research investigates the variability of snow stability, snow strength and snowpack properties as a function of terrain at the physical scale of a small mountain range and the temporal scale of a snow season.

The relatively uncomplicated topography of the Bridger Range suited this research. Six experienced teams sampled data from over 70 points on two different sampling days. A helicopter safely and efficiently shuttled teams around the range. Data included terrain variables (location, elevation, aspect and slope angle), snowpack variables (depth, sub-surface temperature and temperature gradient), snow strength variables (initial ram drop and average ram strength), and snow stability variables (stuffblocks, rutschblocks, depths to failure and a variety of stability indices). I generated a two-dimensional space/attribute data matrix for each sampling day, and analyzed the data using a variety of statistical tests.

## STABILITY

Snow stability decreased with increasing elevation and increasing northerly aspect on both sampling days, a spatial relationship mapped for the Bridgers (Figure 25). These results must be viewed with caution since other research (Schweizer and others, 1996) and informal observations indicate that instability patterns often change significantly from season-to-season, month-to-month, and even day-to-day. Still, the pattern of increasingly unstable conditions on high elevation, northerly aspects is commonly observed in the mountain snowpack because higher elevations are exposed to more wind loading and increased snowfall, and weak layers persist longer in these colder areas. This research is the first time these common observations have been quantitatively demonstrated.

Avalanche forecasters are particularly interested in whether local factors (such as elevation and aspect) or location within a region is more important in predicting snow stability. If local factors dominate, the area can be treated as a region for forecasting purposes, but if relationships change at different locations within the area it might be necessary to break the area into two or more distinct regions. Indeed, identifying "regions" is a core theme of geography. This study shows that local factors such as elevation and aspect are consistently more important in explaining snow stability than location within the Bridgers, suggesting that this range can be treated as a relatively homogenous region. Thus, stability changes within the range may be simply broken down by aspect and elevation, a result that is consistent with seven years of operational avalanche forecasting for this area.

One research goal was to identify the data necessary to characterize stability. In some cases using only terrain provided the best possible model of a certain stability variable. However, snowpack and snow strength variables increased the explanation of other stability variables. In short, the data structure is complex and much variance remains unexplained. This reinforces many of the ideas set forth by LaChapelle (1980), who concluded that since conventional avalanche forecasting is an iterative process, it benefits from large volumes of diverse data. I generated numerous statistical models for stability, but each model used a different array of independent variables for prediction, suggesting that there may be more than one way to combine variables to predict stability. The nature of the data and the magnitude of the unexplained variance emphasizes that avalanche forecasters are taking a wider range of variables into account, and are probably analyzing them differently than the simple statistical models presented in this research. Identifying and quantifying those variables might well provide avalanche scientists with better representations of stability patterns. Future stability research might benefit from some of the many ideas coming out of the science of complexity, and the attempts at quantifying the way the human mind processes data.

## SNOW STRENGTH AND SNOWPACK

The spatial distribution of surface snow strength changed between the two days. On the first sampling day, surface strength decreased with increasing elevation, while on the second day it increased. Since surface snow strength is dynamic, it might help to predict the even more dynamic snow stability. Indeed, initial ram drop was an important predictor of stability in several regression equations. However, while the relationship between surface strength and terrain changed between the two sampling days, the relationship of stability to terrain did not, indicating that surface snow strength may not consistently predict stability patterns.

Areas with increasing elevation and increasingly northerly aspects (Figure 25) had greater average snow strength, increased snow depth, colder snow temperatures, and increasing absolute values of temperature gradient. Snow strength increased due to wind effects and the deeper snowpack, which decreased faceted crystal growth and increased densification from overburden pressures. Snow temperatures decreased due to the colder temperatures at higher elevations and on aspects receiving less insolation. The absolute value of the temperature gradient increased because decreases in temperature dominated over increases in depth.

## CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This research takes a valuable first step in exploring the nature of spatial patterns and temporal variations in snow stability, snow strength and snowpack properties, providing the first time that these measures have been quantified at the scale of a small mountain range. Still, much research remains in order to better explain the spatial distribution of snow stability.

Further research into the geographical concept of a "region" for avalanche forecasting purposes is warranted. In this investigation, local factors such as aspect and elevation dominated locational factors for predicting snow stability, suggesting that the Bridgers form a region for avalanche forecasting. Though not previously quantified, this conclusion is not unexpected since the Bridgers are relatively small and operational forecasters have treated the range as a single region. Future work might expand the data to other nearby locations to try to determine the outer boundaries of this particular region, or might explore the size of avalanche regions in coastal, intermountain, and continental snow climates.

A great deal of unexplained variance still exists for the dependent variables, and ways to reduce it present several avenues of research. One factor inadequately addressed in this research is the effect of the wind on various snowpack, snow strength, and snow stability variables. Perhaps a meso-scale wind model using wind inputs from Bridger Bowl and/or upper air soundings from Great Falls could be combined with a blowing snow model to arrive at a variable that approximates wind deposition and scouring in various areas. This variable might provide valuable insight into the spatial patterns of depth, strength, and stability.

Another factor that adds to the unexplained variance in this work is nature of the data. The statistical techniques used assume linear relationships, but many of the relationships modelled may not be strictly linear. For example, numerous studies have shown that snow depth increases with elevation, yet at higher elevations depths are highly variable due to wind exposure. Such depth variations have significant implications for the snowpack evolution since depth combines with temperature to determine temperature gradients which, in turn, control types of snow metamorphism.

The relationship of stability to terrain is much more complex than depth, and can be extremely non-linear. As an example, consider a situation where a layer of surface hoar forms over a mountain range, but wind speeds are high enough that it does not form at the higher elevations. The next storm comes in warm, with rain falling up to mid-elevations, and a cold spell quickly follows. Now a situation exists where the snowpack at lower elevations has re-frozen and is extremely stable. Meanwhile, the surface hoar at mid-elevations creates a dangerous weak layer and highly unstable conditions. At higher elevations no surface hoar exists and the instability is more moderate. Because of such data irregularities, various non-linear models (such as classification and regression trees (Breiman and others, 1984)) might better explain these complex data, and emerging ideas and models coming out of the science of complexity might also be useful (Waldrop, 1992).

A final factor adding to the unexplained variance is the large amount of small scale variability in snowpack and snow stability due to micro-scale variables such as wind effects, substrate or vegetation. Such variability poses serious difficulties for snow stability studies at the scale of the present research since differences in stability between adjacent points may be significant (i.e., Birkeland and others, 1995; Jamieson, 1995). No methods currently exist to clearly define sample locations that might provide an "average" stability measure of the current slope. More work at this local scale is needed to insure that measurements made in regional scale studies such as the present research are actually representative of a particular slope.

As more people recreate and settle in mountainous areas, understanding the nature, cause, and distribution of snow avalanches will become increasingly important to society. Significant resources have been directed toward avalanche research and mitigation in Europe, where 300-year old alpine villages are tucked into avalanche terrain. Still, though past research has given insight into the nature and cause of avalanches, the spatial distribution of snow stability at the regional scale remains largely unexplored. Geographers are in a commanding position to lead the way in this area of research for several reasons: 1) they have a broad understanding of spatial patterns, 2) they are familiar with the necessary mapping and analysis tools such as geographic information systems, and 3) they are comfortable with interdisciplinary research, which for avalanche research might include snow scientists, climatologists, and natural hazards researchers. Continuing geographic research into avalanches will improve our understanding snow stability patterns, thereby improving our efforts at explaining and forecasting the distribution of snow avalanches over the mountain landscape.

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# APPENDIX A:

# TEAM LEADER QUALIFICATIONS

| Team leader | Experience | Education |
|---|---|---|
| Karl Birkeland | - 8 years professional ski patrol and avalanche control experience<br>- 8 years backcountry avalanche forecasting experience<br>- climbing and skiing experience in the Rockies, Alaska Range, and French Alps | - MS in Earth Sciences (snow and avalanche research)<br>- PhD candidate in Geography |
| Ron Johnson | - 6 years professional ski patrol and avalanche control experience<br>- 6 years of backcountry avalanche forecasting experience<br>- extensive climbing and skiing experience in Alaska, South America, and the Himalaya<br>- climbing ranger in Teton National Park, former climbing ranger in Denali National Park | - MS in Earth Sciences (snow and avalanche research) |
| Doug Chabot | - 6 years professional ski patrol and avalanche control experience<br>- 1 year backcountry avalanche forecasting experience<br>- extensive climbing and skiing experience in Alaska and the Himalaya<br>- climbing guide in Alaska and the Tetons | - BS in Math |
| Scott Schmidt | - 4 years of avalanche control experience while doing research<br>- 1 year professional ski patrol and avalanche control experience<br>- extensive backcountry skiing experience<br>- climbing and skiing experience in the Rockies and the Alaska Range | - PhD candidate in Engineering (snow and avalanche research) |
| Ledine McKittrick | - 4 years of avalanche control experience while doing research<br>- extensive backcountry skiing experience | - PhD (completed Spring, 1997) in Engineering (snow and ice research) |
| Brian Doubek/ Jim Marshall | - 1 year professional ski patrol and avalanche control experience<br>- extensive backcountry skiing experience | - BS in Earth Sciences (Doubek)<br>- Independent avalanche research project (Doubek) |

# APPENDIX B:

# MEASUREMENT ERRORS

This appendix describes the uncertainty associated with collecting data for this research. Measurement errors may arise from three sources: 1) errors made during the actual measurement by a sampling team, 2) errors due to the equipment used, or 3) errors due to differences between sampling teams. Actual measurement errors are difficult to quantify, and this research emphasized minimizing the errors between sampling teams. First, a pre-season training day allowed all the sampling team leaders and many of the assistants to standardized data collection techniques. Secondly, investigators collected only simple, objective data, such as relatively unbiased measures of location, elevation, aspect, slope angle, snow depth and snow temperature. For these data I assume negligible differences between teams, and I estimate possible measurement error based on the equipment used and discussions with the various team leaders (Table 27).

Errors associated with snow stability and strength measurements are not easily estimated and are more likely to be biased by different observers. Though I was unable to compare rutschblock results between sampling teams due to time constraints and difficulties in locating a large enough slope, I was able to take four team leaders (Birkeland, Johnson, Schmidt, and Doubek (see Appendix A)) and compare measurements of stuffblock drop height, initial ram drop, and average ram strength. We collected data

Table 27: Estimated measurement errors associated with the different terrain and snowpack variables.

| Variable Measured | Instrument | Measurement Error |
|---|---|---|
| Location | Rockwell PLGR GPS | Avg: +/- 2.5 m* <br> Max: +/- 15 m* |
| Elevation | Rockwell PLGR GPS | Avg: +/- 7.5 m* <br> Max: +/- 45 m* |
| Aspect | A variety of compasses (mostly Silva-type) | +/- 5 degrees** |
| Slope angle | Life-link inclinometer or Silva compass | +/- 2 degrees** |
| Snow depth | Life-link collapsible probe (marked in m) or a plastic ruler (thinner snowpacks) | +/- 0.05 m** |
| Snow temperature | Ertco dial stem thermometers (calibrated before each sampling day) | +/- 1 degree C** |

* GPS errors are based on tests conducted at the U.S. Forest Service's Missoula Technology and Development Center.
** Errors are estimated based on the instruments used and discussions with sampling team leaders.

on April 10th, 1997 in the vicinity of the 6th snow pit from Nyanuki Bowl (NNB in Figure 6) on a north facing, 35 degree slope at 2315 m in elevation. A cold early April, combined with chilly temperatures on the 10th (-15 degrees C) insured dry snow conditions for the tests. Each person conducted 15 stuffblock tests and collected 15 ram profiles with the ram penetrometer they used on the data collection day (see Appendix C). Johnson's ram broke after he collected 13 profiles.

The stuffblock data are quite consistent, with failure planes at depths of 0.08 and 0.45 m. No variation between observers or between tests existed at 0.08 m, with every one of the 15 tests for each observer having a stuffblock drop height of zero (Figure 30). Although more variability was evident at 0.45 m, results were still remarkably uniform. Drop heights ranged from 0.20 to 0.40 m, and the median was 0.30 m for each observer (Figure 31). A Wilcoxson matched pairs test showed no significant difference between any observer pair (Table 28).

Initial ram drop data are also fairly consistent. Investigators measured mean values of initial ram drop between 0.51 and 0.57 m, though Johnson's measurement variability was greater than the other team leaders (Figure 32). Comparing observers using the Wilcoxson matched pairs test showed a significant ($p < 0.05$) difference between Schmidt and Doubek (Table 29).

Average ram strength data are not nearly as consistent as the initial ram drop and stuffblock data. Although Birkeland, Schmidt and Doubek all

Table 28: P-values for differences in stuffblock results between observers at a failure depth of 0.45 m computed using a Wilcoxson matched pairs test. There are no significant differences ($p < 0.05$) between any observer pairs.

| Observer | Birkeland | Johnson | Schmidt | Doubek |
|---|---|---|---|---|
| Birkeland | - | 0.69 | 0.78 | 0.58 |
| Johnson | 0.69 | - | 1.00 | 0.69 |
| Schmidt | 0.78 | 1.00 | - | 0.79 |
| Doubek | 0.58 | 0.69 | 0.79 | - |

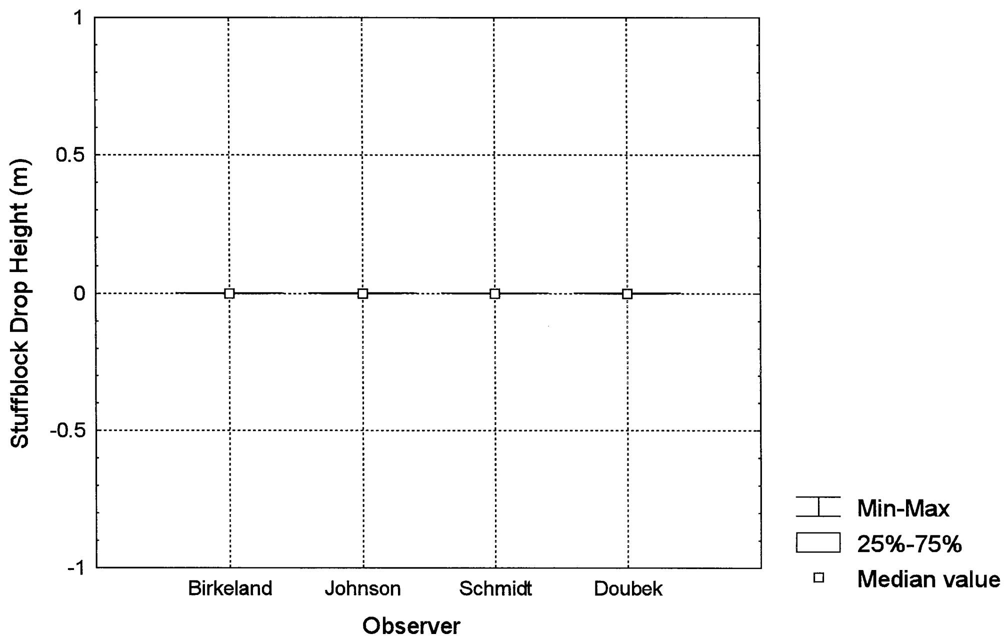


FIGURE 30: Box-whisker plot for the upper failure (failure depth = 0.08 m) for 15 comparative stuffblock tests.

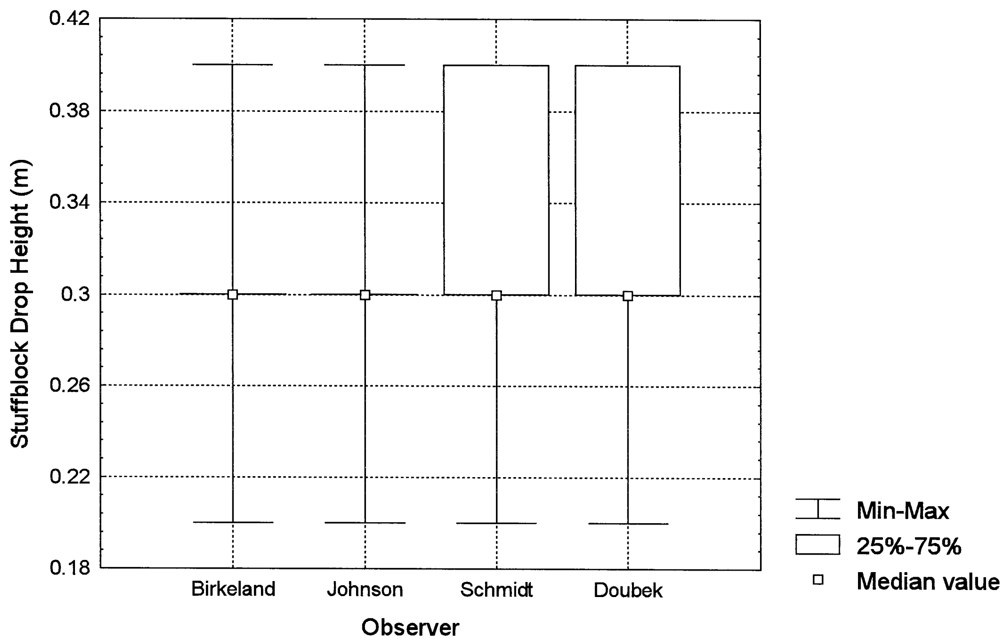


FIGURE 31: Box-whisker plot for the lower failure (failure depth = 0.45 m) for 15 comparative stuffblock tests.

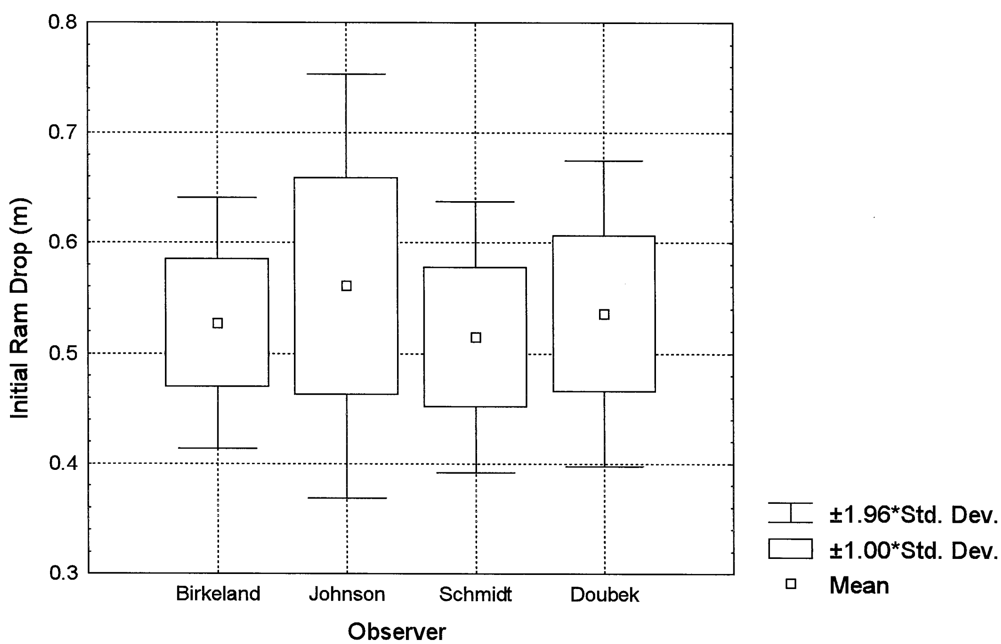


FIGURE 32: Box-whisker plot for 15 (13 for Johnson) comparative measurements of initial ram drop.

Table 29: P-values for differences in initial ram drop results between observers computed using a Wilcoxson matched pairs test. Significant differences ($p < 0.05$) are marked in ***bold/italics***.

| Observer | Birkeland | Johnson | Schmidt | Doubek |
|---|---|---|---|---|
| Birkeland | - | 0.21 | 0.12 | 0.83 |
| Johnson | 0.21 | - | 0.14 | 0.69 |
| Schmidt | 0.12 | 0.14 | - | ***0.01*** |
| Doubek | 0.83 | 0.69 | ***0.01*** | - |

had averages between 13 and 16 N/m, Johnson was much higher with an average of approximately 22 N/m (Figure 33). Birkeland and Doubek had similar results, while Schmidt consistently measured lower ram strength and Johnson measured much higher ram strength, as demonstrated by a Wilcoxson matched pairs test (Table 30).

After establishing the numerous significant differences between the observers when measuring average ram strength, I attempted to ascertain whether those differences were systematic. In short, did a relationship exist between the actual average ram strength and the difference between any two observers? If such systematic differences existed it might be possible to apply a correction factor to the data. I took the average of the four observers as the "actual" average ram strength, and then compared this "actual" ram strength to the difference between each observer pair with a Spearman rank order correlation (Table 31). No significant relationships

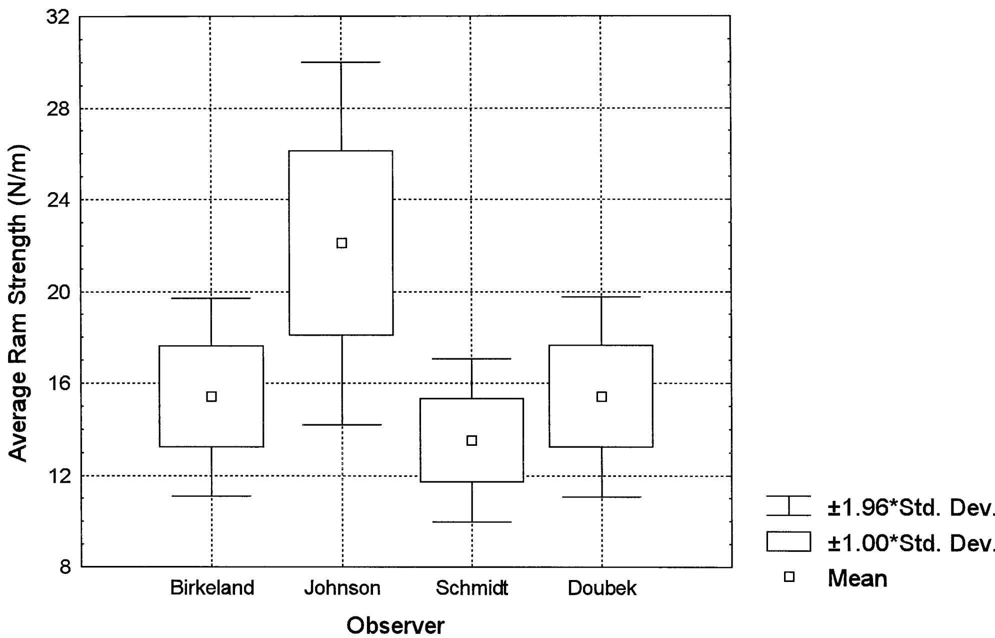


FIGURE 33: Box-whisker plot for 15 (13 for Johnson) comparative measurements of average ram strength.

Table 30: P-values for differences in average ram strength of the upper 1.5 m between observers computed using a Wilcoxson matched pairs test. Significant differences ($p < 0.05$) are marked in ***bold/italics***.

| Observer | Birkeland | Johnson | Schmidt | Doubek |
|---|---|---|---|---|
| Birkeland | - | ***0.00*** | ***0.01*** | 0.73 |
| Johnson | ***0.00*** | - | ***0.00*** | ***0.00*** |
| Schmidt | ***0.01*** | ***0.00*** | - | ***0.00*** |
| Doubek | 0.73 | ***0.00*** | ***0.00*** | - |

($p < 0.05$) existed. Thus, although significant differences existed between observer pairs, there is insufficient statistical evidence to show those differences are systematic.

Though the errors are not necessarily systematic, the difference between Johnson and the other observers is troubling (Figure 33). Johnson's higher average ram values suggest some instrument problem that might inhibit Johnson's ram from being pounded through the snow as effectively as the other rams. Johnson and I discussed the techniques we used and they were similar. It is possible that some of the discrepancy had to do with Johnson's ram which, as mentioned earlier, broke at the bottom of the guide rod after 13 profiles. If the rod was loose, it may not have transmitted the energy of the hammer blows to the snowpack as effectively as the other rams, thereby inflating the average ram values. Since the ram had to be shipped off to be fixed and was not available until after the snow

Table 31: Spearman rank order correlations between the difference in average ram strength measured by each observer pair and the "actual" average ram strength, which was calculated by averaging the results from the four observers (N = 13).

| | Comparison With "Actual" Average Ram Strength | |
|---|---|---|
| Observer Pair | Spearman R | p |
| Birkeland/Johnson | 0.29 | 0.33 |
| Birkeland/Schmidt | 0.43 | 0.25 |
| Birkeland/Doubek | 0.25 | 0.41 |
| Johnson/Schmidt | 0.47 | 0.10 |
| Johnson/Doubek | 0.34 | 0.25 |
| Schmidt/Doubek | 0.01 | 0.97 |

melted, I was unable to determine whether the measurement error was due to the instrument or to differences in measurement techniques. In any case, despite the problems, the average ram strength data collected were the best measures of strength available and I used them in the statistical analyses.

# APPENDIX C:

# SPECIFICATIONS OF THE DIFFERENT RAM PENETROMETERS

# USED BY THE VARIOUS SAMPLING TEAMS

| | | Mass (g) | | |
|---|---|---|---|---|
| Team Leader | Ram Used | Initial Drop | Ram (T) | Hammer (H) |
| Karl Birkeland | Snowmetrics clip together | 1,000 | 1,500 (1 sect.), 2,500 (2 sect.) | 1,000 |
| Ron Johnson | MSU Swiss Ram | 840 | 840 (2 sect.) | 1,000 |
| Doug Chabot | LifeLink (black) | 1,195 | 695 (1 sect.) | 500 |
| Scott Schmidt | Snowmetrics screw together | 1,000 | 1,000 (1 sect.), 2,000 (2 sect.) | 1,000 |
| Ledine McKitrick | LifeLink (black) | 1,195 | 695 (1 sect.) | 500 |
| Doubek/ Marshall | LifeLink (blue) | 1,155 | 655 (1 sect.) | 500 |

# APPENDIX D:

# COMPARISON OF DETAILED STUDY PLOT DATA AND ASSOCIATED SPATIAL DATA SETS

Comparing the spatial data sets from the two sampling days with the detailed study plot data collected the day after spatial sampling assessed the "representativeness" of the study plot location. I compared study plot data with the mean of the spatial data sets, and considered values within one standard deviation to be reasonably representative. The purpose of this analysis was to confirm that the study plot data reasonably represented the snowpack that existed throughout the Bridgers on that particular sampling day.

On February 6th, all snowpack and snow strength variables, and five of eight stability measures, were within one standard deviation of the mean values of the spatial data set (Table 32). The stability measures that differed were all associated with the weakest stuffblock test. At the rope tow study plot the weakest stuffblock was not only extremely weak (stuffblock drop height of 0.00 m) but the depth to failure was quite shallow (0.03 m). This was due to a sun crust that may have formed the day before (possibly during the spatial sampling) that was failing on weak faceted crystals that had formed below it. If those results are ignored, it appears that the study plot location is indeed "representative" of the spatial data set, and the snowpack conditions analyzed here can be considered to be reasonably representative of the conditions observed throughout the range on the sampling day.

TABLE 32: Snow pit data for the rope tow study plot on the day following each sampling day. The data for each day are compared to the previous day's spatial data set to assess the "representativeness" of the study plot data.

| | February 7th | | | April 3rd | | |
|---|---|---|---|---|---|---|
| | Measure | Diff.* | W/in 1 SD?** | Measure | Diff.* | W/in 1 SD?** |
| Snowpack | | | | | | |
| *dpth (m)* | 3.12 | 0.53 | Yes | 3.05 | -0.01 | Yes |
| *t30 (deg C)* | -6 | 0.5 | Yes | 0 | 2.7 | No |
| *tgrad (deg C/m)* | -1.9 | 0.7 | Yes | 0 | 1.1 | Yes |
| Snow strength | | | | | | |
| *ram drp (m)* | 0.40 | 0.05 | Yes | 0.18 | -0.19 | Yes |
| *ram avg (N/m)* | 0.123 | -0.025 | Yes | 0.203 | -.006 | Yes |
| Snow Stability | | | | | | |
| *df wk sb (m)* | .03 | -.19 | No | .18 | -.06 | Yes |
| *df wk rb (m)* | .18 | -.12 | Yes | .18 | -.18 | No |
| *sb wk (m)* | 0 | -.12 | No | .30 | .12 | Yes |
| *rb wk* | 4 | -0.9 | Yes | 6 | -1.2 | Yes |
| *sb wk rb (m)* | .10 | -.11 | Yes | .30 | .01 | Yes |
| *FI wk sb* | 0 | -.567 | No | 1.67 | .845 | Yes |
| *FI sb wk rb* | .556 | -.104 | Yes | 1.67 | .835 | No |
| *TFI* | .180 | -.270 | Yes | .690 | .192 | Yes |

* Diff. is the difference between the value measured at the rope tow study plot and the mean value for the spatial data set measured the day before.
** "W/in 1 SD?" is "Yes" if the rope tow value is within one standard deviation of the spatial set mean and "No" if it is not.

As with February's data, the April 2nd data show all snowpack and snow strength variables to be within a standard deviation of the previous day's mean values except for *t30*, which at 0 degrees C was 2.7 degrees warmer than the mean value from the previous day (Table 32). This might be because these data were collected one day later, and the previous day's weather was sunny and warm. Further, the study plot is on a warmer, southerly aspect. Six of the eight stability variables were within a standard deviation of the mean of the spatial data set. As with the first sampling day, it appears that this site is reasonably representative of the spatial data set collected on April 2nd, and the snowpack observed was reasonably representative of the snowpack conditions throughout the range.

# BIOGRAPHICAL SKETCH

Karl Wessel Birkeland was born on December 27th, 1962 in Oakland California, the son of Peter and Suzanne Birkeland. He grew up in Boulder, Colorado and graduated from Boulder High School in 1981. He graduated from the University of Colorado in 1986 with a Bachelor of Arts degree in Environmental, Population and Organismic Biology and was awarded the Chancellor's Recognition Award for graduating first in his class. While going to high school and college he worked as a professional ski patroller at Lake Eldora Ski Area in Colorado and Snowbasin Ski Area in Utah. After graduating from the University of Colorado, Karl worked as a field assistant doing forest ecology research in southeast Alaska, continued ski patrolling at Snowbasin, and worked as an Aquatic Biologist for Aquatic and Wetland Consultants. He began scientifically investigating snow avalanches in 1988 at Montana State University, was awarded a National Science Foundation Graduate Fellowship in 1989, and graduated in 1990 with a Master of Science degree in Earth Sciences. In 1990 Karl founded the Gallatin National Forest Avalanche Center, where he has worked as an avalanche forecaster for the past seven years. For the present research he was awarded a National Science Foundation Dissertation Improvement Grant. Karl currently serves as the research chair of the American Association of Avalanche Professionals and is a member of the Association of American Geographers, Sigma Xi, and Phi Beta Kappa.