A probabilistic technique for exploring multi-scale spatial patterns in historical avalanche data by combining GIS and meteorological nearest neighbors with an example from the Jackson Hole Ski Area, Wyoming

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Abstract: Many ski areas, backcountry avalanche centers, highway departments, and helicopter ski operations record and archive daily weather parameters and the resulting avalanche activity. This paper proposes a new probabilistic method to allow avalanche forecasters to better utilize their historical weather and avalanche data by incorporating a Geographic Information System (GIS) with a modified meteorological nearest neighbors approach. This approach utilizes concepts from Geographic Visualization (GVis) and Knowledge Discovery in Databases (KDD). The resulting interactive database tool allows avalanche forecasters to visually explore regional spatial patterns of avalanche activity at multiple scales. This technique allows the correlation between weather parameters and the spatial pattern of avalanche activity. An example of this method was implemented using 23 years of historical avalanche data from the Jackson Hole Ski Area with over 10,000 avalanche events to analyze the effect of new snow, wind speed, and wind direction on the spatial patterns of avalanche activity. Patterns were found at the slide path scale and for sub-regional groups, but not for the entire region as a whole, or when slide paths were grouped by aspect categories.

Keywords: Avalanche Forecasting, GIS, Nearest Neighbors, Geographic Visualization, Knowledge Discovery in Databases

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; 2002b). Data used for avalanche forecasting can be categorized as meteorological data, snow-pack structure data, or direct stability data (LaChapelle, 1980). These data are typically used 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. However, many snow safety operations have collected these data, but have not yet devised an effective technique for analyzing them. The purpose of this paper is twofold. First, we present a new technique for analyzing avalanche and weather data. Second, we utilize that technique to explore the relationship between new snowfall, wind speed and wind direction on avalanche activity at the Jackson Hole Ski Area at both the scale of the ski area and the scale of individual avalanche paths.

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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 snow, wind speed, and wind direction lead to selective wind loading and the formation of slab avalanches is relatively easily understood. However, an understanding of which particular slide paths load under which conditions of new snow, wind speed, and wind direction requires additional knowledge that may require decades of local experience. We present a new method with the ultimate goal of increasing knowledge by better utilizing historical data. Specifically, we are searching for the roles that different meteorological variables play in creating regional spatial patterns of avalanche activity.

We chose meteorological data for this study for two reasons. First, they can be 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. Not only do the data increase as a function of time, each year more data are taken by increasing the types of measurements, adding new site locations, and increasing the rate of taking measurements. Typical weather parameters include precipitation parameters (i.e. new snow, snow water equivalent, snow depth), wind parameters (speed and direction, gusts, etc.), temperature parameters (maximum, minimum, mean, etc.) and many others. These measurements are usually taken at multiple locations and are often automated.

A number of techniques have been applied to similar data sets including discriminant analysis, cluster analysis, nearest neighbors, and Classification and Regression Trees (CART). Obled and Good (1980) present an overview and comparison of the first three methods, and an example of CART is presented by Davis *et al*. (1996). These methods all suffer from shortcomings. First, they do not account for the geographic component of slide paths, which experience has shown is quite important. Second, they typically do not 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, they usually treat a day as either a day with avalanches or without. As a result of this type of classification, most are not probabilistic in nature.

Our approach differs from previous methods in both the underlying philosophy and in the specific methodology. Our underlying goal is to improve interaction with large datasets. We want a tool to explore and ask questions of the data in order to find spatial patterns. The ideal tool will incorporate geography, be probabilistically based, and be useful for analyzing avalanche data at different scales (ranging from an individual slide path to the entire region).

Two emerging fields, Geographic Visualization (GVis) and Knowledge Discovery in Databases (KDD), also share our primary goal of finding patterns and relationships in large datasets. GVis and KDD have several underlying concepts in common (MacEachren *et al*. 1999). First, both fields involve the *interaction* of computers and humans and see this interaction as a *process*, attempting to capitalize on the strengths of both. Second, *iteration* allows visualization of patterns at different scales that may illuminate trends that would not be obvious in a static view. 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*. Finally, *multiple perspectives* allow the user to view the data at different scales, measures, or even different concepts.

GVis has two additional criteria. First, the data must have a *geographic component*. Second, representations of the data take advantage of the human eye-brain ability to visually recognize and identify patterns. MacEachren *et al*. 1999 defines GVis as "the use of concrete visual representations – whether on paper or through computer displays or other media – to make spatial contexts and problems visible, so as to engage the most powerful of human information processing abilities, those associated with vision." In contrast, KDD focuses on the data mining methods and algorithms to extract patterns from large databases.

MacEachren *et al*. 1999 illustrates the strength of combining the concepts of GVis and KDD and present an excellent overview. We apply these concepts to historical weather and avalanche data. Avalanche data are well suited to be analyzed using the concepts of Geographic Visualization. Slide paths have a geographic location along with geographic attributes (aspect, elevation, etc.) and can therefore be mapped, analyzed, and viewed with a GIS (Stoffel *et al*. 1998). The nearest neighbors technique has already been used as a searching technique to find similar historical days (Buser 1983; 1989) and is the search algorithm for our KDD approach. Avalanche probabilities for a given set of input parameters are calculated for each slide path based on the set of the most similar historical days found by a nearest neighbor search. Both KDD and GVis consider multiple perspectives to be very important. These data can be viewed three different ways. First, a GIS representation of the slide paths is used to display individual slide path probabilities for each slide path (Figure 1.). This is the GVis perspective. Second, average probability for aspect and elevation categories can be used to relate those geographic attributes to the associated weather parameters (typically viewed with a rose diagram). Finally, the average probability can be created for all slide paths to get an overview of the set of weather parameters.

Iteration is also one of the key concepts of KDD and GVis. The values for a given set of weather parameters for the nearest neighbor search are systematically varied to create a series of avalanche probabilities sets. Each variation is an iteration, and each iteration can be viewed using one of the perspectives described above. More importantly, a feature of any perspective (individual slide path, aspect-elevation category, or average probability) can be analyzed throughout its series. If there is no relationship between the weather parameters and the feature (i.e. an avalanche path), the avalanche probability should not significantly change with changes in the nearest neighbor search values. The response of a feature to changes in weather parameters is in itself a pattern or signature. Finally, by visualizing probability patterns of slide paths along with viewing different perspectives, can we discover unknown patterns (knowledge)? For example, do certain slide paths exhibit similar patterns?

For this paper we consider new snowfall, wind speed, and wind direction. These weather parameters are primary forcing mechanisms for dry slab

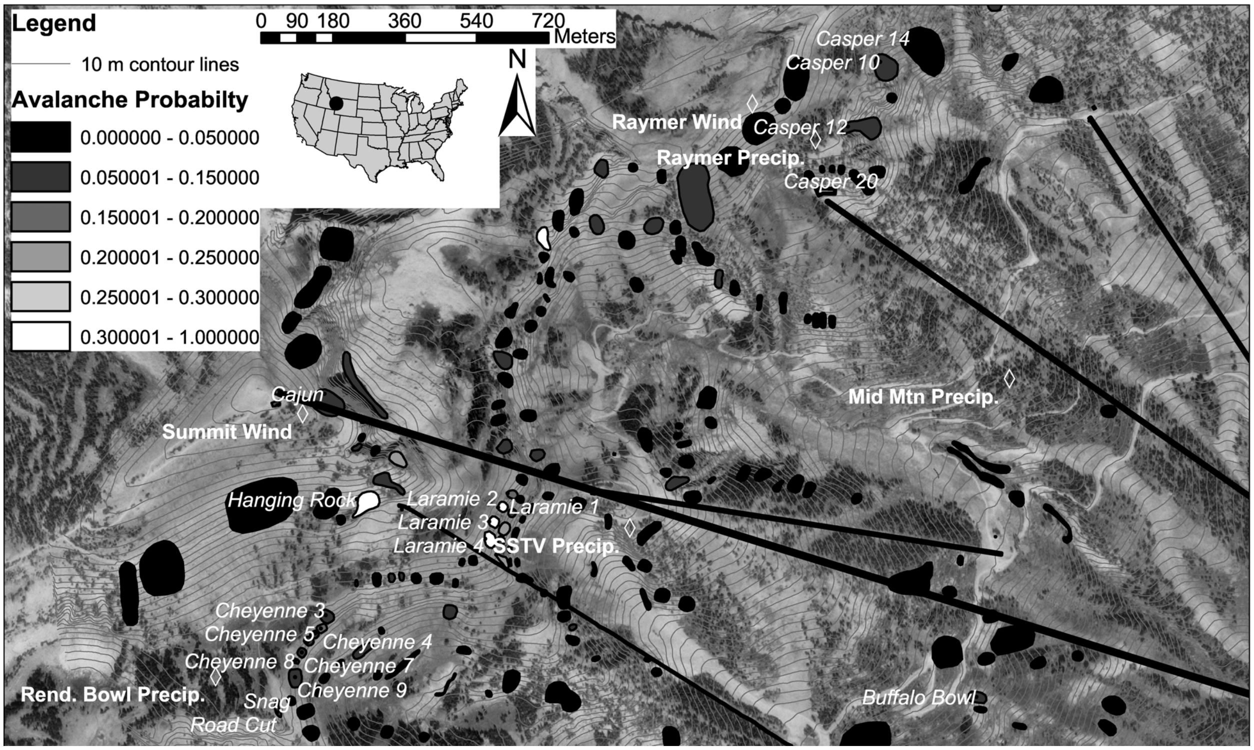

Figure 1: GIS representation of the upper mountain at the Jackson Hole Ski Area, Wyoming, USA. Avalanche starting zones are shaded to display avalanche probability.

avalanches, particularly for wind loading and slab development (McClung and Schaerer, 1993). We are primarily interested in new snow wind loading and slab development because we are utilizing ski area data where ski compaction is a primary consideration. For each weather parameter (new snow, wind speed, wind direction), we analyze how it affects the pattern of avalanche activity for individual slide paths, for aspect-elevation categories, and for the overall average. In the end, we are attempting to discover new patterns at different scales, thereby increasing our knowledge.

2. Methods

2.1 Data

The data for this project are either historical or geographic. The historical data are composed of daily meteorological weather measurements and the associated avalanche activity. The geographic data have a spatial component, which can be represented by a GIS.

The historical weather and avalanche data span 23 seasons, starting with the 1978-79 season and ending with the 2001-02 season. During the original season roughly 50 weather parameters were recorded daily along with the associated avalanche activity. These weather data included four precipitation sites (New Snow, Snow Water Equivalent (SWE) and Total Snow Depth), three temperature sites (6:00 AM, 24 hour minimum, maximum), one summit wind site (4 x 6-hour speed and direction), and numerous subjective parameters such as *snow available for wind transport* and *daily warming*. Throughout all seasons those original weather parameters have been recorded along with new weather parameters that have been added. Today, hundreds of weather parameters 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. Precipitation measurements are manually verified at each site daily. The historical avalanche data is composed of 10,232 avalanche events within the ski area. Avalanche events were recorded using standard U.S. methods (Perla and Martinelli, 1978). Each avalanche event is a record in a table with the date, slide path name, time, type, trigger, depth, U.S. size, and sliding surface as attributes.

The geographic data (Figure 1) include a Digital Ortho Quarter Quad (DOQQ), Digital Elevation Model (DEM), and a polygon representation of the starting zones of 220 in-bounds slide paths. A DOQQ is a black and white aerial photo that has been geo-rectified to account for lens distortion and curvature of the earth. The resolution and accuracy are very high (1-meter pixels), and we use this as a base layer for viewing the geographic data. DOQQs are available from the U.S. Geological Survey, and are named by their associated 7.5 min quadrangle.

Jorgenson Engineering generated the original elevation data for the Jackson Hole Ski Area in an Auto-CAD format with elevation being represented by 10-foot contour lines (3m). We imported the Auto-CAD formatted elevation data into a GIS (Arc-Info 7) and oriented it using common features in the DOQQ. Three-D Analyst, an extension of Arc-View 3.2, was used to create a 5-meter DEM from the 10-foot contour data. A DEM is a representation of a continuous surface using a grid of equal spacing where each grid cell has an elevation value. An aspect grid was created from the DEM using Spatial Analyst.

Using the GIS, the slide path starting zones were digitized on-screen with a mouse using the DOQQ, contour data, and differentially corrected GPS data for reference. The determination of the spatial extent and location of the slide path starting zones was done by Robert Comey, Lead Avalanche Forecaster for both the Jackson Hole Ski Patrol and the Bridger-Teton National Forest Avalanche Center. Unlike the grid representation of the elevation data, the slide path starting zones are in a polygon (vector) format where each starting zone is represented by an enclosed polygon. Each polygon corresponds to a record in a table where attribute data are stored for that polygon. The polygon starting zones in conjunction with their attributes is also known as feature data. These attributes include the name, average elevation, and average aspect of each starting zone. The average elevation for each starting zone was calculated by averaging all elevation grid cells contained in that starting zone's polygon. Similar methods were used to calculate the average aspect for each starting zone.

2.2 Creating slide path avalanche probabilities

Creating individual avalanche probabilities for each slide path is a four-step process. First, a set of weather parameters along with a set of values must be chosen as a basis for searching the historical database. This constitutes a *Target Day*. An example of a target day with three parameters could be: new snow = 25 cm, average wind direction = 270°, average wind speed = 5 m/s. Second, an optional filter may be applied to limit the historical days used. For example, only consider days with new snow greater than 15 cm and less than 35 cm. Third, similar days are found in the historical database using a nearest neighbors technique. 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. This technique has been tested and described by several authors, particularly Buser (1983; 1989).

Finally, slide path probabilities are calculated based on the actual avalanche activity of the most similar days. First, the number of near days to use is chosen. For this example, we consider the 100 nearest days. For each of the 100 near days, the number of avalanche events is summed by slide path and then averaged. If one slide path had 10 avalanches during those hundred near days, it would have an average probability of avalanching of 10%. Likewise, if another slide path had 50 avalanche events out of 100 near days, its avalanche probability would be 50%. This allows the creation of a slide path probability for each slide path and an average probability for the target day. Additionally, the near days can be optionally weighted by an inverse function of the nearest neighbor distance to count more similar days more heavily.

2.3 Creating avalanche probabilities for aspect-elevation categories

To relate the geographic attributes of aspect and elevation of slide paths with weather parameters for the entire ski area rather than for individual avalanche paths, each slide path is categorized based on its average elevation and average aspect attribute data. Low (2000-2500 m), Middle (2500-3000 m), and High (3000+ m) are used as three elevation categories 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. These data can be viewed using a rose diagram.

2.4 Creating series space

The previous methods can be considered a function. The input of the function is the target day and the output of the function is the set of slide path probabilities, aspect-elevation avalanche probabilities, and the average probability for the target day. The combination of the target day and the set of resulting output (slide path avalanche probabilities, rose diagram probabilities, and average probability) constitute what we define as a *Nearest Neighbor Avalanche Probability Profile* (NNAPP).

The effects of weather parameters on avalanche activity are visualized as a multi-dimensional space with the different dimensions as weather parameters. Considering the new snow, wind direction, and wind speed example earlier, we define the *series space* as a three-dimensional box with edges of new snow, wind direction, and wind speed. To explore the response of a certain set of values of new snow, wind direction, and wind speed (an xyz location in the box) a NNAPP is created for that set of values. This can be done systematically by varying one weather parameter at a time, eventually creating a NNAPP to fill each location (variation of parameters) in the three-dimensional series space. The NNAPP attribute avalanche probability now constitutes a fourth dimension. Two of the three weather parameters and an avalanche probability can be graphed, visualized, and analyzed.

2.5 Detailed example: new snow wind loading

New snow, wind speed, and wind direction were chosen to explore their effect on avalanche activity for the Jackson Hole Ski Area. New snow (Rendezvous Bowl precipitation) values range from 0 to 35 cm in 5 cm increments for a total of 8 steps in the *new snow dimension*. Wind direction (summit wind) was varied from 0° to 360° in 20° increments for a total of 19 steps (0 and 360 should be the same and are both calculated as a double checking measure). The *wind speed dimension* has three categories: 5 m/s (low), 10 m/s (moderate), and 15 m/s (high). Wind direction was weighted twice as heavily as new snow and wind speed (2,1,1) to help differentiate the 18 different wind direction categories. All variables were normalized with their variance to standardize distance measurements. Days were filtered (new snow ± 15cm, wind speed ± 4 m/s, wind direction ± 30°) and the inverse of the square root of the nearest neighbor distance was used to weight more similar days more heavily. A minimum of 10 days and a maximum of 100 days were used to create the NNAPPs. Using three dimensions with steps of 8 by 19 by 3 creates a three-dimensional series space with 456 NNAPPs. Every slide path, aspect/elevation category, and the average probability can be analyzed in this series space, giving each its own unique *series signature*.

2.6 Statistical analyses

The goal of our statistical analysis was to compare the pattern observed for a series signature (for an avalanche path or groups of paths) to another series signature. Our primary interest was in the pattern observed, and not in the mean of the avalanche probabilities. To do this we used a simple correlation analysis (Pearson's r) to compare the avalanche probabilities in one series signature to the other series signature.

3. Results and discussion

In this paper we present general results, followed by two sets of examples. Full results are presented in McCollister *et al*., (submitted).

Not surprisingly, an increase in new snow led to an increase in the avalanche probability at all scales, from individual paths to the entire ski area. More new snow results in more stress added to buried weak layers or interfaces, thereby increasing avalanche activity (McClung and Schaerer, 1993).

Unlike new snow, the effect of wind speed is different depending on the scale of observation. At the scale of individual avalanche paths, considerable variability exists. Though most slide paths exhibit an increase in avalanche probability with increase in wind, some different patterns emerge depending on the slide path. Some display a very large increase, such as *Buffalo Bowl*, a low elevation (2404 m) slide path (Figure 1). In contrast, some slide paths, such as *Broadway*, decrease in avalanche likelihood with an increase in wind, presumably because the higher wind speed scours those paths. Others, such as *Cajun Couloir*, increase (load) at certain wind directions, and decrease (scour) at other directions. At the larger scale of the entire ski area there was a general increase between low and moderate wind, but not between moderate and high wind for both the overall average and the aspect-elevation categories. This demonstrates how much variability exists at the scale of single paths within the overall average for the ski area.

Like wind speed, the effect of wind direction is different for different scales. At the scale of individual slide paths, changes in wind direction change the probability of avalanche activity. Conversely, wind direction does not appear to significantly change the series signatures for the aspect-elevation categories or the overall average computed for the entire ski area, presumably because the responses of the individual avalanche paths cancel each other out and "smooth" the data.

In accordance with the principles of KDD and GVis, we used computer interaction, iteration, and visualization to explore the data. As we did this, we noted that many slide paths exhibit similar series signatures. Additionally, slide paths with similar signatures are often in the same geographic area. As an example, we show two paths from the *Cheyenne group* and two from the *Casper group.* Slide paths in the *Cheyenne group* include *Cheyenne 3-9, The Snag*, and *Roadcut* (Figure 1.). A comparison of the series signatures for *Cheyenne 3* (Figure 2) and *The Snag* (Figure 3) in a high wind situation shows that the two are quite similar.

All the slide paths in the *Cheyenne group* exhibit similar series signatures, and are all most likely to avalanche with winds out of 240-260 degrees, which is the predominant wind direction for most storms affecting Jackson Hole Ski Area. In contrast, the slide paths in the *Casper group* (*Caspers 10, 12, 14, 20*) have very different series signatures, and all experience their highest avalanche activity with winds either more southerly or northerly than the predominant wind direction. A comparison of the series signatures for *Casper 12* (Figure 4) and *Casper 10* (Figure 5) shows that these two paths are similar to each other, and quite different from the Cheyenne group.

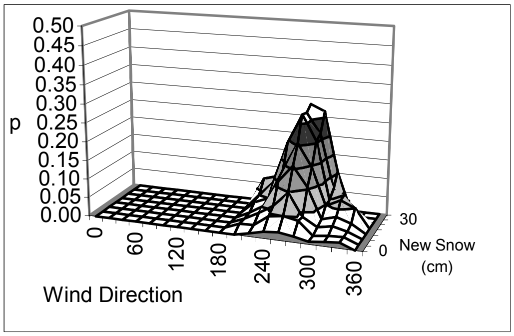

Figure 2: Series signature for Cheyenne 3-high wind.

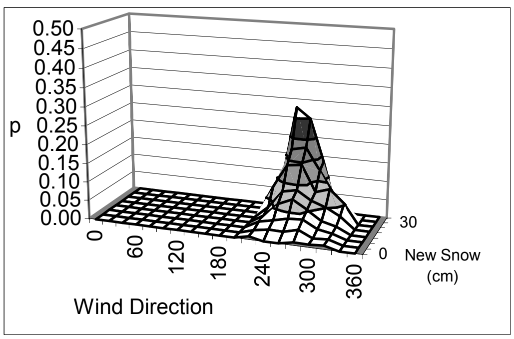

Figure 3: Series signature for The Snag-high wind.

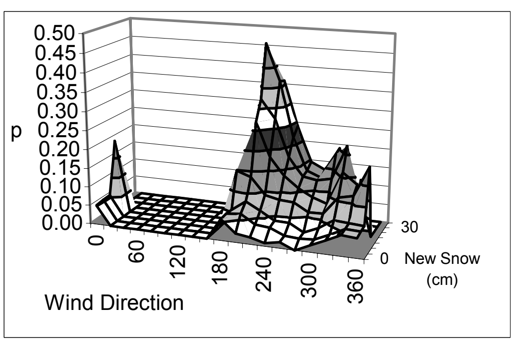

Figure 4: Series signature for Casper 12-high wind.

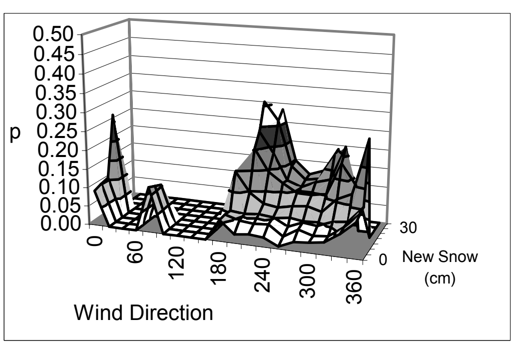

Figure 5: Series signature for Casper 10-high wind.

We used correlation analysis to statistically compare the different patterns observed. Correlations between corresponding points in the series signatures of *Cheyenne 3* (Figure 2), *The Snag* (Figure 3), *Casper 12* (Figure 4), and *Casper 10* (Figure 5) are presented in Table 1, and scatter plots are shown in Figure 6 for visual reference.

Table 1. Series signature correlations

	Pearson R	p (2-tailed)
Casper 12 vs. Casper 10	**0.893**	0.000
Snag vs. Cheyenne 3	**0.838**	0.000
Casper 12 vs. Cheyenne 3	0.303	0.008
Casper 12 vs. Snag	0.320	0.005
Casper 10 vs. Cheyenne 3	0.177	0.127
Casper 10 vs. Snag	0.181	0.118
NE facing vs. E facing	**0.959**	0.000
E facing vs. SE facing	**0.958**	0.000
SE facing vs. S facing	**0.876**	0.000

The statistical analyses reinforce the conclusions drawn from our visual comparisons. Slide paths in the same group (similar patterns) have high correlation ($R > 0.83$; shown in bold type in Table 1.), while comparisons between groups have low correlations ($R < 0.32$). Note that some between group correlations are significant at the $p < 0.05$ significance level. We would expect some correlation since avalanche activity should generally increase with increasing wind and new

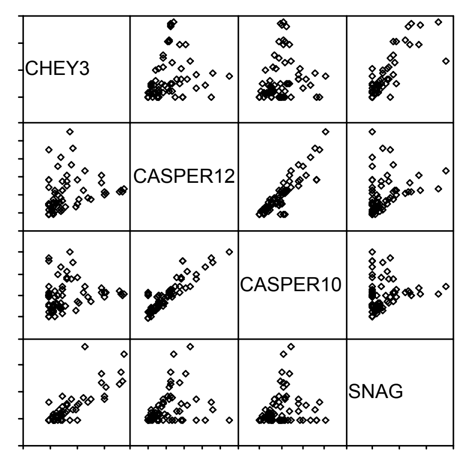

Figure 6: Probability-probability scatter plot for corresponding points between two series signatures.

snowfall. However, in this example we are less interested in whether two series signatures are correlated than we are in the actual strength of correlation.

If we broaden the scale to sets of avalanche paths grouped by aspect, rather than by geographic location, we get a different result. Looking at four high elevation aspect categories (northeast, east, southeast and south facing) shows that their series signatures appear similar; we present an example in Figure 7. Further, a correlation and scatter plot analysis shows that they all correlate well with each other, with R = 0.88-0.96 (Table 1; Figure 8). Thus, while there are sizable differences between individual paths based on their location within the ski area, those sizable differences do not exist between sets of avalanche paths grouped by aspect and elevation.

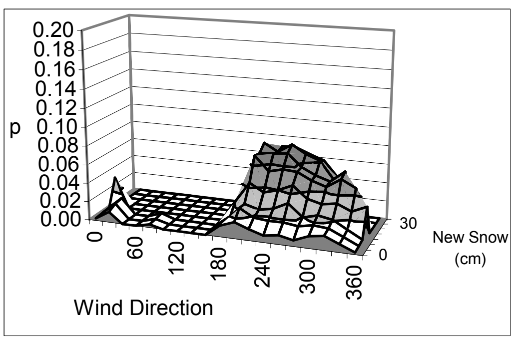

Figure 7: Series signature for upper elevation-northeast aspects at high wind.

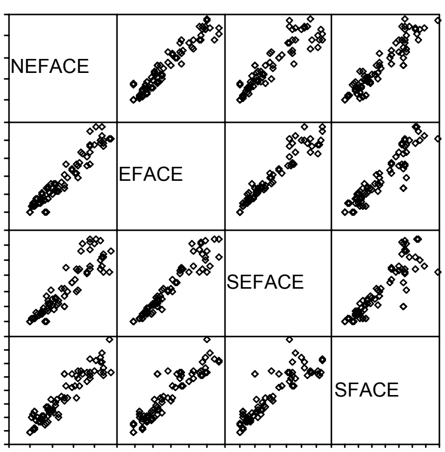

Figure 8: Probability-probability scatter plot for corresponding points between two high elevation aspect category series signatures.

4. Conclusion

In general, each of the three weather parameters investigated affected the avalanche probabilities differently. The effect of new snow is clearly important since it increases avalanche activity at all scales. However, because of its global effect, it does not play a significant role in differentiating between slide paths. In contrast, wind speed does have a different effect depending on the avalanche path location. For example, high wind is very important in the creation of slab avalanches at lower elevations. Of the three weather parameters, wind direction plays the largest role in slide path differentiation, probably because of the way the wind from different directions is redirected by the topography around each avalanche path.

More important than information gained about individual weather parameters, the combination of the three weather parameters along with their series signature representations have given us new knowledge about selective wind loading and slab development at the scale of individual paths. Analysis of the series signatures was the key component to our analyses. The high correlation *among* groups along with the low correlation *between* groups gives us confidence that we are extracting real patterns. Combining this with common geographic properties in the groups has given us several new insights about our region.

One interesting finding from our work was that paths in similar geographic areas are similarly affected by wind direction. The *Cheyenne* group is very selective with regards to wind direction. These paths load most effectively when the wind is coming from the predominant wind direction. In contrast, the *Casper* group is most active with winds either north or south of the predominant wind direction. In addition to this general knowledge, we may be able to extrapolate the wind loading effect for highly unusual situations by looking at the series signatures for a given path, or groups of paths. 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 degrees associated with a large storm.

Another interesting finding from this work was that all of our high elevation aspect categories exhibited similar series signatures. In other words, at the scale of the entire ski area, there is not an obvious relationship between avalanche activity on a given aspect and wind direction. This is interesting, since blanket statements like "East facing slopes are being loaded by westerly winds" may be misleading. This is not to say 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 centrally located to measure an approximation of the free air winds, specific topography around a given path, not simply aspect, is more important when relating wind direction to avalanche activity. For example, the effects of ridges funneling wind and groups of trees acting as snow fences are more likely the most proximate reasons for selective wind loading at the slide path scale when considering the ultimate effect of wind direction.

In essence, our work shows that patterns associated with some weather parameter (like wind direction) exist at some scales, but not others. Patterns existed at the individual slide path scale and for sub-regional groups. In contrast, specific patterns were not discernable for aspect-elevation categories and the overall average.

The concepts behind Knowledge Discovery in Databases and Geographic Visualization as outlined by MacEachren *et al*. (1999) were paramount in this research. The concept of *iteration* was used to create the series signature. The concept of an *interactive process* between humans and computers was utilized by first visually looking at the series signatures. Next came classifying slide paths based on their series signature, and looking for geographical relationships between classifications (groups). Finally, *multiple perspectives* of the data (GIS, series signatures, and aspect-elevation rose diagrams) allowed us to discern patterns at different scales

These methods are not restricted to new snow, wind speed, and wind direction. They can be performed on any set of variables, whether directly measured variables or calculated variables such as density, storm totals, or temperature gradients. We believe there is much potential for the concepts of KDD and GVis to improve the utilization of historic weather and avalanche databases, and to reach this potential, imagination in the application of these concepts is as important as the underlying concepts themselves.

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