ANALYSIS OF AVALANCHE PREDICTION FROM METEOROLOGICAL DATA AT BERTHOUD PASS, COLORADO

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ABSTRACT

In an attempt to identify the most critical meteorological parameters influencing the temporal behavior of avalanche release in a continental snowpack, we analyze a nineteen-year chronological record of meteorological measurements and avalanche occurrence at Berthoud Pass, Colorado, in a classification tree approach.

INTRODUCTION

Several authors have used various statistical methods in an attempt to forecast avalanche occurrence (Bois and Obled, 1973; Bovis, 1974, 1977; Buser and Good, 1984; Fohn et al., 1977; Judson and Erickson, 1973; Judson et al., 1980; Judson and King, 1984; LaChapelle, 1977; Obled and Good, 1980; Salway, 1979). These methods employ linear discriminant function analysis, cluster analysis, and time series analysis in an attempt to classify stable and unstable snow conditions. Some of these studies have been conducted in the central Rocky Mountains of Colorado where a forty-year record of weather and avalanche data has been collected by the U. S. Forest Service and the Colorado Avalanche Information Center (Judson and Erickson, 1973; Judson et al., 1980; Judson and King, 1984). We analyze a nineteen-year chronological record of meteorological measurements and avalanche occurrence from 1967 to 1986 at Berthoud Pass, Colorado, in a classification tree approach to attempt to identify the most critical meteorological parameters and trends influencing the temporal behavior of avalanche release in a continental snowpack.

Berthoud Pass is located in the central Colorado Rocky Mountains. The summit is at 3,440 m and the surrounding peaks range from 3,770 m to 3,880 m. There are 60 avalanche paths in the area, most of which are well above timberline and many of which cross U.S. Highway 40. The most prevalent type of avalanches in this area are soft and hard slab (89%). Weekly avalanche control procedures are conducted by the Colorado State Highway Department during the winter months because the highway is heavily travelled by skiers and commercial truckers.

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METHODOLOGY

The program used to analyze the data is the classification and regression trees methodology, CART™, which is concerned with the use of data to form prediction rules for one variable based on the values of other variables (Breiman et al., 1984). In classification, one makes measurements on an object and then uses some sort of prediction rule to decide what class the object is in. The goals in constructing prediction rules are to construct the most accurate prediction rule possible and to construct the decision rule that gives the most insight. While standard statistical classification methods are discriminant analysis or logistic regression, CART™ constructs binary decision trees to determine prediction rules. Thus one replaces an algebraic expression with a graphical decision tree, which is much easier to interpret and has great intuitive appeal. A performance comparison between neural networks and classification trees has shown that, in most cases, the two methodologies give comparable prediction accuracy (Atlas et al., 1990). The critical problem in tree construction is to optimize the size of the tree such that the tree splits (branches) minimize the true decision error. This is done by splitting the data so that a very large tree is constructed containing as few as five cases in each branch. An algorithm is then applied that selectively prunes branches in such a way that each tree in the sequence has a smaller apparent error rate than any other subtree in the sequence of the same size. Each tree is then an optimal sequence. One of the other advantages of this approach is the ability of the program to handle missing data using surrogate variables when the data from another variable are not available.

The CART™ program presents the data in several ways. It produces a tree showing which variables the various branches bisected on and the value at which the decision was made. It also produces a matrix showing the fraction of true versus predicted classes and a table of the relative importance of the independent variables used in the analysis.

The data bases for this study are the U. S. Forest Service and Colorado Avalanche Information Center forty-year record of avalanche data from approximately 60 monitored avalanche paths, and meteorological data collected at Berthoud Pass, Colorado. The avalanche data are those depicted in the U. S. Forest Service Avalanche Control and Occurrence Chart (Perla and Martinelli, 1976), while the meteorological data are those depicted in the U. S. Forest Service Monthly Summary of Weather and Snow Conditions (Judson, 1970).

For this study, we used the number of avalanches per day as the classification variable and a modified subset of the meteorological data to optimize the class prediction. Data was limited to the period November 7 to April 30 of each year of record, because the meteorological record would be incomplete otherwise.

TABLE 1
AVALANCHE CLASSIFICATION

Avalanches per day	Class
0	1
1—3	2
4—7	3
8 or more	4

The avalanche data is a mixture of soft slab (68%), hard slab (21%), loose (6%), wet loose (3%) and wet slab (2%). Release mechanisms included natural (55%), artificial explosive (37%), artificial ski (5%), and other artificial releases (3%). No attempt was made to discriminate avalanche size or vertical fall distance.

Thirteen meteorological variables were used in the analysis and are listed in Table 2.

TABLE 2
METEOROLOGICAL VARIABLES

1. Maximum Daily Air Temperature
2. Maximum 1-day Air Temperature Trend
3. Maximum 3-day Air Temperature Trend
4. Maximum 7-day Air Temperature Trend
5. Minimum Daily Air Temperature
6. Minimum 1-day Air Temperature Trend
7. Minimum 3-day Air Temperature Trend
8. Minimum 7-day Air Temperature Trend
9. Depth of Snow on the Ground
10. Change in Daily Snow Depth
11. Average Daily Wind Speed
12. Wind Direction for Greatest 1-hr Wind Speed
13. Greatest 1-hr Wind Speed

The temperature trend variables were derived from the temperature measurements using a linear regression and the average daily wind speed was derived from six-hour wind speed averages. The change in snow depth was derived from the difference in daily snow depth and therefore represents accumulation as well as compaction and ablation. Average wind direction was not used because it was often variable, especially during storms.

RESULTS

A total of 3,333 cases were analyzed; 2,330 (70%) were class 1; 455 (14%) class 2; 430 (13%) class 3; and 118 (3%) class 4. The probability matrix for this set is shown in Table 3 and the relative importance of the independent variables is shown in Table 4.

TABLE 3
CLASS PROBABILITY MATRIX

		TRUE CLASS			
		1	2	3	4
PREDICTED CLASS	1	0.95	0.24	0.08	0.30
	2	0.02	0.74	0.08	0.10
	3	0.03	0.03	0.81	0.00
	4	0.00	0.00	0.03	0.60

TABLE 4
VARIABLE IMPORTANCE

Depth of Snow on the Ground	100
Maximum 3-day Air Temperature Trend	90
Minimum 7-day Air Temperature Trend	86
Maximum 1-day Air Temperature Trend	85
Minimum 3-day Air Temperature Trend	80
Maximum Daily Air Temperature	75
Maximum 7-day Air Temperature Trend	73
Wind Direction for Greatest 1-hr Wind Speed	70
Average Daily Wind Speed	69
Minimum Daily Air Temperature	69
Minimum 1-day Air Temperature Trend	67
Greatest 1-hr Wind Speed	67
Change in Daily Snow Depth	61

Table 3 shows that the true and predicted classifications are excellent for class 1 and reasonably good for classes 2 and 3, while class 4 ranks the lowest. Given that the percentage of cases for class 1 is high and diminishes progressively for classes 2, 3 and 4, the ranking is not surprising. However, the result that 30% of class 4 has been misclassified as class 1 is disturbing even though it represents only 35 cases. Table 4 shows that all variables contribute significantly to class prediction. One would expect snow depth to rank high, and 3-day temperature trend may be a better indication of storminess than change in daily snow depth, because if settlement is high, new snow does not show up well except when the pack is shallow. Generally, the temperature trends are an indication of the influence of recent past thermal history on snowpack stability (Armstrong, 1977), although the particular trend ranking currently is not understood.

In order to investigate other options and to increase our understanding of the results, another run was made where the snow depth was arbitrarily set equal to or greater than 25 cm (10 in.) at the meteorological site. The number of cases is now 3,250, with 70% in class 1, 14% in class 2, 13% in class 3 and 4% in class 4. The probability matrix for this set is shown in Table 5 and the relative importance of the independent variables is shown in Table 6.

TABLE 5
CLASS PROBABILITY MATRIX

		TRUE CLASS			
		1	2	3	4
	1	0.98	0.29	0.22	0.25
PREDICTED	2	0.01	0.68	0.06	0.00
CLASS	3	0.01	0.04	0.72	0.12
	4	0.00	0.00	0.00	0.62

TABLE 6
VARIABLE IMPORTANCE

Minimum Daily Air Temperature	100
Maximum 7-Day Air Temperature Trend	94
Average Daily Wind Speed	89
Greatest 1-hr Wind Speed	87
Wind Direction for Greatest 1-hr Wind Speed	85
Minimum 3-day Air Temperature Trend	82
Depth of Snow on the Ground	81
Change in Daily Snow Depth	71
Maximum 1-day Air Temperature Trend	68
Maximum 3-day Air Temperature Trend	66
Minimum 1-day Air Temperature Trend	63
Minimum 7-day Air Temperature Trend	57
Maximum Daily Air Temperature	26

The probability matrix (Table 5) shows that classes 2 and 3 are not predicted quite as well as in case 1. Table 6 also shows a different order of priorities related to variable importance. Minimum temperature, maximum 7-day temperature trend wind speed, snow depth, and snow depth changes are dominant.

DISCUSSION

From the results, it appears that all of the variables contribute significantly to the classification. This is not surprising because the variables are directly related to the classical descriptors of slab stability criteria, such as the bonding of new snow to old surface layers, metamorphic processes in the pack, and weight of the overlying snow (Perla and Martinelli, 1976). Temperature and temperature trends play a role because they are indicators of the metamorphic state of the snow and the snow surface conditions prior to new storm events. Wind loading of avalanche starting zones, total snow depth, and new snowfall alter the balance between strength and stress within the snow pack (Armstrong, 1977). However, one should proceed with caution in placing too much faith in this classification analysis. Measurements such as net solar and longwave radiation and water vapor pressure, which are essential in characterizing the dynamic boundary layer energy balance, are not available in this data set.

CONCLUSIONS

Comparison of the decision tree method and other statistical methods can be made only to the extent of predicting avalanche versus non-avalanche days, as this has been the main objective of the other statistical methods. Given this restriction, the decision tree method gives predictions that are comparable to statistical methods used in the Rocky Mountains (Bovis, 1974, 1977; Judson and Erickson, 1973; Judson et al., 1980; Judson and King, 1984; Salway, 1979) and in Europe (Buser and Good, 1984; Obled and Good, 1980). The method also shows that the classification is complex because all weather parameters contribute significantly to the prediction.

While the use of decision tree methodology gives plausible results for predicting avalanche activity at Berthoud Pass, a data set that contains all parameters needed to ensure that the air-surface dynamic energy balance is described. There are two energy balance models that simulate the evolution of snowpack (Brun et al., 1989; Jordan, 1991) that could be tested to determine snow stability. However, the model input parameters include net radiation and water vapor pressure, which are not in the Berthoud Pass area data base.

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