FORECASTING FACTORS FOR SKIER-TRIGGERED AVALANCHES AT A HELICOPTER SKIING OPERATION

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ABSTRACT: To forecast skier-triggered avalanches, stability, snowpack and meteorological variables, and records of previous avalanche activity are typically used. The relative importance of, and interaction between, variables used to forecast skier-triggered avalanches have received little attention. This study analyzes the influence of forecasting variables at a heli-skiing operation in the Columbia Mountains of British Columbia, Canada.

Forecasting variables are individually assessed using rank correlations to identify which are most relevant for forecasting the potential for skier-triggered slab avalanches. The variables showing the strongest forecasting potential include: the largest skier-triggered avalanche observed on the previous one and two days, 24-hour snowfall and precipitation, storm snow, height of snowpack, and the number of days since December 1. The physical processes that relate these variables to skier-triggered avalanches are discussed.

The predictive potential of combined forecasting variables is assessed using a classification tree model. Verification of the model with the last two years of data shows that the model predicts relatively large avalanches approximately two-thirds of the time.

KEYWORDS: Avalanches; Avalanche forecasting; Avalanche triggering; Skier triggering

1. INTRODUCTION

Typically, a variety of stability, snowpack and meteorological variables, as well as records of previous avalanche activity are used to forecast the potential for skier-triggered, dry slab avalanches. In some areas, methods such as nearest neighbours (e.g. Buser, 1989) and expert systems (e.g. Schweizer and Föhn, 1996) are used for forecasting, usually in conjunction with conventional, experience-based forecasting. More often, however, the forecaster considers current and recent values of these variables to develop a reliable avalanche forecast. The relative importance of each variable is intuitively known by the forecaster from their experience with the forecasting area.

The objectives of this paper are to: (i) assess the relative importance of various forecasting variables for forecasting skier-triggered dry slab avalanches; and (ii) assess the predictive

Corresponding author address: Alan Jones, Dept. of Civil Engineering, University of Calgary, 2500 University Drive NW, Calgary, Alberta T2N 1N4 Canada; tel: 403-220-5821; Fax: 403-282-7026; email: astjones@ucalgary.ca potential of combined forecasting variables using a classification tree model

2. BACKGROUND

Forecasting avalanche activity requires the integration of numerous variables into a model to forecast when and where avalanches will occur. This is particularly difficult for heli-skiing operations due to the large variety of terrain and snowpack conditions encountered on a given day.

Atwater (1954) proposed a list of 10 contributory factors for avalanche hazard evaluation, including variables such as snowfall depth, precipitation rate, air temperature and wind direction. Perla (1970) found the most important variables to be precipitation amount, precipitation intensity, and wind direction for a highway in Utah. Judson and Erickson (1973) found the most significant factors for various avalanche control operations in Colorado to be 24-hour snowfall and water equivalent, maximum precipitation intensity, and maximum precipitation intensity modified for excessive wind.

While noting the lack of a physical explanation, Lev and Mohwinkel (1980) proposed that lunar cycles correlate with large unexpected

avalanches. Sommerfeld (1984) showed that the daily observation cycle correlated with the proposed lunar cycle, confounding Lev and Mohwinkel's correlations. Lev and Mohwinkel (1984) showed that there were days near new and/or full moons for which the number of large unexpected avalanche was significantly above average. However, Sommerfeld (1984) did not observe this effect with a similar dataset.

Attempts have been made over the years to produce avalanche forecasting models using multivariate statistical techniques (e.g. Bois et al., 1974; Bovis, 1977; Salway, 1976). Buser (1983) introduced the multivariate "nearest neighbours" method which has since been tried at some Swiss and Canadian forecasting programs (e.g. McClung and Tweedy, 1994).

The above avalanche forecasting models were developed either at ski areas or highways for the prediction of natural or explosive controlled slab avalanches. Consequently, the results primarily reflect events that occur during or following storms, and do not focus on human triggering of avalanches between storms that are important for heli-skiing operations. Rather than consider a few controlled slopes, as most previous studies have, these operations forecast for a large number of uncontrolled slopes with different aspects, elevations and terrain, and often with highly variable snow conditions.

Little work has been done in assessing the potential for human triggering of avalanches. Jamieson and Geldsetzer (1996) analyzed the trends and patterns for Canadian avalanche accidents. Most recently, Schweizer and Jamieson (2000) summarized snowpack characteristics associated with skier-triggered avalanches, but did not consider meteorological variables or previous avalanche activity. Similar to the present study but using a much smaller dataset, Jamieson (1995) looked at the relationship between the daily maximum size of skier-triggered avalanches involving dry slabs and 15 forecasting variables from a heli-skiing operation.

3. METHODS

The data used for this study are from a heli-skiing operation based in Blue River, British Columbia. The operating area spans more than 5000 km², including portions of the Monashee and Cariboo Mountain Ranges of the Columbia Mountains of western Canada. The dataset includes 1292 days between 1990 and 2000.

The majority of the meteorological data were recorded at a weather station located at Mt.

St. Anne (1900 m) in the Cariboo Range. The total snow depth at this station between December and late March ranges between 175 and 375 cm, which is characteristic of a transitional climate between the maritime and coastal climate regions.

4. FORECASTING VARIABLES

4.1. Response variable

In the following analyses, associations are sought between the predictors and the response variable, Smx, which is the value of the largest class of skier-triggered avalanche observed on the forecasting day. In Canada, avalanches are classified by size, based on destructive potential (CAA, 1995). A Class 1 avalanche is "relatively harmless to people"; a Class 2 avalanche can "injure, bury or kill a person"; and a Class 3 avalanche can "bury and destroy a car, destroy a small building, damage a truck or break a few trees". Avalanches of size class 4 and 5 did not occur in this study. Half sizes, such as 1.5, are used for avalanches that appear to fall between two size classes. Class 0.5 avalanches, although not included in this classification system, are reported at this heli-skiing operation and included in this study as part of the Class 1 avalanche classification.

The 1292 values of Smx are partitioned into avalanches size classes, ranging from 0 through 3 (Figure 1). The distribution is strongly skewed, with 78% of the 1292 days having no observed skier-triggered avalanches (Smx = 0), and the remaining 22% of the days having $0.5 \le \text{Smx} \le 3$.



Figure 1. Distribution of Smx, the largest skiertriggered avalanche for forecast day

4.2. Predictor variables

A predictor variable is a measurement that might be useful for predicting the potential for skier triggering of avalanches (Table 1). The predictor variables used in this study include 16 meteorological variables, 2 variables for previous skier-triggered avalanche activity, and 14 calculated variables. Some predictors, such as the height of snowpack at 5 am (HS5) or air temperature at 5 am (T5), are meteorological measurements obtained either by manual measurement or telemetry. Others are calculated values such as the cumulative snow (Storm), or the number of days since December 1 (Days).

5. ANALYSES

This section assesses the relationships between the daily maximum skier-triggered avalanches, Smx, and the forecasting variables. Monotonic (increasing or decreasing) relationships are assessed in this study with Spearman rank correlations, which are suited to ordinal data. Nonmonotonic (reverse the trend for a portion of the data) relationships are assessed with singlevariable box plots. The predictive potential of

Table 1

Definitions of predictor variables

combined forecasting variables is assessed using classification tree models.

5.1. Rank correlations

Rank correlations are used because of the non-normality of Smx (Figure 1). Rank correlations between the predictor variables and the response variable, Smx, are listed in Table 2. The correlation coefficient is denoted by R, and p is the significance level. Values for significant correlations (p < 0.05) are marked in bold.

The results in Table 2 show that 14 of the 32 predictor variables correlate significantly (p < 0.05) with Smx. All of these variables correlate positively with Smx, except Baro6. The negative correlation of barometric pressure with Smx implies that the daily maximum size of skiertriggered avalanche tends to be greater when the barometric pressure is low. These variables are discussed in Section 6 in terms of the underlying physical processes.

Baro6	Barometric pressure at 6 am (mb)
∆Baro	Change in 6 am barometric pressure from previous day (mb)
∆Baro/Baro6	Ratio of change in 6 am barometric pressure from previous day to barometric pressure at 6 am
HS5	Height of snowpack at 5 am (cm)
HNY	Height of new snowfall for previous 24 hours (cm)
HNF	Height of new snowfall for forecast day (cm)
Storm	Cumulative new snowfall (storm) snow since last day with less than 0.3 mm of precipitation (cm)
PcpY	Precipitation for previous day (mm)
PcpF	Precipitation for forecast day (mm)
RH5	Relative humidity at 5 am (%)
∆RH5/RH5	Ratio of change in 5 am relative humidity from previous day (%)
RHminY	Minimum relative humidity for previous day (%)
RHmayY	Maximum relative humidity for previous day (%)
RHminF	Minimum relative humidity for forecast day (%)
T5	Air temperature at 5 am (°C)
∆T5/(T5+40)	Ratio of change in 5 am air temperature from previous day (°C)
TminY	Minimum temperature for previous day (°C)
TmaxF WS5	Maximum temperature for previous day (°C) Maximum temperature for forecast day (°C) Wind speed at 5 am (kmh ⁻¹)
WD5M90	Wind direction at 5 am (minus 90 degrees modulo 360) (east as base azimuth) (°)
WrunY	24-hour wind run for previous day (km)
WSa	Average upper air wind speed (kmh ⁻¹)
WDaM90 Days	Average upper air wind direction (minus 90 degrees modulo 360) (east as base azimuth) (°) Number of days since December 1(days) Solumar cycle (1=no birth or moderate, 2=moderate but no birth, 3=birth during day) (I ev. 1984)
Lun2	Number of days from full/new moon (days) (Lev and Mohwinkel, 1984; Sommerfeld et. al., 1984)
Sky	1 = clear, 2 = scattered, 3 = broken, 4 = overcast, 5 = obscured (CAA, 1995)
Smx1Prev	Class size of largest skier triggered avalanche observed on previous day
Smx2Prev	Class size of largest skier triggered avalanche observed 2 days previous

Table 2 Correlations of forecasting	variables	with	Smx
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and the second			
Forecasting Variable	N	Spearman R	p
	1276	0.180	1.E-10
Smx2Prev	1284	0.171	7.E-10
Smx1Prev	1174	0.148	4.E-07
HNY	1177	0.143	8.E-07
PcpY	1016	0.146	3.E-06
Storm	1243	0.131	4.E-06
HS5	1296	0.112	5.E-05
Days	1213	0.094	0.001
RHminy	1245	0.092	0.001
ABaro6/Baroo	1245	0.092	0.001
ABarob	1210	0.079	0.006
RHmax	1230	0.072	0.012
RH5	1213	0.070	0.015
RHminr	1269	-0.061	0.030
Barob	1194	-0.053	0.066
T5	1224	-0.042	0 143
Tmaxy	1212	-0.038	0.190
Imint	1130	0.038	0.201
WDawieu	1086	-0.037	0.201
wrunt	1214	-0.034	0.222
Imaxr	1203	-0.034	0.245
	1136	-0.034	0.253
ADUS/DUS	1203	-0.032	0.200
ATS	1166	-0.029	0.329
	1295	0.017	0.550
AT5/(T5+40)	1166	-0.017	0.566
M/Sa	1155	-0.015	0.601
WD5M90	1245	0.013	0.660
Lun1	1289	-0.011	0.688
HNE	1166	-0.007	0.000
Sky	1178	-0.007	0.876
PopE	1170	0.005	0.070
r opi-	1170	-0.002	0.952

5.2. Box plots

Box plots were prepared showing the distribution of the predictor variables plotted against the values of Smx. The box plots were inspected for either non-monotonic or other substantial shifts in the distribution of the data that cannot be detected with rank correlations.

Box plots are shown for Δ Baro, WS5 and Lun2 (Figure 2). The change in barometric pressure, Δ Baro, shows a non-monotonic relationship with Smx = 3, whereby large negative changes in barometric pressure are apparent on days with Smx = 3. The local (ridgetop) wind speed, WS5, shows a relationship between larger (Smx = 3) avalanches and increased wind speeds of between 25 and 35 km/h. A similar relationship was noted for upper air wind speeds of between 40 and 70 km/h. The number of days from a full or new moon, Lun2, shows a possible relationship with Smx, showing a shift in the median for days with Smx = 3, corresponding to Lun2 = -2.



Figure 2. Box plots of the daily maximum size of skier-triggered avalanche, Smx, against WS5, ∆Baro6 and Lun2, showing median (small rectangle), 25th and 75th percentiles (box), minima and maxima (whiskers), outliers (small circles) and extremes (small asterisks)

5.3. Classification tree

5.3.1 Background

To assess the combined predictive potential of the forecasting variables associated with skier-triggered avalanche activity, a classification tree model is used (Breiman et al., 1984). Classification trees allow for complex relationships between the predictor and the response variables, and allow a categorical response variable with more than two levels for avalanche activity (Davis and Elder, 1995).

Classification trees consist of a series of splits or decisions forming nodes of a tree structure. For each split, a critical value for each

variable is selected that divides the data into two subsets. The split with the best-combined fit of the predicted classes to observed classes for the two subsets is selected by the program. This program could continue until there was only one case (day) in each node, but was stopped when there were less than 5 days in a node, called a terminal node. The model runs through a series of such trees and selects the optimized tree as that which is simplest (i.e. has the fewest terminal nodes) and has the lowest cost of misclassifying the data, a value calculated by the model for each tree (Breiman et al., 1984).

5.3.2 <u>Analysis</u>

Of the 32 predictor variables, 29 were used in the development of the classification tree. Calculated variables Δ Baro6/Baro6, Δ T5/(T5+40), and $\Delta RH5/RH5$ were excluded from the model due to redundancies noted in the correlation analyses. There were 492 days for which all the remaining variables were available from 1990 to 1998, and these were used to develop the tree model. An additional 126 forecasting days from 1998 to 2000 were used to validate the model. Because of the disproportionate number of days with larger avalanches as compared to nonavalanche days (Figure 1), the response variable, Smx, was reclassified into a separate categorical response variable, Cmx. Class A represents nonavalanche days (Smx = 0), Class B represents days with Smx = 0.5 and 1, and Class C represents days with skier-triggered avalanches size 1.5 and greater.

The upper portion of the "best" tree model

is shown on Figure 3, showing the splits that most improve the fit. For each split, the left branch is for observations for which the "less than" condition is true. The predicted values of Cmx (terminal nodes) are shown as solid boxes.

The predictor variables can be ranked on a relative scale of 0 to 100 in terms of their potential importance in accounting for responses on the dependent variable (see Breiman et al., 1984, pp. 146-150). The 10 most important variables in order of decreasing predictive value are change in barometric pressure, height of snowpack, minimum relative humidity, largest skier triggered avalanche for previous day, 24hour snowfall, 24-hour precipitation, storm snow, largest skier-triggered avalanche 2 days previous, relative humidity and sky condition, all of which correlate significantly with Smx, except for sky condition (Figure 4).



Figure 4. Predictor variable importance rankings for 10 highest ranked variables (dependent variable Cmx) (rankings on scale from 0 = low importance to 100 = high importance)



Figure 3. Upper portion of classification tree for size class of skier-triggered avalanches, Cmx, showing important predictors. Solid boxes show terminal nodes; dashed boxes show prior estimates for Cmx. (A = non-avalanche day, Smx = 0; B = Smx class 0.5 or 1, C = Smx class 1.5 +)

Graphical representations of the classification tree model results are shown on Figures 5a, 5b and 5c. Figure 5a shows a comparison of observed Cmx versus predicted Cmx produced by the classification tree for the 492 forecasting days with. The model fits 52%, 67% and 88% of the observed values of Cmx for Class A, B and C, respectively. Because of the imbalance of Class A days, as compared to Class B and C days, the model was weighted by factors of 1, 14 and 11 for Classes A, B and C,

respectively, to better forecast for avalanche days. Weighting the model in this manner results in poor fit for Class A, but improved fit for avalanche days, which are of greater interest to forecasters.



Figure 5a. Predicted versus observed class Cmx from classification tree model for model building dataset (learning sample), N=492



Figure 5b. Predicted versus observed class Cmx from validation of tree model (test sample), N=126



Figure 5c. Predicted versus observed class Cmx for complete dataset (learning sample), N=618

The model developed using 492 observation days was validated using a test sample of 126 additional days from 1998 to 2000. The results of the validation are shown on Figure 5b. The model predicts avalanche days in the test sample for approximately two-thirds of the cases (62% for Class B and 67% for Class C). Because of the weighting of the model, the model only predicted 26% of the non-avalanche days correctly. However, of these misclassified nonavalanche days, 41% were classified as days with only small skier-triggered avalanches (Smx = 0.5 or Smx = 1)

A second tree model was developed using the complete dataset from years 1990 to 2000. Adding these last two years to the model significantly increases the fit both in terms of avalanche days and non-avalanche days (Figure 5c). The model predicts 77% of the nonavalanche days (Class A) and 96% of the avalanche days (Classes B and C) for the complete dataset.

6. DISCUSSION

The strong positive correlation of Smx1Prev and Smx2Prev with Smx is consistent with the accepted use of recent avalanche activity as a predictor of expected avalanche activity for the forecast day. Smx2Prev probably correlates better than Smx1Prev because of persistence in snowpack instabilities and the increased number of slopes skied on two days compared to one day.

The positive correlations of both HNY and Storm imply that the maximum size of skiertriggered avalanches tends to increase as the 24hour and storm snowfall increase. PcpY is the water equivalent of HNY, and therefore also has a strong correlation with Smx. There is a strong positive correlation between the height of snowpack (HS5) and Smx. Between December and March the height of snowpack typically increases in a linear manner, due to a large number of storms passing through the Columbia Mountains. This relationship is complicated by a bias in the data since the number of skier-days is reduced in December and early January, compared to the remaining period to 31 March. Winters with greater average snowpack depth will have greater values of storm snow and associated increase in Smx.

The strong positive correlation between the number of days since December 1 and Smx may also partly reflect the increasing number of skier-days through the winter, and therefore an increasing occurrence of skier-triggered avalanches.

Four of the six relative humidity variables, RHminY, RHmaxY, RH5 and RHminF, show moderate to weak positive correlations with Smx, suggesting the relevance of relative humidity for some backcountry forecasting programs. High humidity (about 85% to 100%), associated with deposition of wind-transported snow, is related to the formation of wind slabs (McClung and Schaerer, 1993, p. 161). The minimum relative humidity from the previous 24 hours shows the strongest correlation of the four variables.

All of the forecasting variables related to barometric pressure show moderate to weak correlations with Smx. Δ Baro6/Baro6 and Δ Baro show positive correlations whereas Baro6 shows a negative correlation with Smx. Skier-triggered avalanches are related to low, increasing barometric pressure, which is likely to occur at or near the end of a storm period when skiers may return to avalanche terrain.

Although 18 of the 32 forecasting variables did not show significant correlations with Smx, this does not preclude them as important forecasting variables. Most notably, wind speed and direction (WS5, WSa, WD5M90, and WDaM90) have been shown to be important forecasting variables at many operations (e.g. Judson and Erickson, 1973). WS5 and WSa showed substantial shifts in distribution, reflecting an apparent relationship between larger (Smx = 3) avalanches and increased wind speeds of between 25 and 35 km/h for local and between 40 and 70 km/h for upper air wind speeds.

Lun2, WDaM90 and WD5M90 also show possible relationships with Smx, showing substantial shifts in the median for days with large avalanches. Although these variables did not significantly correlate with Smx in this study, they may still have predictive merit at this and possibly other forecasting areas.

7. SUMMARY

Based on eight to ten years of meteorological data, the size of the largest skier-triggered dry slab avalanche increased with the maximum size of skier-triggered avalanche in the previous one or two days, increased snowfall or precipitation in the previous day, increased accumulated snowfall during storm periods, increasing depth of the snowpack, elapsed days since December 1, increased relative humidity as well as low and rising barometric pressure.

A classification tree model developed with eight years of data was able to predict the class of hazardous skier-triggered avalanches on 67% of days, although hazardous avalanches were predicted on 29% to 34% of days without hazardous avalanches.

This model, which is based on meteorological variables and previous avalanche activity, could be improved by including snowpack properties to better forecast skier-triggered dry slab avalanches on the regional scale.

ACKNOWLEDGEMENTS

We thank Bert Davis and Kelly Elder for helpful discussions on classification trees. For their careful fieldwork we are grateful to Jill Hughes, Leanne Allison, Ken Black, Aaron Cooperman, Nick Irving, Bill Mark, Jordy Shepherd, and Mark Shubin.

This study was funded by the BC Helicopter and Snowcat Skiing Operators Association (BCHSSOA), Natural Sciences and Engineering Research Council of Canada, Canada West Ski Areas Association, Intrawest Corporation, and the Canadian Avalanche Association. The supporting members of the BCHSSOA include Canadian Mountain Holidays, Cat Powder Skiing, Crescent Spur Helicopter Holidays, Great Canadian Helicopter Skiing, Great Northern Snow Cat Skiing, Island Lake Lodge, Klondike Heli-Skiing, Last Frontier Heliskiing, Mike Wiegele Helicopter Skiing, Monashee Powder Adventures, Peace Reach Adventures, Purcell Helicopter Skiing, R.K. Heli-Skiing, Retallack Alpine Adventures, Robson Heli-Magic, Selkirk Tangiers Heli-Skiing, Selkirk Wilderness Skiing, Sno Much Fun Cat Skiing, TLH Heliskiing, Whistler Heli-Skiing and White Grizzly Adventures. The supporting members of Canada West Ski Areas Association include Apex Mountain Resort,

Banff Mt. Norquay, Big White Ski Resort, Hemlock Ski Resort, Mt. Washington Alpine Resort, Silver Star Mountain Resorts, Ski Marmot Basin, Sun Peaks Resort, Sunshine Village, Whistler Blackcomb, Whitewater Ski Resort, and the Resorts of the Canadian Rockies including Skiing Louise, Nakiska, Kimberley Alpine Resort, Fortress Mountain and Fernie Alpine Resort.

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