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Exploring multi-scale spatial patterns in historical avalanche data, Jackson Hole Mountain Resort, Wyoming

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Abstract

Many ski areas, backcountry avalanche centers, highway departments, and helicopter ski operations record and archive daily weather and avalanche data. This paper presents a probabilistic method that allows avalanche forecasters to better utilize historical data by incorporating a Geographic Information System (GIS) with a modified meteorological nearest neighbors approach. This nearest neighbor approach utilizes evolving concepts related to visualizing geographic information stored in large databases. The resulting interactive database tool, Geographic Weather and Avalanche Explorer, allows the investigation of the relationships between specific weather parameters and the spatial pattern of avalanche activity. We present an example of this method using over 10,000 individual avalanche events from the past 23 years to analyze the effect of new snowfall, wind speed, and wind direction on the spatial patterns of avalanche activity. Patterns exist at the slide path scale, and for groups of adjacent slide paths, but not for either the entire region as a whole or when slide paths are grouped by aspect. Since wind instrumentation is typically located to measure an approximation of the free air winds, specific topography around a given path, and not simply aspect, is more important when relating wind direction to avalanche activity.
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1. Introduction

Avalanche forecasting utilizes inductive and deductive reasoning along with data and knowledge to reduce the uncertainty of the avalanche hazard for a given area (LaChapelle, 1980; McClung, 2002a,b). Data used for avalanche forecasting can be categorized as meteorological, snow pack structure, or direct stability data (LaChapelle, 1980). These data are typically used in real time and are incorporated into the day's forecast. When these data are recorded and archived, they can be analyzed to gain intrinsic knowledge about the local area. The purpose of this paper is twofold. First, we present a technique for analyzing avalanche and weather data. Second, by implementing that technique using our program **Geo-**

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graphic **W**eather and **A**valanche E**X**plorer (GeoWAX), we investigate relationships between new snowfall, wind speed, and wind direction on the avalanche activity at the Jackson Hole Mountain Resort at three scales: (1) the entire ski area (10^7 m^2), (2) groups of adjacent slide paths and groups based on aspect and elevation (10^3–10^4 m^2), and (3) individual avalanche paths (10^2–10^3 m^2).

A scientific understanding of avalanches, as well as knowledge of the local patterns of avalanche activity (gained through experience) is crucial for avalanche forecasters (McClung, 2002a). The former can be taught, but the latter is much more difficult to teach, communicate, or even define. For example, how new snowfall, wind speed, and wind direction conceptually lead to selective wind loading and the formation of slab avalanches is relatively easy to teach and understand. However, an understanding of which slide paths load under specific conditions of new snowfall, wind speed, and wind direction requires additional knowledge that may require decades of local individual observations and experience. Our method utilizes historical data to help aid in the visualization of the data, and to generate hypotheses regarding the role that different meteorological parameters play in creating spatial patterns of avalanche activity at Jackson Hole Mountain Resort.

This study utilizes meteorological data for two reasons. First, they are directly related to historical avalanche data. Second, they are readily available and highly abundant. In addition, due primarily to the automation of data collection, the volume of these data is increasing exponentially as a function of time and amount of daily data being recorded. Each year more data are being recorded by increasing the number of different weather parameters, adding new data collection site locations, and increasing the rate of taking measurements. These typical weather parameters include, but are not limited to, precipitation (new snowfall, snow water equivalent, snow depth), wind (speed and direction, maximum gust), and temperature (maximum, minimum, mean).

A number of techniques have been and are being used to help forecast avalanches utilizing historical weather and avalanche data. These include discriminant analysis, cluster analysis, nearest neighbors, and binary decision trees. Obled and Good (1980) present an overview and comparison of the first three methods, Buser (1983, 1989) details the nearest neighbor method, and Davis et al. (1996) present an example of binary decision trees. Nearest neighbor and binary decision tree methods are now operationally used by a number of avalanche forecast operations. Recently, other tools have been developed to aid data visualization and hypothesis generation. Cornice, a model currently used by the Scottish Avalanche Warning Service (Purves et al., 2002), facilitates both of these goals. SNOWBASE (Hägeli and Atkins, 2002), a program used by Canadian Mountain Holidays helicopter-skiing operation, focuses on visualization and data storage.

Our methods attempt to build on this past research in three ways. First, we incorporate the geographic component (i.e., the location, aspect, and elevation) of the slide paths. Second, we analyze the data at the individual slide path scale, which is of primary importance to ski patrollers and others doing avalanche hazard reduction work. Finally, instead of treating a day as either a day with avalanches or without, we create a probability of avalanching for each individual slide path, which can be geographically viewed using a GIS. Our primary goal is to create a tool to visualize, explore, and ask questions of weather and avalanche data sets, thereby allowing us to find spatial patterns and facilitate hypotheses generation.

Geographic Visualization and Geographic Knowledge Discovery are two emerging fields that share our primary goal of finding patterns and relationships in large spatial data sets. Both fields have several underlying concepts in common (MacEachren et al., 1999). First, both involve the *interaction* of computers and humans and see this interaction as a *process*, attempting to capitalize on the strengths of both (Miller and Han, 2001; MacEachren et al., 1999; Andrienko and Andrienko, 1999; Ramakrishnan and Grama, 1999; Fayyad et al., 1996; Hibbard and Santek, 1989). Second, *iteration* allows visualization of patterns with different attributes, at different times, or at different scales that may illuminate trends that would not be obvious in a static view (Andrienko et al., 2001; Ramakrishnan and Grama, 1999; MacEachren et al., 1999). Iteration is also familiar to avalanche forecasters, who typically use iteration while forecasting to reduce uncertainty and improve forecast accuracy (LaChapelle, 1980). Third, high interactivity between the user and computer allows the user to pose "what if" questions for hypothesis generation (Gahegan et al., 2001; MacEachren et al., 1999). Finally, *multiple perspectives* allow the user to view the data at different scales, measures, or even different concepts (Andrienko et al., 2001; MacEachren et al., 1999). Purves et al. (2002) emphasize the importance of multiple perspectives for avalanche forecasting tools.

The rest of this paper will outline the study area for our project, the methods we used to develop GeoWAX, and provide an example of how we used GeoWAX to investigate of the role of new snow, wind speed, and wind direction on the spatial patterns of avalanching at Jackson Hole Mountain Resort at a variety of scales.

2. Study site

This study uses historical data recorded by the Jackson Hole Mountain Resort, which is located on Rendezvous Mountain in the southern end of the Teton Range in northwestern Wyoming, USA (Fig. 1). The base elevation of the mountain is 1923 m, rising to a summit elevation of 3185 m. The Jackson Hole Mountain Resort is situated at 43°36′N latitude and is roughly 1000 km from the nearest moisture source (Pacific Ocean), giving the area an intermountain climate (Mock and Birkeland, 2000). In the winter, precipitation is mainly in the form of snow. Mid-latitude cyclones from the Pacific are intensified by orographic uplift as they encounter the western side of the Teton Range, especially when they travel along the relatively low and flat Snake River Plain to the west. The yearly average snowfall for the study plot at the top of the resort is 12.8 m of snow containing 1.5 m of snow water equivalence, while the base receives 2.6 and 0.5 m, respectively (Kozak, 2002). The predominant wind direction for most storms affecting Jackson Hole Mountain Resort is west–southwest (Birkeland et al., 2001). The town of Jackson, WY, has kept climatic records since 1948. The yearly average high and low temperatures are 12.1 and − 5.1 °C, with the coldest month being January (− 2.8 and − 15.0 °C) and the warmest month being July (27.2 and 4.4 °C).

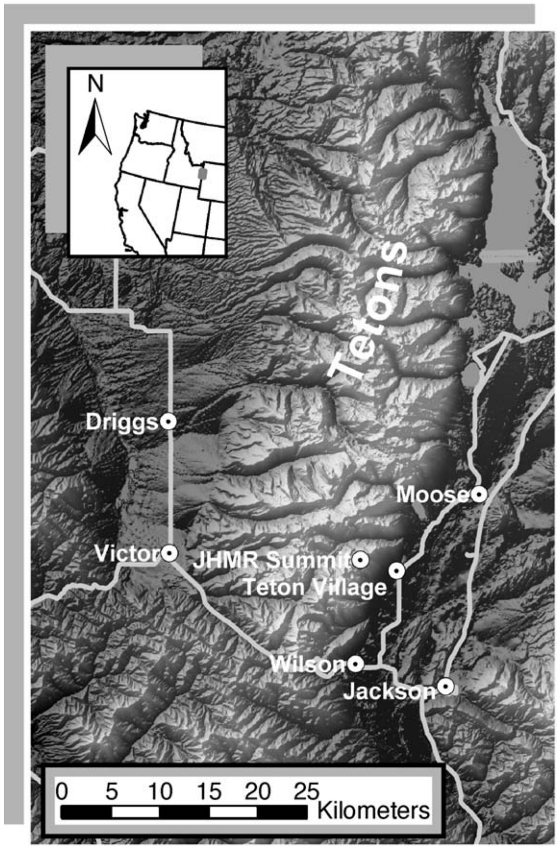

Fig. 1. Regional map displaying the location of the Jackson Hole Mountain Resort, Wyoming, USA (43°36′ N, 110°52′).

3. Methods

3.1. Applying Geographic Visualization and Geographic Knowledge Discovery to historical avalanche data

We applied the concepts of Geographic Visualization and Geographic Knowledge Discovery to historical weather and avalanche data. Slide paths have a geographic location along with geographic attributes, such as aspect and elevation, and can therefore be mapped, analyzed, and viewed with a GIS (Stoffel et al., 1998). The *k*-nearest-neighbors technique is our data-mining algorithm, and is used to generate avalanche probabilities. We base these avalanche probabilities, which are related to a given set of input parameters for each slide path, on a set of the most similar historical days found by the nearest neighbor search. Multiple perspectives of the data included a GIS representation of the slide paths to display individual slide path probabilities for each slide path (Fig. 2), a rose diagram to relate average probabilities for aspect and elevation categories to the search parameters, and graphical displays of the total nearest neighbor distance, the inverse distance weighting, and the partial distances for the nearest days.

The meteorological parameters used for this study include new snowfall, wind speed, and wind direction. We are interested in these parameters because the daily disruption of the snow pack due to skier traffic and avalanche hazard reduction activities minimizes the importance of older layers in the snow pack. We also only used three search parameters to minimize the potential problematic effects of high dimensionality, which can occur in nearest neighbor techniques using as few as 10–15 weather parameters (Aggarwal et al., 2001; Hand et al., 2001; Hinneburg et al., 2000; Beyer et al., 1999).

For each of the three weather parameters, we analyzed how they affected the pattern of avalanche activity for individual slide paths, for aspect–elevation categories, and for the average avalanche probability. After investigating the effects of the individual weather parameters, we analyzed them together to find wind loading patterns associated with new snowfall. When analyzed together, a specific pattern is created for each slide path, each aspect–elevation category, and for the average avalanche probability. This pattern is a specific signature for each feature and can be used to identify similarities and differences between similar feature types such as two slide paths. Next, we analyzed these signatures to identify the scales on which these three weather parameters operate. Hägeli and McClung (2000) concluded that the scales of weather parameters used in avalanche models might not be representative of the scales of natural processes in this complex earth system.

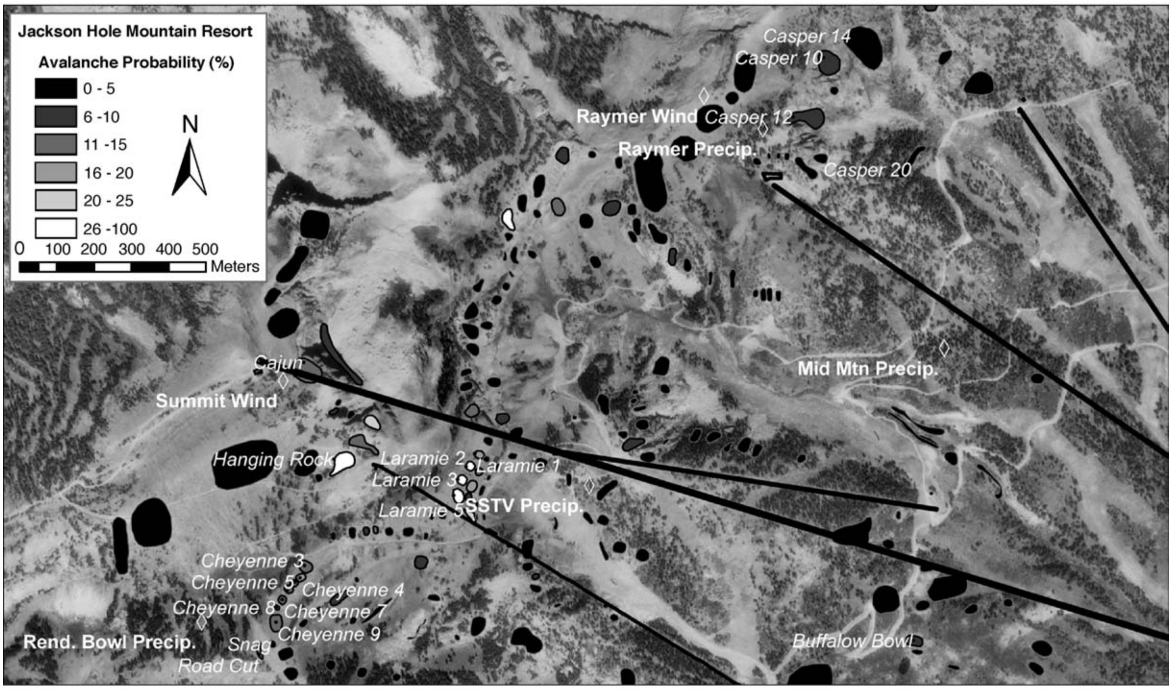

Fig. 2. A GIS representation of the upper mountain at the Jackson Hole Mountain Resort, Wyoming, USA. Avalanche starting zones are shaded to display avalanche probability, and specific slide paths mentioned in the text are labeled with italics. Weather stations are designated by diamond symbols and labeled in bold type.

3.2. Data

The data for this project include both historical and geographic data. The historical data are composed of daily weather measurements and the associated avalanche activity from the Jackson Hole Mountain Resort, Wyoming. The historical weather and avalanche data span 23 winter seasons, from 1978–1979 to 2001–2002, which include 3304 days and over 10,000 individual avalanche events.

By the 1978–1979 season, 34 parameters consisting of 204 weather measurements were recorded daily along with the associated avalanche activity. These weather data included measurements from four precipitation sites (Rendezvous Bowl, SSTV, Mid-Mountain, and Base, see Fig. 2) that recorded new snowfall, snow water equivalent (SWE), and total snow depth; three temperature sites recording 6:00 AM, 24 h minimum, and maximum temperatures; one summit wind site (4 × 6-h average speed and direction); and numerous subjective parameters such as snow available for wind transport and daily warming. Throughout subsequent seasons, those original weather parameters have been recorded along with new additional weather parameters. Today, over 50 parameters, consisting of hundreds of individual weather measurements, are recorded daily, which include data from five precipitation sites, four temperature sites, and three wind sites, most of which are remote and automatically recorded up to four times per hour. Precipitation measurements are manually verified at each site daily. The historical avalanche data consists of 10,232 avalanche events within the ski area. Avalanche events are recorded using standard U.S. methods (Perla and Martinelli, 1978), which include the date, slide path name, time, type, trigger, depth, U.S. size, and sliding surface as attributes. These data reside at the Jackson Hole Mountain Resort.

The geographic data sources include a one-meter resolution USGS Ortho Quad, a digital elevation model (DEM), and a polygonal representation of the starting zones of 220 in-bounds slide paths. The elevation data for the Jackson Hole Mountain Resort, in an Auto-CAD format (Schriber, 1998), was imported into a GIS (ArcInfo 7.0, ESRI) and oriented using common features in the Ortho Quad. Three-D Analyst, an extension of Arc-View 3.2 (ESRI), was used to create a 5-m DEM from the original 10-ft contour data. An aspect grid was created from the DEM using Spatial Analyst 2.0 (ESRI). Using the GIS, the lead avalanche forecaster for the Jackson Hole Mountain Resort digitized the slide path starting zones on-screen using the Ortho Quad and contour data for reference. The slide path starting zones were in a polygonal (vector) format where each starting zone was represented by an enclosed polygon with the attributes of name, average elevation, and average aspect of each starting zone. The average elevation and aspect for each starting zone were calculated by averaging all respective grid cells contained in that starting zone's polygon.

3.3. Creating slide path avalanche probabilities

Creating individual avalanche probabilities for each slide path is a seven-step process. First, a set of weather parameters along with a set of values is chosen as a basis for searching the historical database. These criteria constitute a *target day*. An example of a target day might be the following: new snowfall = 25 cm, average wind direction = 270°, average wind speed = 5 m/s. Second, an optional filter is applied to limit the historical days used. For example, we might only consider days with new snowfall greater than 15 cm but less than 35 cm. Third, as in other nearest neighbor approaches (i.e., Buser, 1983, 1989), all variables and target day values are normalized by their standard deviation. In step 4, optional parameter weights can be chosen to increase differentiation of a specific weather parameter.

Some nearest neighbor models optimize the parameter weights. Gassner et al. (2000) did this by using a local expert to set the weights and then created a measure of correctness to compare different weighting schemes. Purves et al. (2002) used a genetic algorithm to determine optimal weights. Though this can be useful, we chose not to optimize weights for two reasons. First, it was computationally expensive for our analyses since we were analyzing individual avalanche paths. Second, most nearest neighbor models define weight as relative importance, and therefore when a weather parameter is weighted heavily, the nearest days have less variation around the heavily weighted target value.

Step 5 involves the calculation of the nearest neighbor distance for all days in the filtered, standardized database. This technique creates a distance measurement for each day in the historical database based on its similarity to the target day. The more similar a historical day is to the target day, the shorter the distance measurement. In step 6, similar days are found in the historical database by ordering the historical days by their nearest neighbor distances.

In the final step, slide path probabilities are calculated based on the actual avalanche activity of the most similar days as defined by their nearest neighbor distance. First, the user chooses the maximum number of days to used. For example, if we consider the 100 nearest days, the number of avalanches is summed and averaged for each slide path over those 100 nearest days. If one slide path had 10 avalanches during those 100 nearest days, its avalanche probability is 10%. Likewise, a slide path with 50 avalanche events out of 100 nearest days has an avalanche probability of 50%. Additionally, the nearest days can be optionally weighted by an inverse function of the nearest neighbor distance to count more similar days more heavily. Our method creates a weighted average of the nearest days using a nonlinear function similar to methods described by Zhang et al. (1997) and Stanfill and Waltz (1986) by weighting a day with the inverse of the nearest neighbor distance (NNDist) plus a zero distance value (ZDV) to avoid dividing by zero, all raised to the inverse distance exponent (IDE). An IDE value of 0 would count each nearest day equally, while a IDE value of 1 would be traditional inverse distance weighting. The numerator of Eq. (1) is the summation of weighted avalanche events where days with no avalanches receive a 0, and days with an avalanche receive a 1. The denominator of Eq. (1) is the 100% maximum probability of avalanching equaling the weighted summation of an avalanche event on each of the nearest days.

$$\text{Slidepath Avalanche } P = \frac{\displaystyle\sum_{\text{MND}}^{\text{Day}_i=1} \frac{\text{Avalanche Event}_{\text{Day}_i} \ni : \{0,1\}}{(\text{NNDist}_{\text{Day}_i} + \text{ZDV})^{\text{IDE}}}}{\displaystyle\sum_{\text{MND}}^{\text{Day}_i=1} \frac{1}{(\text{NNDist}_{\text{Day}_i} + \text{ZDV})^{\text{IDE}}}} \tag{1}$$

The resulting set of slide path avalanche probabilities allowed the creation of the GIS representation (Fig. 2).

3.4. Creating avalanche probabilities for aspect–elevation categories

Creating avalanche probabilities for the aspect–elevation categories is a two-step process. In the first step, the combined geographic attributes of the aspect and elevation of slide paths are related to weather parameters for the entire ski area rather than for individual avalanche paths, with each slide path being categorized based on its average elevation and average aspect. Low (1829–2286 m), middle (2286–2743 m), and high (2743+ m) are used as three elevation categories along with eight aspect categories (N, NE, E, SE, S, SW, W, NW) for a total of 24 possible categories. Next, the slide path probabilities are averaged for all slide paths based on their aspect–elevation category, and are viewed using a rose diagram.

3.5. Creating series signatures

The combination of the target day and the set of resulting output (slide path avalanche probabilities, aspect–elevation probabilities, and the average slide path probability) constitute what we define as a Nearest Neighbor Avalanche Probability Profile (NNAPP). A NNAPP encapsulates the total response of the system for a set of search parameters.

The effects of weather parameters on avalanche activity can be visualized as a multi-dimensional space where each weather parameter is represented by a different dimension. New snowfall, wind direction, and wind speed define a three-dimensional space. To explore the response to changes of new snowfall, wind direction, and wind speed, a NNAPP is created for each set of search parameters by systematically varying one weather parameter at a time, eventually creating a NNAPP to populate each location (variation of parameters) in the three-dimensional series space. We call this a series signature. The NNAPP attribute avalanche probability now constitutes a fourth dimension. Two of the three weather parameters and an avalanche probability are graphed, visualized, and analyzed. Examples of series signatures start in Section 4.1.

3.6. GeoWAX

We developed GeoWAX to implement the previous methods using Microsoft's Visual Basic 6.0 along with ESRI's Map Control in ArcView 8.1 to implement the embedded map. GeoWAX is an interactive program to enable avalanche forecasters to explore their historical data and aid in visualization of data and hypotheses generation. The forecaster can vary the search parameters used in the nearest neighbors search and the parameter weights, and can filter the weather data based on a range of each search parameter or any set of fixed values. When creating the slide path probabilities, the forecaster can also vary the number of nearest days to be used along with the nearest neighbor distance weighting function.

Since GeoWAX was developed for the exploration of data, all levels of interconnectivity of the data representations are retained and available to the forecaster. For example, when viewing a series signature, all of the NNAPPs are retained and can be viewed (GIS representation of slide paths, aspect–elevation rose-diagram, and mean avalanche probabilities). Likewise, the actual weather and avalanche events for all nearest days can be viewed along with a GIS representation of a day's avalanche events.

3.7. Case study: wind loading of new snowfall

We chose new snowfall, wind speed, and wind direction to explore their effect on avalanche activity for the Jackson Hole Mountain Resort. New snowfall (Rendezvous Bowl precipitation) values ranged from 0 to 35 cm in 5-cm increments for a total of eight steps in the new snowfall dimension. Wind direction (summit wind) was varied from 0° to 360° in 20° increments for a total of 19 steps and was weighted twice as heavily as new snowfall and wind speed to help differentiate the different wind direction categories. The wind speed dimension had three categories: 5 m/s (low), 10 m/s (moderate), and 15 m/s (high). All variables were normalized with their standard deviation to normalize distance measurements. Days were filtered with ranges based on the target values. New snowfall ranged ± 15 cm, wind speed ± 4 m/s, wind direction ± 30° around their respective target values and the inverse of the square root of the nearest neighbor distance was used to weight more similar days. A minimum of 10 days and a maximum of 100 days were used to create the 456 NNAPPs. Every slide path, aspect/elevation category, and the average probability were available for analysis, producing individual, unique series signatures.

3.8. Statistical analyses

The goal of our statistical analyses is to compare the pattern observed for one series signature (for an

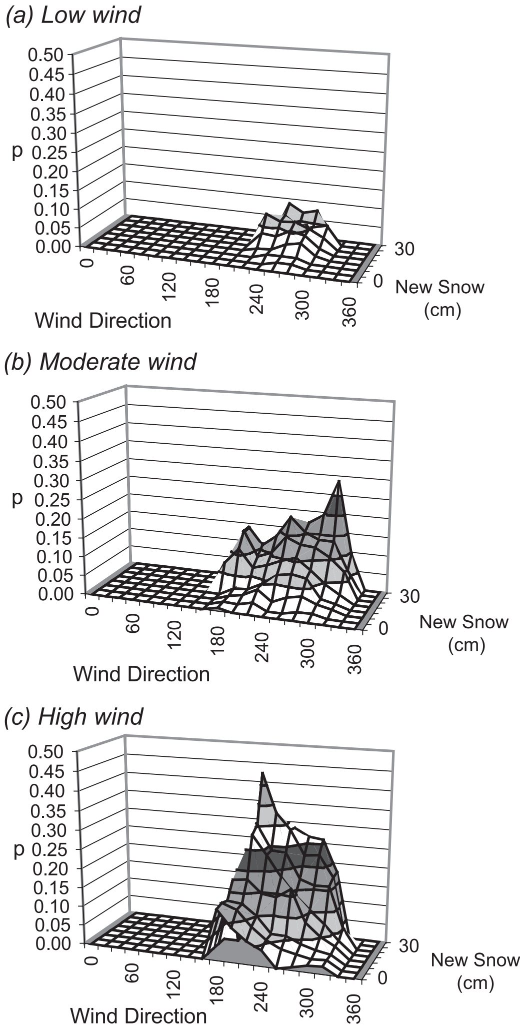

Fig. 3. Series signatures for Buffalo Bowl in low (a), moderate (b), and high (c) wind showing a dramatic increase in avalanche probability with an increase in wind speed. The mean avalanche probability for the series signatures are significantly different ($p < 0.001$).

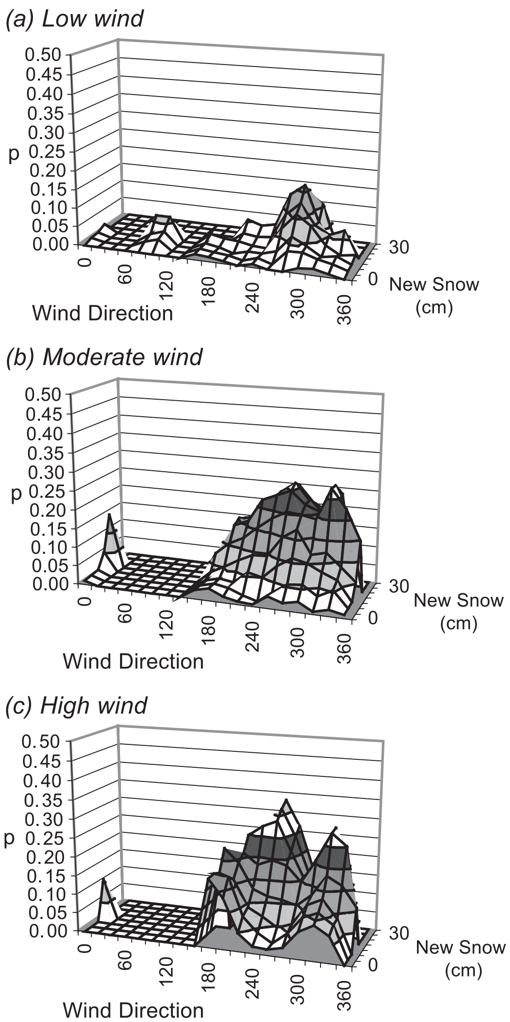

Fig. 4. Low (a), moderate (b), and high (c) wind series signatures for Cajun Couloir showing different responses to wind direction for different wind speeds. At some wind directions, high wind speeds decrease the avalanche probability, suggesting that those wind directions may scour this particular avalanche path.

avalanche path or groups of paths) to another series signature. We use two types of nonparametric statistics to analyze our data. First, we use a Mann–Whitney *U*-test to compare the means of two series signatures. This test is applicable when we are interested in the effect of only one parameter, such as wind speed. When our primary interest is in the pattern observed, we use Spearman's rho, a nonparametric correlation analysis similar to Pearson's *r*, to compare the avalanche probabilities in one series signature to the other series signature.

4. Results and discussion

4.1. Individual weather parameters

Our investigation focuses on how snowfall, wind speed and wind direction affect the spatial patterns of avalanche activity at Jackson Hole Mountain Resort. An increase in new snowfall leads to an increase in the avalanche probability at all scales, from individual paths to the entire ski area. More new snowfall results in more stress added to buried weak layers or interfaces, thereby increasing the probability of avalanche activity (McClung and Schaerer, 1993), and the effect of this can be seen at all scales, ranging from individual paths to the entire resort.

In contrast, the effect of wind speed differs depending on the scale of observation. At the scale of individual avalanche paths, considerable variability exists. Most slide paths exhibit an increase in avalanche probability with an increase in wind, with a few paths displaying a large increase, such as Buffalo Bowl, a middle elevation (2404 m) slide path. The series signatures for low, moderate, and high wind situations for Buffalo Bowl show this large increase in avalanche probability for increasing wind speed (Fig. 3), and all were significantly different (p values < 0.001). In contrast, some slide paths, such as Broadway, decrease in avalanche probability with an in-

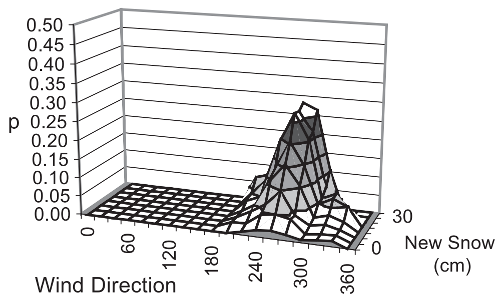

Fig. 5. Series signature for Cheyenne 3 in high wind showing most active avalanche activity with westerly winds (240–260°), which is representative of other slide paths in the Cheyenne group in high wind.

crease in wind; perhaps the higher wind speeds scours those paths. Others, such as Cajun Couloir, increase in avalanche probability under certain wind directions, and decrease at other directions (Fig. 4). At the scale of the entire ski area, there is a general increase in avalanche probability between low and moderate wind, but not between moderate and high wind, for both the overall average and the aspect–elevation categories. These results demonstrate how much variability exists at the scale of single paths within the overall average for the ski area.

The effect of wind direction also differs for different scales. At the scale of individual slide paths, changes in wind direction change the probability of avalanche activity. Although changes in wind direction also lead to changes in avalanche activity for slide paths grouped by aspect and elevation, these changes are similar to each other and the overall average computed for the entire ski area. The responses of the individual avalanche paths may cancel each other out and "smooth" the data.

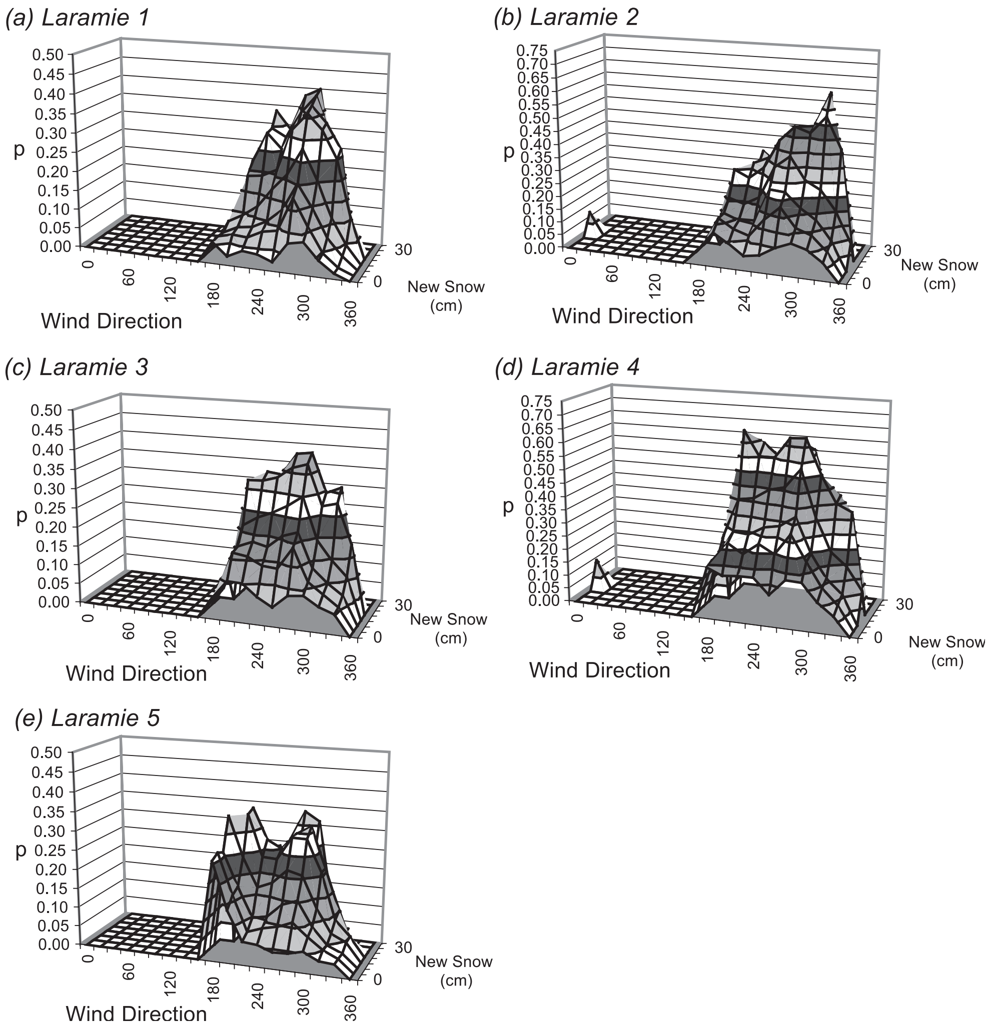

Fig. 6. The high wind series signatures for the Laramie group. The Laramie group is the most active slide path group at Jackson Hole with high activity associated with southerly, westerly, and northerly winds.

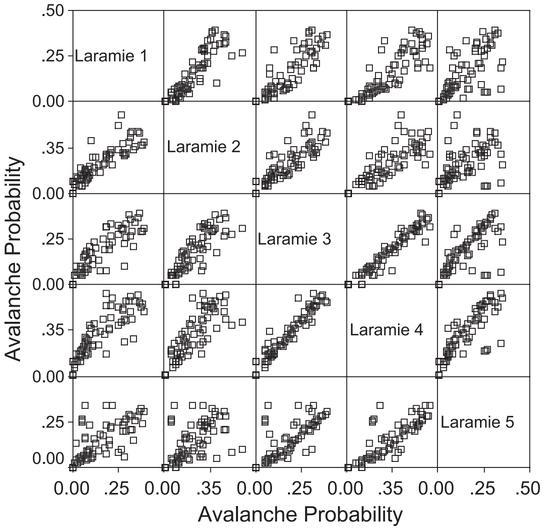

Fig. 7. Probability–probability scatter plot for corresponding search parameters in the series signatures for the Laramie group showing strong relationships between slide paths. Correlation coefficients (rho) between the series signatures ranged from 0.80 to 0.96.

4.2. Series signature patterns

Our data exploration with GeoWAX shows that many slide paths exhibit similar series signatures. Additionally, slide paths with similar signatures are often in the same geographic area. Examples of grouped spatial similarity include the Cheyenne group, the Laramie group, and the Casper group, which gives us insight into possible scales of avalanche processes that may exist at the Jackson Hole Mountain Resort.

Slide paths in the Cheyenne group include Cheyenne 3–9, The Snag, and Roadcut, and all exhibit similar series signatures, with high avalanche activity associated with winds out of 240–260°. When the slide paths within the Cheyenne group are compared to each other the Spearman's correlations (rho) range from 0.746 to 0.983 (p values < 0.001), showing strong inter-group similarities. The series signature for Cheyenne 3 is a typical series signature for this group (Fig. 5).

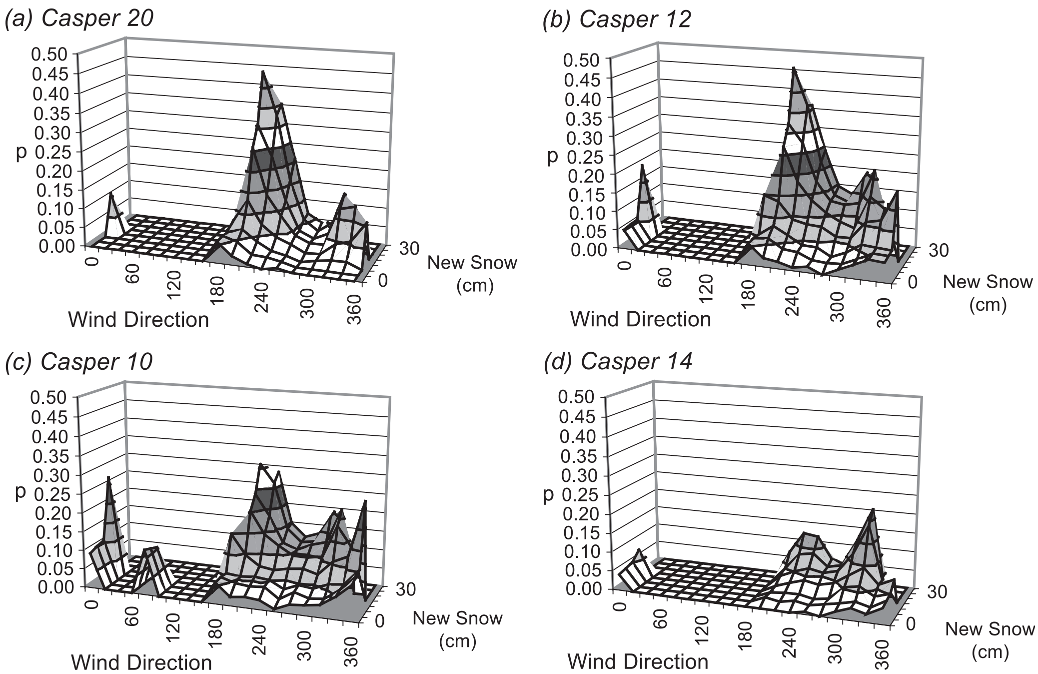

Fig. 8. The high wind series signatures for the Casper group. The Casper group is characterized with high avalanche activity associated with southerly and northerly winds, but not westerly winds.

A similar situation exists for the slide paths in the Laramie group, which include Laramies 1–5. These are some of the most active slide paths on the mountain, with series signatures displaying high avalanche probabilities with winds from 180° to 360° (Fig. 6). Their correlation values range from 0.801 to 0.962, with p values <0.001 (Fig. 7), again showing strong similarities within the group. There are also some smaller scale (individual slide path) trends. Laramie 5, an east–northeast-facing starting zone just on the lee side of a small ridge, had its highest avalanche probabilities with southerly winds. In contrast, Laramies 1–4 had their highest avalanche probabilities with more westerly winds.

In contrast to both the Cheyenne and Laramie groups, the slide paths in the Casper group (Caspers 10, 12, 14, 20) all experience their highest avalanche activity with winds either more southerly or northerly than the predominant west southwest winds (Fig. 8). Although the correlation values are all significantly correlated with p values <0.001, the amount of similarity is much less, ranging from 0.478 to 0.863 (Fig. 9). The two slide paths that are most dissimilar to each other are also the farthest apart in distance (Caspers 20 and 14). Here a sizable difference between slide paths in the same group exists. Both

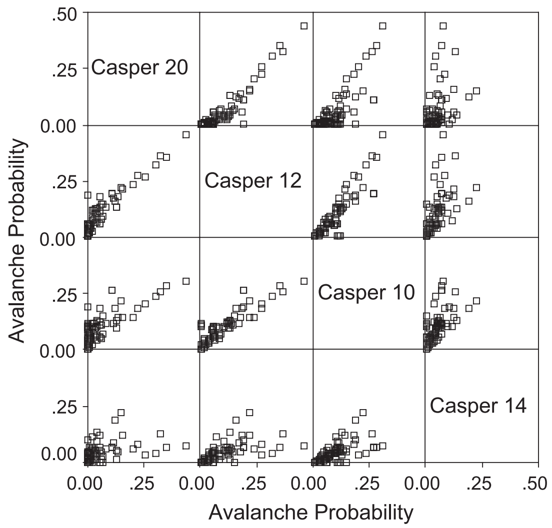

Fig. 9. Probability–probability scatter plot for corresponding search parameters in the series signatures for the Casper group showing strong relationships between slide paths. Correlation coefficients between the series signatures ranged from 0.48 to 0.86.

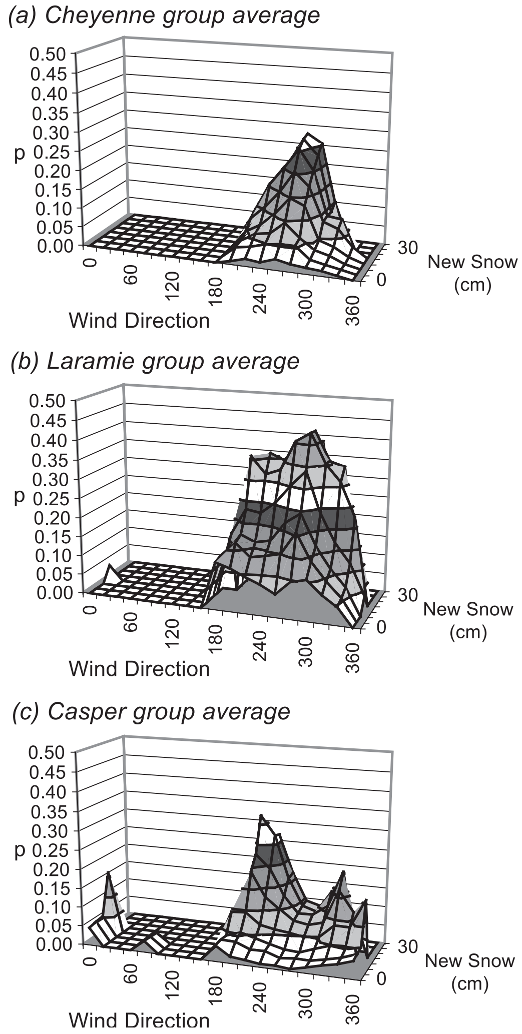

Fig. 10. Average high wind series signatures for the Cheyenne group, the Laramie group, and the Casper group. The Casper group is differentiated from the others by the marked decrease in avalanche probability for winds out of the west.

Caspers 12 and 20 experience high avalanche activity with southerly winds while Caspers 10 and 14 become more active with northerly winds. We suspect this is due to the geographic location of the slide paths. Caspers 12 and 20 are both situated at the southern end of Casper bowl, and are leeward of a ridge with southerly winds. In contrast, Caspers 10 and 14 are in the center of Casper bowl and may be more sheltered from southerly winds. Similar to the Laramie group, the Casper group also shows some differences at the

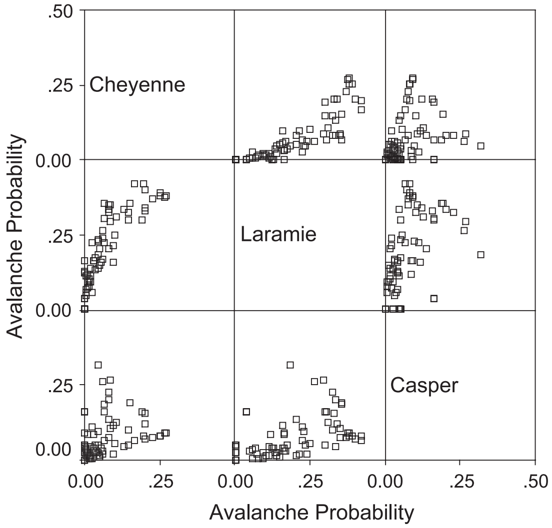

Fig. 11. Probability–probability scatter plot for corresponding search parameters in the high wind series signatures for the Cheyenne group, the Laramie group, and the Casper group showed the similarities between the Cheyenne and Laramie groups and the marked difference between the Casper group and the other two groups.

slide path scale, yet still had similarities at the group scale.

After finding similar series signatures for different groups, we created an average series signature for each group and compared these group averages with each other using their series signatures (Figs. 10 and 11). The *Cheyenne group* and the *Laramie group* are quite similar with a correlation of rho = 0.923. In contrast, the *Cheyenne group* and the *Laramie group* are more poorly correlated to the *Casper group* with rho values of 0.496 and 0.591, respectively (p values <0.001).

4.3. Compare aspect–elevation series signatures

Enlarging the scale of our analysis to sets of avalanche paths grouped by aspect, rather than by geographic location, gives us different results. A look at four high-elevation aspect categories (northeast-facing, east-facing, southeast-facing, and south-facing) shows that their series signatures appear similar with no obvious relationship to wind direction (Fig. 12).

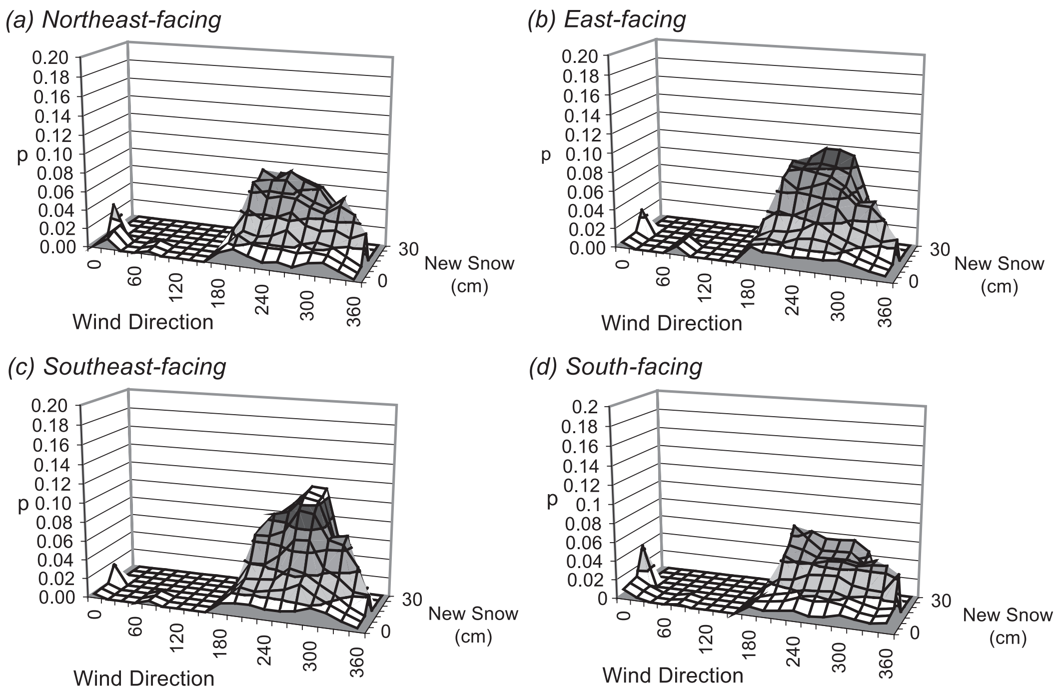

Fig. 12. Series signatures for four high elevation, high wind aspect zones (northeast-facing, east-facing, southeast-facing, and south-facing) are all similar and show no obvious relationship differences with wind direction.

Table 1
Series signature correlation rho values

	Spearman's rho	p (two-tailed)
Cheyenne group	0.746–0.983	0.000
Laramie group	0.801–0.962	0.000
Casper group	0.478–0.863	0.000
Cheyenne vs. Laramie	0.923	0.000
Cheyenne vs. Casper	0.496	0.000
Laramie vs. Casper	0.591	0.000
NE-facing vs. E-facing	0.952	0.000
NE-facing vs. SE-facing	0.927	0.000
NE-facing vs. S-facing	0.899	0.000
E-facing vs. SE-facing	0.966	0.000
E-facing vs. S-facing	0.909	0.000
SE-facing vs. S-facing	0.888	0.000

Spearman's rho values used as a measure of similarity among grouped slide paths and between grouped slide paths.

Further, a correlation and scatter plot analysis shows that they all correlate well with each other, with rho = 0.89–0.97 (Table 1; Fig. 13). Thus, while sizable differences exist between some groups of slide paths based on their location within the ski area (i.e., comparing the Cheyenne and Casper groups), those sizable differences do not exist between sets of avalanche paths grouped by aspect and elevation. The differences at the scale of individual slide paths and groups of slide paths shown in the previous section must cancel each other out when averaged based on aspect–elevation categories. These results do not support a direct relationship between wind direction collected at a central location and slide path aspect for numerous slide paths in complex terrain.

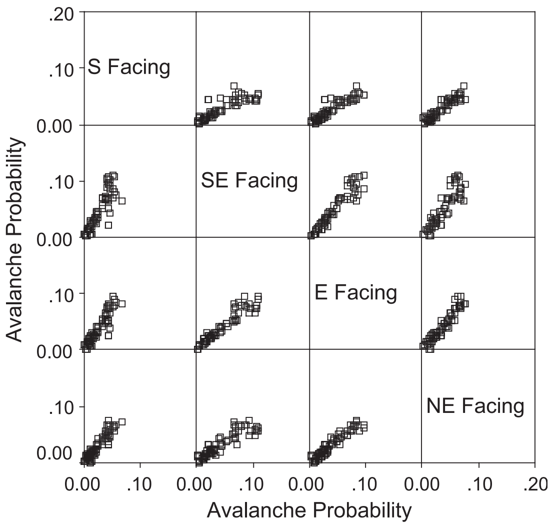

Fig. 13. Probability–probability scatter plot for corresponding search parameters between four high-elevation, high-wind aspect–elevation category series signatures (northeast-facing, east-facing, southeast-facing, and south-facing) do not display a direct relationship to wind direction.

4.4. Wind correlation between summit and Raymer wind sites

Our results indicate that patterns emerge due to changes in wind direction. We suspect specific wind flow patterns cause the observed slide path differences. To explore the possibility that specific wind flow patterns exist, we plotted the hourly mean wind direction for our two wind sites over two seasons (Fig. 14). When the two seasons were plotted separately, the same distinct pattern was observed. These distinct wind patterns suggest specific wind flow patterns develop around the mountain according to specific upper air wind directions. Font et al. (2001) found similar results when they created aeolian susceptibility maps that categorized small-scale wind patterns by the aeolian features created by different local wind directions and then related this to a centralized wind station. In their work, specific centralized wind direc-

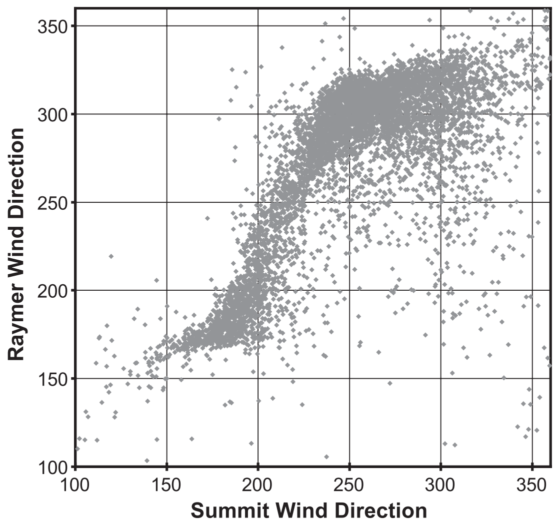

Fig. 14. Two-season hourly average (2000–2002) direction–direction scatter plot for the summit and Raymer wind sites showing the consistent wind direction relationship between the two wind sites.

tions led to consistent patterns of wind erosion and deposition as determined by the maps, which is consistent with our findings.

5. Conclusion

Each of the three weather parameters we investigated affected the avalanche probabilities differently. New snowfall increases avalanche activity at all scales. However, it does not play a significant role in differentiating avalanche activity between individual slide paths. In contrast, wind speed does have a differentiating effect, depending on the avalanche path location. For example, high wind is important in the creation of avalanches at lower elevations, which may be due to a wind threshold needed for slab development that only occurs at lower elevations with high summit winds. Of the three weather parameters, wind direction is the most important for differentiating individual slide path avalanche probabilities, probably because winds are being redirected by topography, and are selectively loading specific avalanche paths.

The combination of our three weather parameters, along with their series signature representations, provides new knowledge about selective wind loading at a variety of scales, from individual avalanche paths to groups of paths. Analyzing series signatures was critical for our analyses, which resulted in a high correlation between adjacent slide paths and relatively low correlations between different groups of slide paths. In addition to this interpolated knowledge, we can use the series signatures for a given path, or groups of paths, to extrapolate the wind loading effect for highly unusual situations. For example, we would be much more concerned with avalanche paths in the Casper group than the Cheyenne group if we had high winds out of 140–160° (SSE) associated with a large storm.

All of our high-elevation aspect categories exhibit similar series signatures. At the scale of the entire ski resort (10^7 m^2), there is no obvious relationship between avalanche activity based on aspect and wind direction. This result is important to demonstrate that wind direction measured at a central, high elevation location does not necessarily directly relate to the specific aspects being wind loaded. We are not implying that aspect with respect to wind direction does not play a role in avalanche development; clearly, at the scale of individual paths, wind direction is critically important. However, since wind instrumentation is typically located to measure an approximation of the free air winds, specific topography around a given path, and not simply aspect, is more important when relating wind direction to avalanche activity.

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