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Numerical avalanche prediction: Bear Pass, British Columbia, Canada

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Abstract

A numerical avalanche prediction scheme offering prediction rates greater than 70% is presented for the Bear Pass highway operation, British Columbia. One-way analysis of variance (ANOVA) and canonical discriminant analysis are used to identify the principal variables that allow discrimination between avalanche and non-avalanche time periods. The optimum variable set is then used in a discriminant analysis to classify each time period into an avalanche or a non-avalanche period. The analysis is performed for all areas in a combined analysis and also for individual sub-areas defined within the Pass. Improvements on classification rates to three out of the four sub-areas are observed compared to the analysis for the whole Pass.

Keywords: Avalanche; Prediction; Numerical; Modeling

1. Introduction

Conventional forecasting techniques as described by LaChapelle (1980) and McClung and Schaerer (1993, p. 164) may be complemented by the use of computer models in an avalanche forecasting operation (Föhn, 1998). Computer models provide a useful tool to verify a forecaster's opinion about the prevailing avalanche conditions. In addition, they allow the forecaster to 'test out' possible scenarios by assessing the impact of changes to one or more of the present weather variables.

In this paper, one-way analysis of variance (ANOVA) and canonical discriminant analysis techniques are used to determine the principal variables for numerical avalanche prediction for Bear Pass. The significant variables are used in a discriminant analysis to build a set of predictor functions from the whole data set that allow each time period to be classified as either an avalanche or a non-avalanche period. This will form the mathematical basis for an operational forecasting model.

Results are also compared for the whole Pass and for individual areas within the Pass. The rationale for this is that by splitting up the Pass into areas that are more homogeneous, better discrimination might be possible for individual sub-areas than is possible for the Pass as a whole.

2. Characteristics of Bear Pass

Bear Pass is located on Highway 37A between Meziadin Junction and Stewart on the west coast of northern British Columbia, Canada. The area experi-

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ences a wet, maritime climate with temperatures moderated by proximity to the Pacific Ocean. This climate leads to high annual snowfall rates, which average 8.5 m/year.

The avalanche season runs from approximately mid November to the end of April. However, there are paths in the Pass that produce avalanches triggered by glacial icefall and these can occur at any time of the year. One of these paths is considered a hazard to the highway. The hazard due to icefall release on this path cannot be forecasted using meteorological and snowpack information and therefore this path is not used in the model.

2.1. Individual areas within the Pass

Four distinct areas within the Pass were identified on the basis of having avalanche paths of similar aspect, size and start zone elevation. Information was gleaned from the Ministry of Transportation database and from personal communication with Ministry of Transportation avalanche forecasters.

The Little Bears area is the area closest to Stewart and contains five east-facing avalanche paths on a portion of the highway that runs north–south. These paths have vertical falls (the distance between the starting zone and the runout zone) of 1400–1900 m. They are characterized by broken slopes with shallow gullies and some immature vegetation is present in the paths. Return periods for avalanches which affect the highway range from 3 to 10 years.

The Summit Sluffs is a small area of short, low elevation avalanche paths located approximately in the middle of the Pass. This area faces south and is characterized by frequent lower magnitude avalanche occurrences. Vertical falls range from 160 to 205 m. The slopes forming these paths are open and of uniform aspect and angle. Since the highway crosses the lower part of these paths, several avalanches a year affect the highway from each of these paths.

The South Aspect area contains the remainder of the avalanche paths on the north side of the highway that face south. Most of these paths are large with vertical falls ranging from 900 to 1660 m. However, there are some smaller paths towards the west of the pass. The return periods for these paths are much greater, which distinguishes them from the Summit Sluffs paths. Some of the larger paths are capable of producing large (Class 4) avalanches. Such avalanches occur infrequently, with return periods of up to 20 years. The smaller paths are vegetated in their runout zones and produce small ‘tongues’ of debris that flow onto the highway approximately once every 5 years.

The North Aspect area contains the comparatively large avalanche paths on the south side of the highway. Vertical falls range from 980 to 1900 m and the paths are characterized by complex, rocky terrain. Most of these avalanche paths have runout zones that are a significant distance from the highway, in some cases up to 1 km. This means that only large avalanches running down these paths will impact the highway.

3. Preparation of the data

3.1. Weather and snowpack data

The data used in this study consisted of manually recorded weather and snowpack measurements from November 1985 to April 2002. The manual weather station in the Pass was relocated in 1994, so the data set is a combination data set from two different locations. However, the old and the new stations were run concurrently for a period of 2 years to ensure that the recorded values for the new station were consistent with those of the old.

Variables used in the study are listed in Table 1. It was attempted to introduce memory effects into the model using lagged temperature variables. In this study, these lagged variables are simply the maximum, minimum and present temperature values for two 12-h periods prior to the period of the avalanche observation.

The data set was thoroughly screened for incomplete records. These records were discarded and not used in the analysis.

Following Bovis (1976) and McClung and Tweedy (1994), the transformation $X_i \rightarrow \ln(X_i + 1)$ was applied to the precipitation and snow board variables to counter a positive skewness in the distribution of these variables. The transformed variables show a very nearly Gaussian distribution with the exception of the snow boards which have a spike at zero, indicating a large number of days with no snow

Table 1
All variables considered in the analysis with group means, F-ratio and p-values from the ANOVA shown for each variable

Variable	Group means		F-ratio	p-value
	No	Yes		
New precipitation (mm water equivalent)	2.08	6.90	198.0	< 0.001
Storm snow board (cm)	0.99	1.92	109.2	< 0.001
Foot penetration (cm)	26.0	38.5	89.1	< 0.001
New snow board (cm)	0.62	1.26	86.2	< 0.001
Minimum temperature (°C)	− 6.32	− 3.12	74.6	< 0.001
Snowpack depth (cm)	156.5	182.7	65.4	< 0.001
Present temperature (°C)	− 4.31	− 1.32	64.4	< 0.001
Interval snow board (cm)	0.60	1.11	60.4	< 0.001
Relative humidity (%)	85.2	90.2	34.7	< 0.001
Snowfall rate (cm h^{-1})	0.46	0.57	34.0	< 0.001
Minimum temperature lagged (°C)	− 6.45	− 3.99	32.3	< 0.001
Maximum temperature (°C)	− 1.63	0.32	27.4	< 0.001
Present temperature lagged (°C)	− 4.40	− 2.13	25.5	< 0.001
Present temperature trend (°C per time period)	− 0.01	0.94	18.8	< 0.001
Maximum temperature lagged (°C)	− 1.60	− 0.63	4.0	0.0461
Wind speed (km h^{-1})	3.23	2.84	3.8	0.0515

For the group means, *no* indicates the group of non-avalanche periods and *yes* indicates the group of avalanche periods.

observed. To counter this problem, data records were eliminated where the total snowpack depth was zero, since, even though starting zones might contain some snow, avalanches would be unlikely to occur on such days. A problem with this action is that it also excludes days when no snow is recorded at the weather station but avalanche conditions were present on the higher slopes. Thus the prediction capability of the model will be limited for avalanches that occur during the very beginning or at the end of the season. However, with the zero snowpack depth days removed, the overall prediction rate increased by about 2%. This overall increase in prediction rate justifies removal of these records and a possible reduction in performance of the model at the margins of the avalanche season.

For most days in the data set, there is a morning and an afternoon weather observation (i.e. two records per day). More recently however, only the morning weather observations were available. For this study, time periods of 12 h were used. The morning daily records were used simply as if they had been recorded over a 12-h period and no attempt was made to artificially convert them to 12-h periods (for example, by dividing the new precipitation by 2). Thus with this assumption, the new record still indicates the change in conditions since the last weather reading was taken. This is potentially a major limitation with the model, especially since it is likely that weather observations in the Pass will continue to be taken only in the morning and in the future they may be phased out entirely in favor of automated systems.

3.2. Avalanche occurrence data

Each recorded avalanche occurrence was assigned to one of the 12-h weather observation time periods according to the date and time of the occurrence. Following McClung and Tweedy (1994), occurrences falling between 0000 h midnight and 1200 h midday were grouped with the morning weather observations; the remainder were grouped with afternoon records.

Avalanche occurrences were filtered by size for each individual avalanche path. The Canadian size classification system was used in this study which features a five-point (plus half-sizes), absolute size classification scale (Canadian Avalanche Association, 1995). For each path, a minimum size of avalanche that was considered hazardous to the highway was set using the forecasters' expert knowledge of the paths affecting the Pass. Filtering by size in this way does not necessarily improve the numerical forecasting prediction rates. However, it provides a scheme compatible with the forecaster's prediction objectives in that the forecasted avalanche periods will be those likely to produce avalanches of sufficient magnitude to impact the highway.

Avalanche occurrences were also filtered according to the avalanche trigger. After much consideration, a scheme was used that included all occurrences from the Summit Sluffs area and only naturally triggered avalanches for all other paths. The justification for this is that control work on the Summit Sluffs paths is generally conducted either after paths have already produced avalanches or when avalanches on the paths are considered imminent. In either case, the control work is conducted using roadside case charges that may be detonated in most weather conditions. Explosive control work in the remainder of the Pass is done either from an artillery position or using helicopter control missions. These operations are often carried out during weather periods that would not normally produce natural avalanches. This is especially true for helicopter control missions where clear weather is preferred for flights. If such avalanches were included in the record, they would skew the model toward predicting avalanches on fine weather days.

4. Analysis of variance

One-way analysis of variance (ANOVA) may be used to test whether the population means differ between two or more groups (e.g. Manly, 1994, p. 44). The *F*-ratio is the ratio between the mean square (a measure of between group variance) and the mean square error (a measure of within group variance). The *F*-ratio will approximate unity for variables that do not discriminate between groups. An assumption for this test is that variables are normally distributed. Group means as well as the *F*-ratio and corresponding *p*-value for each of the variables in the analysis are shown in Table 1.

The results indicate that all the variables except wind speed and the maximum temperature lagged by 24 h allow significant discrimination between avalanche and non-avalanche days using a significance level of 5% ($\alpha = 0.05$). Since we seek highly significant variables for inclusion in the model, these two variables are rejected from the analysis.

5. Canonical discriminant analysis

The next stage was to perform a canonical discriminant analysis (CDA) using the significant variables from the previous analysis. This method is similar to that presented by Bois et al. (1975), Bovis (1977), Obled and Good (1980) and McClung and Tweedy (1994), although in this case, a greater emphasis is placed on the coefficients of the canonical variates. CDA seeks to find a linear combination of the predictor variables, $Z = A_1X_1 + A_2X_2 + \ldots A_nX_n$, which exhibits the largest difference between group means relative to the within-group variance.

Unlike McClung and Tweedy's (1994) study at Kootenay Pass, separate schemes were not constructed for wet avalanches and dry avalanches. This is because poor discrimination between wet and dry avalanche periods was achieved in Bear Pass. This is probably due to the relatively warm maritime climate compared to the transitional climate zone of Kootenay Pass (McClung and Tweedy, 1993).

If one group is significantly different in size from the other, it is possible, with discriminant analysis, to assign Baysian prior probabilities to increase the likelihood of a member of the group with the larger population size being selected (e.g. Duda et al., 2001, p. 22). When this was attempted, however, classification rates for non-avalanche periods were disproportionately higher than those for avalanche periods. This is presumably due to the weak group separation meaning that a small increase in prior probability is enough to force many of the periods into the non-avalanche category. Instead of assigning prior probabilities, groups of roughly equal size of avalanche and non-avalanche time periods were selected by trimming the number of non-avalanche days from the database using a random number generator. This enabled equal prior probabilities of group membership to be used and produced a very similar classification rate between avalanche and non-avalanche days.

In addition to equalizing the group sizes, a random sample of 35% of the time periods was initially withheld from the analysis and used as an independent testing set.

An assumption of CDA is that the variance–covariance matrices are homogeneous across groups (e.g. Manly, 1994, p. 112). This assumption was tested using Wilks' lambda (Schatzoff, 1966). Wilks' lambda gives information on multivariate group separation with a value close to zero indicating that the two groups are well separated and a value of unity indicating no group separation. The corresponding *F*-statistic and the likelihood ratio statistic were also calculated for testing the null hypothesis that the variance–covariance matrices are equivalent. Since we have only two groups, these values are reliable (Wilkinson, 1990, p. 270). The results gave a value for Wilks' lambda of 0.74, indicating that the group means are not well separated. The value of the F-statistic was 28.0 with a p-value of 0.001, indicating that the group separation that is present, however, is significant. Therefore, we may retain the null hypothesis that the variance–covariance matrices are similar for the groups.

The standardized canonical coefficients give information on the relative importance of each variable in the discriminating function. These coefficients are listed in Table 2. The total canonical correlation was 0.51, indicating that 51% of the variance of the original variables is expressed by the canonical variates. Also shown in Table 2 are the canonical scores for the group means. These indicate the position of the groups relative to the canonical variates.

5.1. Interactions between variables

Many of the variables were found to be highly correlated with each other. Table 3 shows the total Pearson correlation matrix for all variables used in the CDA. When variables are highly correlated, standardized canonical scores can become unstable (Whitaker, 1997). This is because the scores are derived from the amount of unique variance explained by each variable. In the case of two highly correlated variables, the scores may 'flip' between preferring one variable or the other due to a relatively small change in the model parameters (for example, removing a third variable from the analysis that also has some correlation with these two variables).

One example of this interaction is between the new snow board and storm snow board variables. These variables are highly correlated with each other (0.96). The new snow board has a canonical score of 0.43, indicating that it is directly correlated with the avalanche group. The interval snow board, however, which often records exactly the same values as the new snow board, has a canonical score of − 0.55 and is therefore inversely correlated with the avalanche group. A possible explanation for this is that the portion of the variance unique to the interval snow board arises from periods when there is less snow on the interval snow board than the new snow board (presumably because it has been cleared as additional weather observations are taken during a storm). Therefore, the canonical score for the interval snow board is negative. Out of these two snow boards, we rejected the interval board for use, since readings of this board are subject to variations during different weather conditions.

There is also an apparent two-way link between the present temperature and the present temperature lagged by 24 h. There is also a high correlation between these variables (0.85). Again, from an analysis of the group means, one would expect both the present temperature and the lagged present temperature to show a direct correlation with the avalanche group of time periods. The canonical analysis reveals that the best discrimination occurs when there is a high present temperature and a lower present temperature 24 h ago. This corresponds physically to a rising temperature trend.

Many of the temperature variables were removed from the analysis due to problems with collinearity. This does not necessarily mean that these variables had no ability to discriminate between avalanche and non-avalanche periods. Instead, it is likely that most of their discrimination power was already accounted for by another, slightly stronger variable.

Table 2
CDA results using all variables

Variable	Standardized canonical coefficient
Present temperature lagged	− 0.69
Present temperature	0.68
New precipitation	0.59
Interval snow board	− 0.55
Snowpack depth	0.53
Minimum temperature	0.52
New snow board	0.43
Foot penetration	0.43
Maximum temperature	− 0.28
Minimum temperature lagged	0.24
Present temperature trend	0.19
Storm board	− 0.15
Precipitation rate	0.14
Relative humidity	− 0.004
Group	**Canonical scores for group means**
Non-avalanche	− 0.575
Avalanche	0.6

Canonical coefficients standardized by within-group variance are shown.

Table 3
Total correlation matrix for the variables used in the CDA

	Present temperature lagged	Present temperature	New precipitation	Interval snow board	Snowpack depth	Minimum temperature	New snow board	Foot penetration	Maximum temperature	Maximum temperature lagged	Present temperature trend	Storm snow board	Snowfall rate	Relative humidity
Present temperature lagged	1.00													
Present temperature	0.85	1.00												
New precipitation	0.06	0.16	1.00											
Interval snow board	− 0.15	− 0.04	0.54	1.00										
Snowpack depth	− 0.01	0.02	− 0.06	− 0.01	1.00									
Minimum temperature	0.90	0.94	0.18	− 0.01	0.00	1.00								
New snow board	− 0.15	− 0.03	0.56	0.96	0.00	− 0.01	1.00							
Foot penetration	− 0.27	− 0.21	0.35	0.57	0.02	− 0.17	0.61	1.00						
Maximum temperature	0.90	0.92	0.07	− 0.16	0.05	0.89	− 0.16	− 0.35	1.00					
Maximum temperature lagged	0.92	0.83	0.00	− 0.22	0.02	0.83	− 0.23	− 0.40	0.92	1.00				
Present temperature trend	− 0.21	0.21	0.23	0.26	0.06	0.09	0.28	0.15	0.05	− 0.21	1.00			
Storm snow board	− 0.07	0.05	0.50	0.74	− 0.03	0.11	0.78	0.63	− 0.10	− 0.20	0.28	1.00		
Snowfall rate	− 0.17	− 0.14	0.35	0.44	− 0.15	− 0.08	0.44	0.34	− 0.21	− 0.22	0.06	0.38	1.00	
Relative humidity	− 0.08	− 0.05	0.31	0.35	− 0.07	0.17	0.36	0.28	− 0.07	− 0.11	0.07	0.42	0.31	1.00

5.2. Optimal variables

An optimum variable set was sought comprising variables that offered good ability to discriminate between avalanche and non-avalanche periods. The analysis was repeated a number of times to test the effect of altering the variable set used in the analysis. It was found that the dominant variables performed consistently well in the analysis despite the removal or inclusion of other variables. Only these were retained in the final variable selection.

Table 4 shows the standardized canonical coefficients for the best variable group. These variables were as follows: the amount of new precipitation, present temperature, snowpack depth, foot penetration and the present temperature trend.

5.3. Discussion of variables

It is expected that increased precipitation should allow discrimination between avalanche and non-avalanche periods, since loading of avalanche prone slopes by new snow (or rain) is frequently sufficient to trigger avalanches on these slopes (e.g. McClung and Schaerer, 1993, p. 152). From the analysis, the new precipitation variable (recorded using a precipitation gauge) was found to be a superior variable in discriminating between avalanche and non-avalanche periods than the new snow board. This is probably due in part to the increased precision of the precipitation gauge over measuring the height of snow on the new snow board and in part due to the fact that the precipitation gauge will record rain events, which can be an avalanche trigger.

Table 4
CDA results for the best variable group

Variable	Standardized canonical coefficient
New precipitation	0.57
Present temperature	0.52
Snowpack depth	0.44
Foot penetration	0.43
Present temperature trend	0.19
Group	**Canonical scores for group means**
Non-avalanche	− 0.55
Avalanche	0.57

Standardized canonical coefficients for the best variable group are shown.

The positive canonical score for the present temperature variable indicates a tendency for avalanches to occur during warmer conditions. In a relatively warm, maritime climate, avalanches due to the formation of depth hoar over prolonged cold weather periods are usually not frequent enough to affect an analysis such as the present one. Instead, avalanches appear to occur most frequently during warmer periods, characterized by precipitation laden storms, which can include rain or snow.

The analysis shows that more avalanches occur when the snowpack depth is large. Probably the most important reason for this correlation is the fact that most avalanches occur during midwinter and late winter storms, at which time the snowpack depth is greatest. In other words, this is simply the main snowfall season.

Foot penetration has a positive canonical score, indicating the greater the penetration of the foot into the snow, the more likely avalanches are to occur. This could simply indicate the presence of new snow, since a large amount of freshly fallen snow will give a high foot penetration reading. However, foot penetration is only weakly correlated with the amount of new precipitation (0.35). It could be that if significant settlement occurs after a storm cycle, then the snowpack becomes relatively stable and a low foot penetration reading results. Conversely, if settlement does not occur, then instabilities in the snowpack will remain and foot penetration readings will be high.

Although the canonical score for the temperature trend variable is relatively low (0.19), it is not highly correlated with the other temperature variables (i.e. explains unique variance) and it performed consistently (i.e. did not behave in an unstable way when altering the variable group) making this variable important in the analysis. Once again, this variable indicates a tendency for avalanches in Bear Pass to occur during periods of warming temperatures.

The absence of wind speed as a significant variable in the analysis is maybe surprising, since accumulation and wind loading on lee slopes can lead to slab formation. The most likely explanation is that the location of the anemometer is not in a position where meaningful wind measurements may be made. The Pass trends east–west and the weather station is located towards the east end of the pass in the valley bottom. The low elevation of the anemometer means that recorded winds are not representative of start zone conditions. In addition, an anemometer in this position should record easterly or westerly winds relatively accurately but record northerly or southerly winds with less accuracy due to the parallel shape of the valley which creates a funneling effect for the wind. Most of the paths face either north or south, meaning that the winds most important for avalanche formation are not recorded accurately.

5.4. Classification rates

The discriminant functions built using the variables above were used to classify each day into either an avalanche day or a non-avalanche day. The results using the testing data set give classification rates of 73% for avalanche periods and 72% for non-avalanche periods with a sample size of 465 periods. The prediction rates for the testing data (as previously stated, a random sample of 35% of the records) are only marginally lower than those for the training data set (75% for both avalanche and non-avalanche cases), which indicates that the model is not too closely fitted to the training data set. This gives confidence in the prediction ability of the model in a field-testing environment.

Fig. 1 illustrates how the calculated avalanche prediction differs from the observed avalanche occurrences for a small subset of the data from 1st January to 31st March 1995. Mostly, the calculated prediction rates fit well to the observed avalanche activity with a prediction rate of approximately 0.6, indicating an avalanche period is likely. There are, however, periods where the model fails to predict an avalanche occurrence, most notably at the start of this 'season', when avalanches occurred when the calculated avalanche probability was between 0.2 and 0.4.

6. Analysis of individual areas

In addition to testing all paths, the method was also applied to the individual areas within the Pass (described in Section 2.1). The variables that showed consistently high discrimination power across all of the groups were the following: the amount of new precipitation, the snowpack depth, and the foot penetration. The minimum temperature was found to be an important variable for the Summit Sluffs area whereas the present temperature was found to be important for the three other areas. The new snow board depth was found to be important for both the North Aspect area and the Little Bears area.

The importance of the minimum temperatures in the Summit Sluffs area is possibly due to the tendency of the area to produce small avalanches (all avalanche occurrences from the Summit Sluffs paths were

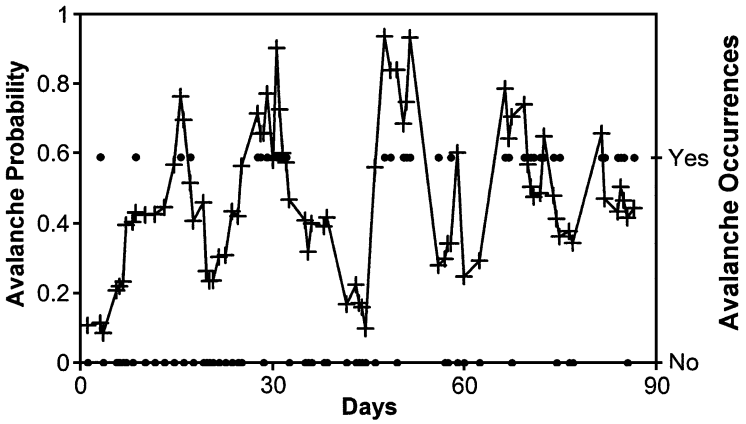

Fig. 1. Avalanche probability vs. avalanche occurrences for 1st January to 31st March 1995. Avalanche probabilities (+) are calculated from the discriminant analysis. Avalanche occurrences (•) are grouped by whether (yes) or not (no) there were any avalanche occurrences during that time period.

Table 5
Classification matrix (using the test sample) for both individual areas and for the whole pass

Area	Sample size	Classification rates (%)		
		Avalanche	Non-avalanche	Overall
Little Bears	130	78	77	78
Summit Sluffs	171	78	80	79
South Aspect	273	77	71	74
North Aspect	224	64	76	70
All areas	465	73	72	72

included since even a small avalanche has the ability to impact the highway). Colder minimum temperatures may indicate clear weather periods where sun can play a role in triggering avalanches.

The importance of the new snow board variable for the North Aspect and Little Bears areas is possibly due to the fact that these areas contain large avalanche paths that require comparatively large avalanches to impact the highway. Avalanches of this magnitude only occur during times of unusually high snowfall.

The results of the classification by individual area are given in Table 5. All of the areas, with the exception of the North Aspect area, perform better than the all-area model. The North Aspect area is the most heterogeneous area containing avalanche paths in complicated terrain that produce high magnitude but infrequent avalanches. It is this type of avalanche that is the hardest to predict. The Summit Sluffs area performs best with an overall classification rate of 79%. This area represents the most homogeneous area within the Pass and produces more easily predictable avalanches.

7. Conclusions

Based on the statistical analysis, the principal variables useful for forecasting snow avalanches in Bear Pass were found to be as follows: the amount of new precipitation, present temperature, snowpack depth, foot penetration and the present temperature trend.

The instabilities in the canonical variates that occur when subtracting or adding variables from the model clearly illustrate one of the principal dangers of determining the principal variables in an analysis of this type. Wilkinson (1990, p. 335) refers to piecemeal selection of variables (specifically stepwise discriminant analysis, which was not used in this analysis) as a 'fishing expedition' and advises against the indiscriminant use of this kind of 'artificial intelligence'. Therefore, any variables selected through the use of this statistical method, especially when deviations from a Gaussian distribution are suspected, must be rationalized by a physical justification to be included. Also, collinearity must be analyzed to eliminate redundant variables.

Reducing the number of variables in the analysis does not improve the classification rates. However, it does give an understanding as to which variables are most important in the analysis. The resulting discriminating functions built using the best variable group for the whole Pass gave an overall success rate of 72%, when tested against an independent data set. Very good parity was achieved between prediction rates for avalanche and non-avalanche periods.

There is good justification in dividing the Pass into smaller areas, as prediction rates for all areas except the North Aspect area improved when this division was made. These improvements are achieved despite a reduction in sample size for the individual areas. Some differences in the principal variables were noted between the different areas but most of the principal variables were consistent among the areas.

Further development of the model will be in combining the discriminant analysis with a nearest neighbours approach that will give forecasters information about weather and avalanche occurrences for periods similar to that being forecasted. For further progress to be made in avalanche prediction rates, the hourly, remote weather station data must be utilized.

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