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Measurement and Data Analysis of Weather and Avalanche Records
Recent Directions and Perspectives with Case Studies

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ABSTRACT

Records of avalanche occurrence and control efforts have traditionally been correlated to snow and weather observations from local study plots. Recent attempts to rank or score the sensitivity of various study plot and meteorological observations to avalanche activity are reviewed with discussion on the utility of different methods of analysis. The discussion is expanded by showing examples using decision-tree methodology on data from a site under a maritime climate regime. It is shown that characterization of avalanche activity does not seem to affect the ranking of important variables, but it is important to overall classification accuracy. The rank order of the five primary variables was: new snow (24 hr) depth, snow water equivalent of the storm snow, storm total snow depth, average wind speed and total snow depth. The probability of correct classification was much higher for the maximum size class, compared with the total number of avalanche releases.

INTRODUCTION

Operational considerations in areas subject to avalanche damage require that high priorities be given to collection, use and archiving of weather data with the highest correlation to avalanche activity. Classic works in the early literature report that the importance of various meteorological variables associated with avalanche hazard changes with geographic region. Moreover, experience with local factors leading to avalanche conditions and knowledge of interelationships among variables are difficult to transfer from one practitioner to another, and usually require long periods of apprenticeship and field practice. In addition to the difficulties with conventional forecasting techniques, legal precedents show that litigation in avalanche-related cases can depend on computer-aided analysis of avalanche and weather data (cf. Kennedy, 1984; Penniman, 1986).

One of the fundamental problems of statistical or deterministic studies is to describe the dependent variable by a meaningful metric that is physically justified and statistically unique. Many attempts throughout the world have partitioned avalanche response into a variety of genetic and morphologic classifications. These approaches confounded comparison of forecasting methods and results on regional and international levels. Definitions of avalanche activity or response range from individual path observations and descriptions (Judson and King, 1985) to hazard levels based on frequency of events (Elder and Armstrong, 1986) to binary outcome of avalanche-day versus non-avalanche-day, ignoring positive frequency effects greater than absent or present (Bois et al., 1974).

Correct identification and quantification of independent variables leading to avalanche release potentially present a more difficult problem. Again, this problem has been attacked from a broad array of methods controlled by model constraints, data availability, ultimate application of results and current understanding of avalanche phenomena. Unfortunately, data availability often represents the most severe constraint and scientists are forced to make do with data that has already been collected. While

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these data are necessary because long-term databases are critical to all non-deterministic forecasting techniques, they have usually been collected for another purpose (weather forecasting for cities, agriculture, etc.). Collection sites are often located in valley bottoms, urban areas, and at low elevations, which make it difficult to extrapolate to conditions in avalanche starting zones.

BACKGROUND

No quantitative method has yet replaced the human element in avalanche forecasting. A long-standing challenge has been to identify and rank variables that can be measured efficiently and reliably, according to their importance as indicators of avalanche activity. This information can provide guidance on degree of avalanche activity, identify outlying conditions which may be important to control activities, aid in training new professionals and suggest priorities for maintaining measurement programs. Recent work has become increasingly quantitative, in both the weather and terrain variables evaluated and the avalanche activity parameters. Great improvements have been made in physically-based deterministic modeling, but we believe it is likely that future avalanche forecasting aids will arise from hybridization between empirical and physically based modeling because of the intensive data requirements of physical models.

Perla (1970) revisited Atwater's (1954) ten contributory factors for avalanche hazard evaluation and found precipitation and wind direction to be the most important parameters. Föhn et al., (1977) compared conventional forecasting techniques with four statistical methods ranging from principal components analysis (PCA) and discriminate analysis of local and regional data to cluster analysis of local data. They found that all the methods produce about the same results at 70 to 80 percent accuracy, with some slightly better than others. Each method had distinct advantages and disadvantages.

The nearest-neighbor method has been applied in a number of climates with a variety of input variables. Buser (1989) gave results from a nearest-neighbor forecasting program introduced by Buser (1983) and used operationally in Switzerland by the ski patrol in the Parsenn area. The program identified the ten days in the record with the most similar conditions to the day in question. Similarity is based on the proximity of weighted meteorological and snowpack variables in data space. The program also creates "elaborated" variables, for example the time-trend in a particular meteorological measurement.

Buser et al. (1985) reviewed a broad range of avalanche forecasting methods for short and long time scales and over local and regional spatial scales. Input data collected by conventional field methods and by instruments designed and built for specialized tasks, such as FMCW radar, were discussed for different applications. Forecasting methods from conventional induction to complex statistical models were reviewed.

Although not directly addressing forecasting, Jaccard (1990) used fuzzy factorial analysis to identify important interaction of avalanches related to snowpack, meteorology, terrain and vegetation parameters based on expert opinion. Slope angle and aspect, overall weather conditions and precipitation were found to be the most important factors related to avalanches.

Avalanche hazard forecasting has been addressed from a number of different angles and approaches from nearly all of the affected regions of the world. Tables I and II summarize some of the key research on the subject. The lists in Tables I and II are not exhaustive and represent only a portion of the research published in the English language. However, a survey of the literature and conversations with practitioners indicate that even with considerable effort devoted to the subject, we can still only forecast avalanches to an accuracy of about 80 percent. We must develop new techniques and methods, both deterministic and statistical, in order to improve the accuracy of forecasting capabilities.

In the following section we review the methodologies proposed by Davis et al. (1992), to illustrate a recent approach using binary decision trees. Examples analyzing a data set from Mammoth Mountain, California show the types of weather data common to many avalanche-prone areas and the types of avalanche response parameters of interest to operational field programs.

Table I. Key articles in literature on quantitative analysis methodologies.

Study (date)	method	data inputs
Judson (1973)	regression analysis discriminant analysis	meteorological (local/regional) snowpack artificial avalanches
Bovis (1977)	discriminant analysis	meteorological (local) snowpack avalanche days wet/dry avalanches
Föhn et al. (1977)	conventional	meteorological (local/regional)
Obled and Good (1980)	principal components discriminant analysis	snowpack avalanche days wet/dry avalanches
Buser (1983, 1987, 1989)	nearest neighbor	meteorological (local) snowpack avalanche days
Jaccard (1990)	fuzzy factorial analysis	meteorological (local) terrain vegetation snowpack
Davis et al. (1992)	classification tree	meteorological (local) snowpack avalanche days
McClung and Tweedy (1993)	univariate correlation analysis	meteorological (local) snowpack avalanche activity index

Table II. Advantages and disadvantages of using selected quantitative methods.

METHOD	ADVANTAGES	DISADVANTAGES
conventional	-well established -time-tested -effective	-difficult to teach -site specific and anecdotal -years of experience necessary -results increase with experience -algorithm dies with forecaster
univariate correlation analysis	-simple	-only gives univariate relationships -will not identify variable interaction
principal components discriminant analysis	-objective	-sensitive to data errors -need large data set
nearest neighbor	-memory aide to forecaster -defacto database results	-sensitive to data errors -need large data set -does not forecast just gives similar conditions
deterministic methods	-satisfy ultimate goal of being -physically based	-not yet effective or well-developed -massive data requirements -data requirements include uncommon variables
binary tree classification/regression	-well suited to mixed data types -handles hierarchical relationships -handles nonlinear cases -simple to interpret results -can control model fit -can control objectivity/subjectivity -emulate other methods (nearest neighbor, etc.) -handles missing data well	-need large data set

TREE-BASED MODEL BASICS

There are two types of simple binary decision trees; regression and classification. Regression trees are appropriate where the dependent variable is a ratio scale data type. In other words, if the dependent variable can assume any value over the range of observations, and if the differences are quantitative and consistent, then we want a model that can predict these values and one that is not constrained to particular members. An example is number of avalanches per day. A regression model will predict somewhere between zero and a reasonable maximum number of avalanches for a given day based on the independent variables.

A classification tree is appropriate where the independent variable itself belongs to the data types nominal (named) or ordinal (ordered). Nominal data includes such variables as slope aspect: east, west, etc. Ordinal data exhibits relative, rather than quantitative differences: for example, magnitude 1 through 5 avalanche events. Avalance magnitudes, like earthquake magnitudes, are expressed on a log scale of magnitude. The difference is that earthquake magnitudes are objectively measured, while avalanche magnitudes are estimated by an observer. Thus a magnitude 4 event is larger than a 2, but not necessarily 10^2 as large. A regression tree would not make sense in this case because it would predict unsuitable results such as a magnitude 2.76 or 4.89 event.

The type of model chosen, regression or classification, depends in part on the dependent variable type. You cannot apply a regression tree model to classification data. However, you can apply a classification tree model to ratio scale data by generalizing the data into classes. Days with any avalanche activity could be called "avalanche days" and days without activity called "non-avalanche days" (as has been done in many previous studies). Then a classification tree model could be used on number of events observed, where the observations have been reexpressed into nominal data, avalanche versus non-avalanche days.

Advantages of tree-based regression and classification models over alternative methods (such as those listed in Table I) include:

- The models are not affected by monotone reexpressions of data, so results are independent of data form and magnitude. In other words, linear mathematical operations such as addition or multiplication can be performed on the data without affecting the results. This characteristic also means that one variable may be expressed in millimeters and another in kilometers without affecting the model.
- Gaussian assumptions are not violated by the distribution of one or more independent variables, (tree-based methods are nonparametric or "distribution free"). Trees are valid even using mixed data sets containing multiple distributions. It is not necessary that data be normally distributed or that non-normal data be transformed before analysis.
- Model results are less dependent on missing values in the independent variables (methodology finds "surrogate" values for each decision node). Many statistical models cannot use data sets where one or more attributes for a given observation are missing. Binary trees can use the existing data to statistically predict what the missing elements should be, or to use only the elements that do exist.
- Tree-based models allow complex interactions between the independent variables, which must be specified *a priori* in standard linear models. For example, snow accumulation may increase up to a critical elevation, then decrease with increasing elevation above that critical point. Standard linear models can only take advantage of that fact if a mathematical expression for the relationship is formulated and expressed before model implementation.
- Interpretations of complex interactions are clear and often more easily understood than other model constructions. A tree is far more easily interpreted by most people than mathematical expressions or nonlinear equations.

Binary decision trees or predictive tree classifiers of the type used in this study take a vector of measurements **x**, (x_m, m = 1,2,...) of variables from the measurement space **X** of a result y and calculate the probabilities (P_1,$P_{2,...}$) that y is in each of the possible classes. The tree is constructed by repeated partitioning of subsets of **X** into two descendent subsets or nodes, where **X** itself is the root node and the partitions end in a set of terminal nodes. The terminal nodes are assigned a value based on the probabilities that they belong to a given class y. The partition or split at each node is made on the values in y conditionally on values in the sample vector $\mathbf{x}$, based on a single variable in $\mathbf{x}$. For ordinal or ratio scale data, splitting decisions are posed in the form: is $\mathbf{x}_m \leq c$? where c is within the domain of $\mathbf{x}_m$. For categorical variables, the decisions may be expressed as: is $\mathbf{x}_m \in S$?, where S includes all possible combinations of subsets of the categories defined in $\mathbf{x}_m$.

In the present study these decisions take the form: is new snow depth $\leq 10\, inches$ or is the snow surface temperature $\leq -4.0°$ C ? The categorical analog would be similar to: does the azimuth of the starting zone of path $\mathbf{x}_m$ belong to the subset *north* ? A portion of the finished binary *classification* tree may look like the following:

if $(SST_i \leq 6.5°\,\mathrm{C})$ and $(MAXWS_i \leq 21.5\, mph)$
then avalanche activity AA_i is
most likely to be in final decision class AA_2,

and a final decision set for a node in a binary *regression* tree may look like the following:

if $(SST_i \leq 6.5°\,\mathrm{C})$ and $(MAXWS_i \leq 21.5\, mph)$
then avalanche activity AA_i is
most likely to produce 22 releases
under current conditions,

where SST, $MAXWS$, AZ are the independent variables of snow surface temperature, maximum wind speed, and slope azimuth, respectively; i is the co-registered datum of the variables.

A collection of such decision rules is obtained through a technique referred to as *recursive partitioning*. Three elements must be defined before the sample data may be recursively partitioned into a binary decision tree:

1) method for determining the best split at each node,

2) basis for deciding when to continue or stop splitting a node,

3) method for assigning class probabilities for each terminal node.

The details of these decisions are beyond the scope of this paper but are explained at length in the standard reference on classification and regression trees (Breiman et al., 1984). We have used both the tree-based model implementation in CART (Breiman et al., 1984) and in the S-PLUS mathematical language, which follows closely the development in Breiman et al. (1984). Both software packages have unique advantages and the user should explore both implementations. Details of the S-PLUS software are explained in Chambers and Hastie (1992). Two applications of tree based models in the natural sciences can be found in Michaelsen et al. (1987 and *in press*).

The output of the software packages includes a ranking of the independent variables in order of importance as primary decision makers, or as surrogates for other independent variables, as well as the decision tree. This is the focus of our discussion.

EXAMPLES USING DECISION-TREE METHODS AND DISCUSSION

In the earlier study, Davis et al. (1992) aggregated the avalanche observations into three classes: 1) days with no avalanches or control activities, 2) control days with no avalanches and 3) avalanche days, in which any notable release was the threshold criteria. Results showed that class 1 days were classified with about 99 percent accuracy, but class 2 and 3 days were classified with 86 and 80 percent accuracy, respectively. Although this study offered little in the way of guidance about the degree of avalanche activity, it did show 1) the promise of using this method to rank snow plot and weather data, 2) the difficulty in distinguishing control days with and without releases, and 3) the potential for better results using different response variables or more data.

In this study, as in Davis et al. (1992), decision tree methods were applied to observations from Mammoth Mountain, California at elevations from 2,590 to 3,371 m in the eastern Sierra Nevada. Mammoth Mountain is the major site of the Mammoth/June Ski Resort, and is subject to frequent direct action avalanches, where releases commonly occur within a few days of winter storm events. As in Davis et al. (1992), we used data from two winters, 1989-1990 and 1990-1991, which consisted of snow plot measurements, weather variables and avalanche release observations. The two-year data set consisted of 380 cases (days) of which there were no days with missing data. The weather and snow data were collected from a snow study plot by the Main Lodge at Mammoth Mountain, at an elevation of 2,743 m on the northern base of the mountain. Avalanche observations were from the entire inbounds ski area. Variables used for this analysis were those recorded at the study plot or nearby, as listed in Table III.

Table III. Input data used in CART analysis from daily data record.

1)	Total snow depth	(inches)
2)	Storm total snow depth	(inches)
3)	New snow depth	(inches)
4)	Snow water equivalent - storm	(inches)
5)	Fractional density, new snow	(percent)
6)	Average wind speed	(mph)
7)	Maximum wind gust speed	(mph)
8)	Maximum 24-h air temperature	($^{\circ}$F)
9)	Minimum 24-h air temperature	($^{\circ}$F)
10)	Current air temperature	($^{\circ}$F)
11)	Snow surface temperature	($^{\circ}$C)

Control activities and avalanche observations were recorded at Mammoth Mountain in a format consistent with the standard U.S. Forest Service avalanche control and occurrence chart. This protocol consists of codes for the date, time, path, patroller identification, control type, control number, control surface, avalanche class type (hard slab, soft slab, etc.), avalanche trigger mechanism, avalanche size, and so forth (Perla and Martinelli, 1978). It should be noted that the avalanche size class is somewhat subjective when comparing the data from different areas, but consistent within this study area.

Avalanche observations were aggregated into two response variables, the total number of avalanche releases on a given day, and the maximum size class. Our premise for specifying these avalanche activity characteristics was that the number of releases may provide an indication of how widespread the avalanche hazard (i.e. spatial dispersion), and that the maximum size may provide an index of the local intensity of the hazard. Therefore, a regression tree method was used to evaluate the data with the total number of releases as the response variable; and a classification tree method was used to evaluate the data with the maximum size class on a given day as the response variable.

Both the regression tree and the classification tree analyses produced the same ranking of weather and snow plot variables (also the same as Davis et al., 1992). This shows the robustness of the method. Table IV shows the ranking. The first five variables in Table IV contributed most of the information critical to the model fit. The rest showed minor importance as decision criteria or surrogates. The first three variables are measured manually by patrollers at the snow plot, the depths observed on snow boards and the water equivalent measured with hand-held equipment.

The overall probability of a case falling into the correct terminal node for the regression tree (total number of releases with a range 0 - 41) was 0.68. The probability of correct classification for the classification tree (maximum size class with a range 0 - 5) was 0.95. Although preliminary, these results indicate that two things: 1) the ranking of variables in terms of sensitivity to avalanche activity appears insensitive to the avalanche response variable for the examples here and in Davis et al. (1992); 2) the binary tree methods (both classification and regression) may be valuable tools for avalanche forecasting and may provide a mechanism for improving results. In order to test this technique effectively and objectively, we need to study other data sets from areas with longer records which will allow model construction and validation either through unique elements or cross validation. We would also like to test the method in different snow climates to assess model performance and objectively confirm the existence of different snow climates and avalanche response. Both studies are in progress at this time.

Table IV. Ranking of weather and snow plot variables

New snow depth
Snow water equivalent storm
Storm total snow depth
Average wind speed
Total snow depth
Fractional density
Snow surface temperature
Maximum wind gust
Current air temperature
Minimum 24-h air temperature
Maximum 24-h air temperature

SUMMARY

Various statistical techniques have been tried to rank critical variables in terms of their sensitivity to avalanche activity. Classification and regression tree methodology shows promise because of distinct advantages over standard statistical techniques. While the ranking is robust with respect to the choice of dependent variables describing avalanche activity, the accuracy of classification and regression trees shows sensitivity to the choice of the dependent variables. In the example used for discussion in this work, the methodology was better at correctly classifying the maximum size of releases than it was at predicting the total number of releases.

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