MARCH WET AVALANCHE PREDICTION AT BRIDGER BOWL SKI AREA, MONTANA

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ABSTRACT: Few avalanche forecast models are tailored specifically for wet avalanche forecasting. Bridger Bowl (intermountain climate) is a good area to develop a wet avalanche probability model. The primary archived data consists of eight variables. The archived data for March from 1968 to 2001 (1996 data unavailable) were used to develop 68 predictor variables related to temperature, snowpack settlement, and precipitation. The original dataset was divided into days with snowfall in the past 48 hours (new snow) and days without (old snow). There were 33 significant old snow variables and 22 significant new snow variables. Six variables are common to both old and new snow. The best predictor variables for old and new snow are different. The variables were analyzed with binomial logistic regression to produce probability models for old snow and for new snow wet avalanche conditions. The old snow model uses the prediction day minimum temperature and the two-day change in total snow depth as predictor variables and has a 89% overall success rate. However, the majority of this success is due to correct prediction of days without wet avalanches (96% of all correct predictions). The new snow model uses the prediction day minimum temperature and three-day cumulative new snow water equivalent as predictor variables, but is less useful. The models are applicable only to Bridger Bowl. The numerical forecast models can be used as one of the tools in the forecasting toolbox but limited data and complexity of process require that the decisions about closure remain in the hands of the ski patrol.

Keywords: wet snow, avalanche, probability, forecast, model

1. INTRODUCTION

As spring approaches, wet snow avalanches become a hazard for ski areas in all snow climates (maritime, intermountain and continental). Ski patrols must take measures to reduce skier exposure to wet avalanche danger. Wet avalanche conditions are particularly problematic because they are difficult to control artificially with explosives. The physical properties of wet snow suppress the propagation of a shock wave which is essential for release (Armstrong and Fues, 1976). Bridger Bowl Ski Area in Southwest Montana (Fig. 1) is concerned about wet snow avalanches because a majority of natural or skier-triggered wet slides start in expert terrain and can run out onto heavily used intermediate and beginner ski slopes below. Bridger wants to know when the expert terrain on the upper mountain should be closed to protect the skiers below from skier-triggered wet avalanches. The patrol faces the difficult task of identifying times when ski slopes transition from a stable wet snow situation to a dangerous one. One approach to the problem is the use of models as tools to assist patrollers

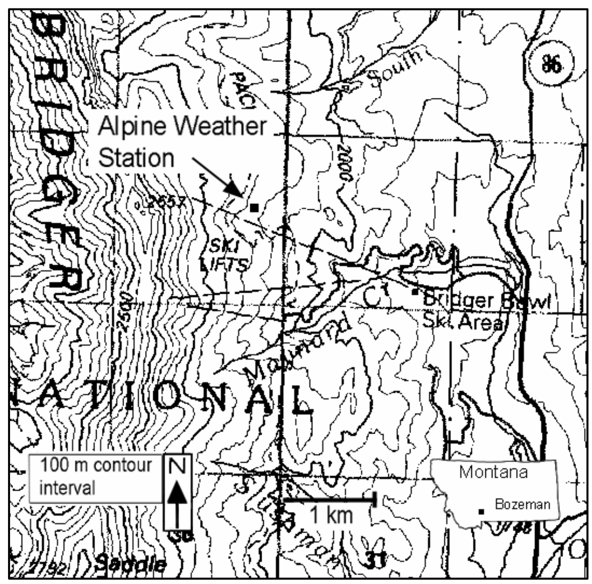

Figure 1. Bridger Bowl is 15 km northeast of Bozeman, southwest Montana, USA

in their efforts to forecast unstable conditions.

A variety of approaches have been used to forecast instability over the years. They include univariate analysis (Perla, 1970, Judson and Erickson, 1973) and multivariate techniques such as discriminate analysis (Bovis, 1977), forward and backward step-wise discriminate analysis, principal component analysis, dynamic clustered analysis and linear and quadratic discrimination

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(Fohn et al., 1977), classification and regression tree (CART) analysis (Davis et al., 1999), and nearest neighbor analysis (Merindol et al., 2002). Three (Bovis, 1977; Fohn et al., 1977; and Judson and King, 1985) considered wet avalanches when developing their models. Bovis (1977) was the only analysis which designed prediction models specifically for wet avalanches, but the model was developed for a highway corridor in a continental climate. Bridger Bowl is a ski area in an intermountain snow climate, a climate that has not yet been modeled for wet snow avalanches.

The Bridger-Bowl dataset also provides an opportunity to examine whether there is a difference between wet avalanches on days with snowfall in the past 48 hours (new snow) and days without (old snow). This difference is potentially important because instabilities in new snow may be influenced more by early warming or solar radiation events, while old snow may require more prolonged warming or solar radiation before instabilities develop. The difference between old and new wet snow avalanche has not been studied before.

The work consists of a hypothesis testing phase and the model development phase which examines the probability of wet avalanche occurrence at Bridger Bowl. This paper focuses on the model development phase. The details of both phases can be found in Romig (2004).

2. METHODS

The 1968 to 1995 meteorological and avalanche records reported by Bridger Bowl were downloaded from the West Wide Avalanche Network (WWAN, 2002). The 1997 to 2001 records were obtained from the Bridger Bowl archives (1996 data were missing). Thirty-two years of data were examined. Meteorological and snowpack data have been recorded from 1968 to present by the Bridger Bowl Ski Patrol each morning during the ski season at the Alpine weather station on the north side of the Bridger Bowl Ski Area at an elevation of 2260m (Fig. 1) (Mock and Birkeland, 2000). The station has not been moved since 1968. Instruments include an 8 inch (20 cm) orifice paper-recording, weighing precipitation gage (cone out), maximum-minimum mercury thermometer, snow board, and snow stake. The site is in a small opening in evergreen trees just north of the Alpine run.

Primary weather and snowpack data include 24 hour maximum air temperature, 24 hour minimum air temperature, total snowpack depth, 24 hour new snow depth, 24 hour new snow water equivalent, 24 hour rain totals, and day of year (1 January = 0). Air temperature data are recorded to the nearest 1°F (0.6°C), snow depth measurements are recorded to the nearest 1.0 inch (25 mm), and snow-water-equivalent measurements are recorded to the nearest 0.01 inch (0.25 mm).Temperatures were converted to Celsius. Visual inspection of the data showed three recordation errors identifiable because of inconsistencies between three adjacent days. These three days were removed from the dataset.

Avalanche data were reported with the U.S. avalanche classification, which includes avalanche type (dry slab, dry loose, wet slab and wet loose), cause of release (artificial or natural), size of avalanche relative to avalanche path, running surface (ground, old snow or new snow surface) and location of release (Perla and Martinelli, 1978). For the purpose of this study, only wet slab and wet loose avalanches are analyzed. The method used to identify wet avalanches varies with the observer at Bridger Bowl. Methods include hand tests in the starting zone and deposition zone (Colbeck et al., 1990, p.4), the presence of sun wheels, development of melt around trees, the presence/absence of a powder cloud, bed and flank striations, and the appearance of the avalanche debris. Bridger Bowl closes in early April but on a different day each year. March is a consistent time period which spans the wet-snow-avalanche-hazard period of highest interest. Therefore, only data from March are in the database that was analyzed.

The presence or absence of a recorded wet avalanche is treated as a binomial response. Days with one or more recorded wet avalanches, regardless of size or type of release are labeled as wet avalanche days and are assigned a one. Days with no recorded wet avalanches are assigned a zero. A day with a dry avalanche and no wet avalanches is assigned a zero

The primary weather and snowpack data were used to calculate 14 additional variable classes. These classes include average temperature, temperature range (maximum, minimum, and average), day-time temperature range, overnight temperature range, and degree-day temperature. (Degree day temperature values index the heating above a specified reference temperature (0°C) over multiple days. For example, the degree day value for the prediction day and the day prior is the sum of the difference between the maximum temperature and 0°C on the prediction day and the same difference on the day prior.) Snowpack and precipitation classes include change in snow depth, total snowpack settlement, age of new snow, new snow depth, new snow water equivalent, and new snow density. Rainfall was not assessed because rainfall is rare in March at Bridger Bowl. Within each variable class there were several variables which reflected time lags. Studies by Bovis (1977), Fohn et al. (1977), Davis et al. (1999) and Gassner et al. (2000) incorporated up to five preceding days into the variables used in their studies and found that three-day-prior variables were the oldest significant variables. This study limits the number of preceding or leading days to three. Prediction day (0) always refers to the day the model is predicting for, and is the day that the one day prior (-1), two days prior (-2) and three days prior (-3) variables lead up to. The procedure to calculate the three-day-cumulated value of a variable is to add the three days prior data to the prediction day value. The data was divided into a new snow dataset and an old snow dataset. A new-snow day has measured newly fallen snow in the past 48 hours, while an old-snow day has no measured newly fallen snow in that time period. A total of 68 primary and calculated variables were tested (Romig, 2004).

After the variables were developed, the data in the new snow and old snow dataset were analyzed using MINITAB® . First the data were assessed for normality with the Anderson-Darling Normality Test (α = 0.05 significance level) (Minitab, 2003). An F-Test was then used to determine equal variance for variables that were normally distributed (Minitab, Inc., 2003). Levene's Test for equal variance was used for variables with nonparametric or non-normal distributions (Minitab, 2003). If necessary, up to three transformations were attempted for each variable to correct for lack of normality and unequal variance. The Box-Cox Transformation procedure was used on each variable which required transformation, where lambda (λ) is the estimated exponent for each variable being transformed (Minitab, 2003). A 2-Sample t-test with pooled sample variance was used to test the means of those variables with normal distributions and equal variance (Neter et al., 1996). A 2-Sample t-test with unpooled variance was used to test the means of those variables with normal distributions and unequal variance. The Mann-Whitney test for equal medians was used for variables that remained nonparametric with equal variance after transformation (Neter et al., 1996). The details of the significance tests can be found in Romig (2004).

For model selection and testing purposes, the new and old snow datasets were divided into training and testing datasets. A random number generator was used to select 80% of the new snow dataset to create the new snow training dataset. The remaining 20% was used to create the new snow testing dataset. The same procedure was employed to create the old snow training and testing datasets.

After the significant (α = 0.05 significance level) old snow and new snow variables were identified, correlation tests were performed and binomial logistic regression was used to test the predictive capabilities of the variables, as well as to develop and test the models on the training and testing datasets (Minitab, 2003).

3. RESULTS

The original Bridger Bowl dataset containing all days in March from 1968-2001 (excluding 1996) has a total of 1,046 days, 72 of which have recorded wet avalanches. The remaining 974 days either had recorded dry avalanches or no avalanches at all. Only 15 days out of the 1046 total number of days in the dataset had recorded rain totals. Rain was not examined further as a variable. Wet slab avalanches make up 31% of the total number of wet avalanches and wet loose avalanches make up the remaining 69%. Naturally released wet avalanches make up 42% of the total number of recorded wet avalanches at Bridger bowl and the remaining 58% were artificially released wet avalanches. The results therefore, are applicable only to the Bridger Bowl ski area and not the surrounding back county terrain.

The original dataset was divided into a new snow dataset and an old snow dataset. Forty four variables showed a significant difference between old and new snow (Romig, 2004). Although there are nearly twice as many days in the new snow dataset than there are in the old snow dataset, the number of wet avalanche days differs by just six days between the two datasets.

4. DISCUSSION

The variables that were found to have the best predictive capabilities for old snow and new snow wet avalanche conditions are listed in Table 1. These variables had the highest percent concordant pairs (approximately 60% or greater) when tested individually and in combination with other variables. Concordant pairs indicate good correspondence between predicted probability of a wet avalanche and a wet avalanche day. The decision point for the concordant, discordant and

Table1. Data used to develop the 'old snow' and 'new snow' models.

Variable		Wet Avalanche Day Mean or Median†	No Wet Avalanche Day Mean or Median†	P
OLD SNOW				
Day of Year		78†	72†	0.007
Prediction Day Maximum Temperature*	°C	9.1	5.1	0.000
Prediction Day Minimum Temperature	°C	-1.1†	-5.0†	0.000
Prediction Day Average Temperature*	°C	3.2	-0.3	0.000
Two Day Change in Total Snow Depth	cm	-10.2†	-5.1†	0.000
NEW SNOW				
Prediction Day Minimum Temperature	°C	-7.6†	-8.9†	0.005
Prediction Day Overnight Temperature Range	°C	7.3	9.9	0.001
Two-Day Snowpack Settlement	cm	-10.2†	-7.5†	0.003
Two-Day Cumulative New Snow Depth	cm	21.7†	15.2†	0.003
Three-Day Cumulative New Snow Depth	cm	32.4†	20.3†	0.002
One-Day Cumulative New Snow Water Equivalent	cm	1.3cm†	0.8cm†	0.010
Two-Day Cumulative New Snow Water Equivalent	cm	1.9cm†	1.2cm†	0.000
Three-Day Cumulative New Snow Water Equivalent	cm	2.6cm†	1.5cm†	0.000
Averaged One-Day New Snow Density	kg/m^3	93.1†	74.5†	0.023
Averaged Three-Day Cumulative New Snow Density	kg/m^3	93.1†	75.9†	0.029

* Variable transformed but shown here as an untransformed value of median or mean
† Identifies a value that is a median not the mean. Means are not marked.

tied pairs in the binomial logistic regression program is 50%.

The selected variables maintained a significant p-value ($\leq$0.05) in the majority of the binomial logistic regression tests. In most cases, only the best predictor from a group of correlated variables was retained. However some slightly less well correlated variables were retained such as one, two, and three-day new snow cumulative snowfall and new snow water equivalent, as well as the averaged one and three-day cumulative new snow density variables. These correlated variables had nearly identical predictive success or their success depended upon which temperature or snowpack settlement variable it was tested with.

At this point, the old snow and new snow training and testing datasets were created. All possible combinations of the old snow and new snow variables listed in Table 1 were entered into a binomial logistic regression model of the old snow and new snow training sets and then tested on the appropriate old snow and new snow testing datasets. Model performance was ranked primarily on p-values and percent concordant pairs. A high percentage of concordant pairs indicates good correspondence between predicted probability of a wet avalanche and days with wet avalanches. The final criterion is whether the user will need to use forecasted information to calculate the model variables or if that information is readily available without forecast. This requirement does not imply that variables with better predictive success were discarded because they would be more difficult for the user to calculate. More elaborate variables, or those variables that required more information, were only discarded if there was an alternative, more straight-forward variable that had a comparable predictive success rate. The top three old snow and new snow models were retained for further analysis, all other models were discarded (Romig, 2004).

To further test the predictive capabilities of the top three old snow and new snow models, each model was converted into a binomial logistic regression logit equation of the general form:

$$g(P(i)) = \beta_0 + \beta x'_j = \ln (P(i)/(1-P(i))) \quad (1)$$

Where P(i) represents the probability there will be a wet avalanche on the i^{th} day, β_0 is the intercept, β is a vector of coefficients associated with the predictors which are estimated by maximum likelihood methods, x'_j is a vector of predictor variables associated with the j^{th} covariate (e.g., prediction day minimum temperature). The link function has a mean of zero and a variance of $\pi^2 / 3$ (Minitab, 2003).

Model B was selected as the best for spring-time wet avalanche prediction (Table 2). The predictor variables in Model B are prediction day minimum temperature and two-day change in total snow depth. The test dataset showed similar results to the training dataset (Table 2). But the P-values for two-day change in total snow depth are not significant. The data from the training and test data set were then combined to produce a single old snow dataset. The probability (P(i)) on a day of interest can be evaluated using the following equation:

$$P(i) = e^{x'_j \beta}/(1+ e^{x'_j \beta}) \quad (2)$$

Where $$e^{x'_j \beta} = \exp\{ \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i}\} \quad (3)$$

for two predictor variables. The subscripts 1 and 2 identify the two predictor variables on the i^{th} day. The coefficients β_0, β_1, β_2, are the regression coefficients for the intercept, the first predictor variable and the second predictor variable. Unfortunately, the intercept value β_0 was omitted from the equation in Romig (2004).

Table 2. Binomial logistic regression results for the old snot model B and new snow model E (Romig, 2004).

	Old Snow Training Dataset Results			**Old Snow Testing Dataset Results**		
Model B predictors: prediction day minimum temperature ($MinT_0$) and two-day change in total snow depth (HS_0-HS_{-2})						
Predictor Variables*	$MinT_0$	HS_0-HS_{-2}		$MinT_0$	HS_0-HS_{-2}	
P-Values	0.013	0.004		0.080	0.300	
Odds Ratios	1.16	0.90		1.17	0.94	
% Concordant, Discordant & Tied Pairs	Concordant 75.0%	Discordant 24.0%	Tied 1.0%	Concordant 72.8%	Discordant 24.1`%	Tied 3.1%

	New Snow Training Dataset Results			**New Snow Testing Dataset Results**		
Model E predictors: prediction day minimum temperature ($MinT_0$) and three-day cumulative new snow water equivalent ($HNW_{0,-1,-2,-3}$)						
Predictor Variables*	$MinT_0$	$HNW_{0,-1,-2,-3}$		$MinT_0$	$HNW_{0,-1,-2,-3}$	
P-Values	0.013	0.001		0.016	0.078	
Odds Ratios	1.13	1.40		1.24	1.51	
% Concordant, Discordant & Tied Pairs	Concordant 72.1%	Discordant 26.4%	Tied 1.5%	Concordant 71.9%	Discordant 27.3%	Tied 0.7%

This error is corrected here, and the β coefficients and the standard error coefficients for the two combined models are reported in Table 3. The binomial logistic regression results are correct, only the predicted probabilities for each prediction day are incorrect.

Table 3. Coefficients and standard error for calculation of probability for combined old snow and combined new snow datasets. $MinT_0$ = prediction day minimum temperature.

HS_0-HS_{-2} = two day total change in snow depth. $HNW_{0,-1,-2,-3}$ = three day cumulative new snow water equivalent.

	Combined Old Snow Dataset		Combined New Snow Dataset	
β_0	Intercept	-2.32	Intercept	-2.40
SE Coeff.		0.364		0.373
β_1	$MinT_0$	0.148	$MinT_0$	0.146
SE Coeff.		0.048		0.043
β_2	HS_0-HS_{-2}	-0.087	$HNW_{0,-1,-2,-3}$	0.328
SE Coeff.		0.030		0.092

Figure 2 shows a histogram for old snow. The calculated probability of days with wet snow avalanche is shown as is the calculated probability of days with no observed wet snow avalanches. The line that divides both distributions and produces the largest number of correct predictions is at 22% and constitutes a basis for estimating the success of the model. Of the 32 wet avalanche days, 21 (66%) are incorrectly classified (probability < 22%). These constitute Type II error in which a no wet avalanche day is predicted but one occurred on that day. Fourteen days with wet avalanches (34%) are correctly classified (probability ≥ 22%). Similarly, of the 300 days with no wet avalanches, 14 (5%) are incorrectly classified (probability ≥ 22%). This represents Type I error in which a day without wet avalanches is predicted but one occurred. Two hundred thirty one days (95%) with no wet avalanches were correctly predicted by the model (probability ≥ 22%). The old snow model has an 89% overall success rate ((11 d+286 d)/ 3307 d), but much of that success is attributable to the correct prediction of days without wet avalanches rather than days with wet avalanches. The model does not provide a yes/no answer to the question, "Will there be a wet avalanche day today?" Rather, the model calculates a probability that the day will have a wet avalanche.

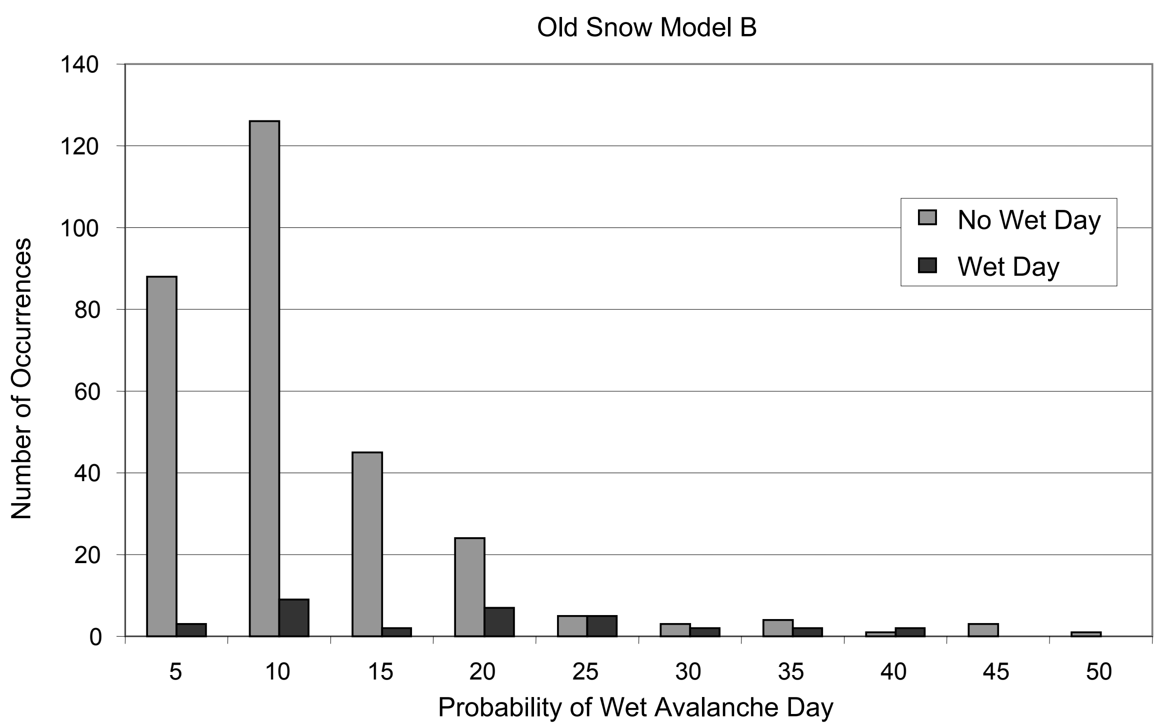

Figure 2. Histogram of Model B for old snow combined training and testing data.

The selected new snow model (E) uses prediction day minimum temperature and three-day cumulative new snow water equivalent as predictor variables (Table 2). The testing dataset results are fairly consistent with the training dataset for model E (Table 2), but the three-day cumulative new snow water equivalent in the testing data set is insignificant while it is significant in the training data set. The new snow training and test datasets were then combined to produce a single dataset. The combined dataset was used to re-compute the coefficients for equation 3. Those coefficients are reported in Table 3 and were applied to the new snow data sets to find probabilities for each prediction day for which there were observations.

Figure 3 shows a histogram of the calculated probability of days with wet snow avalanche and the probability of days when no wet snow avalanches were observed. This figure does not display a dividing line for estimation of model success because reduction of the total error can only be achieved if the cutoff is big which is equivalent to always saying there will be no avalanche. This result reiterates the point that any success Model E has is due to the correct classification of non-avalanche days. Unfortunately the days with wet avalanches are of interest. For this reason Model E success is not reported.

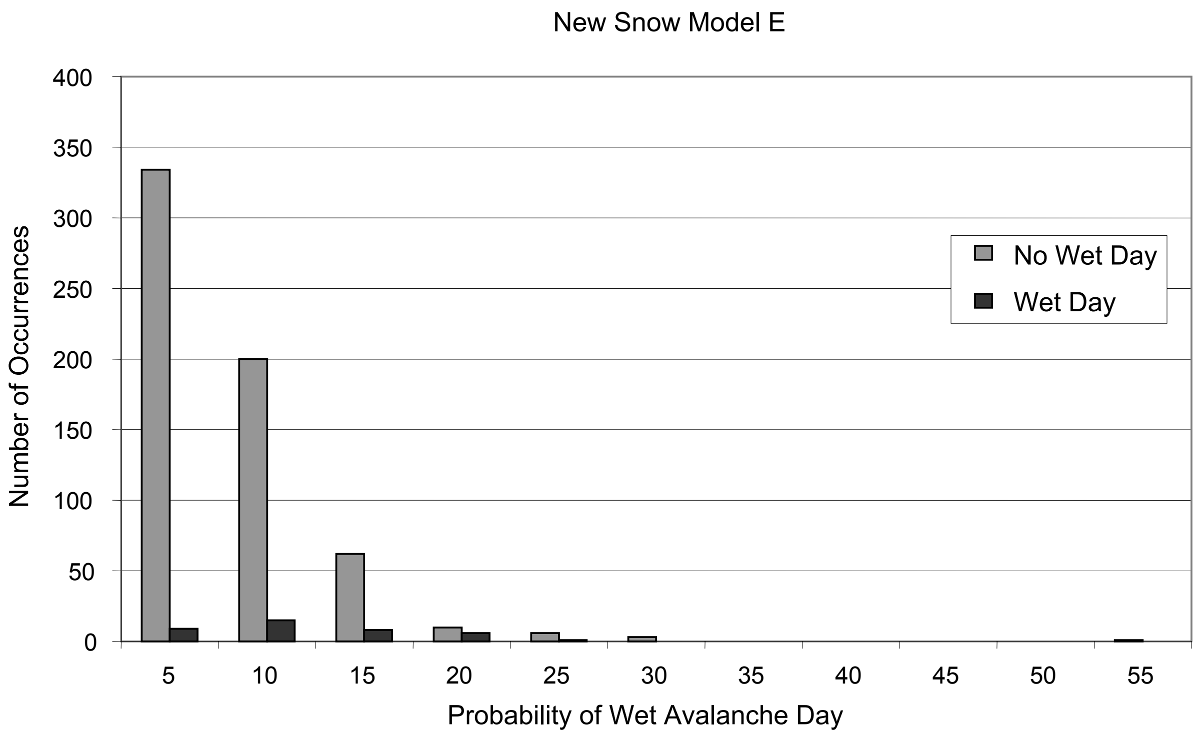

Figure 3. Histogram of Model B for new snow combined training and testing data.

There is some limited evidence that separation of old and new snow is justified from the perspective of assessing wet snow avalanche days. The six variables significant in both the new snow and the old snow data sets were tested. For each variable, a probability was calculated to determine whether the mean or median for old snow on days with wet avalanches was different from the mean or median for new snow on days with wet avalanches (Table 4). Only the temperature variables were significant. The settlement variables showed no significant difference between medians using the Mann-Whitney test. Several new-snow variables which are related to new snow depth, snow water equivalent and density could only be in the new snow data set and so could not be used to test whether the new snow variable was different than the old snow variable. Old snow wet avalanche days may be different than new snow wet avalanche days.

Table 4. Test of whether means or medians of variables significant for predicting both old snow and new snow wet avalanche days are different (α=0.05). See text for symbol definitions.

Significant Variables	**Test**	**Old Snow Wet Avalanche Day Mean or Median**	**New Snow Wet Avalanche Day Mean or Median**	**Old Snow – New Snow Wet Avalanche Day Means or Medians**	**Significant?**
$MinT_0$	2-Sample T-Test	-1.1°C	-7.6C	6.5°C	Yes
$AvgMinT_{0,-1}$‡*	2-Sample T-Test	-3.5°C	-7.3°C	3.8°C	Yes
$AvgT_0$*	2-Sample T-Test	3.2°C	-2.9°C	6.1°C	Yes
$Stl_{0,-1}$	Mann-Whitney	-5.1 cm	-5.1 cm	0.0 cm	No
$Stl_{0,-1,-2}$	Mann-Whitney	-10.2 cm	-10.2 cm	0.0 cm	No
$Stl_{0,-1,-2,-3}$	Mann-Whitney	-15.2 cm	21.7 cm	6.5 cm	No

*Transformed Variables
‡Variables that used unpooled sample variance in 2-Sample T-Test. All other variables used pooled sample variance in 2-Sample T-Test.

Medians are Mann-Whitney values, all others are means.

5. CONCLUSIONS

The idea for this study came from discussions with Bridger Bowl avalanche professionals who expressed their concern about uncertainties they face during the spring when wet avalanche conditions develop quickly and pose a risk to the skiing public. This study focuses on wet avalanche conditions at Bridger Bowl in March, but could be reasonably extended to late February and early April. Because the data comes from a ski area that uses avalanche control, the model developed should not be used outside the boundaries of the ski area.

Sixty eight variables were derived from seven primary pieces of data collected on 1,046 days. The variables reflect temperature, snow settlement, and precipitation. The dataset was split into days with snow ≤ 48 hours old and days with snow > 48 hours old. There is some justification for separating old and new snow data. Three temperature variables in particular are significantly different for the two data stets. Five old snow variables and ten new snow variables had the best predictive success and were retained for the final model building process. The final old snow model uses the prediction day minimum temperature and total change in snowpack depth between the prediction day and two days prior to calculate a wet avalanche probability. This model has an 89% overall success rate, but much of that success is related to correct prediction of days with no wet avalanches. The final new snow wet avalanche prediction model uses the prediction day minimum temperature and the cumulative snow water equivalent measured from the prediction day to the three days prior to prediction day for calculations. The overall success rate of the new snow model was not estimated because the division point to maximize the success rate is too large to produce a reasonable result. The models are much better at predicting conditions on days with no wet avalanches than they are at successfully predicting days with wet avalanches. This emphasizes the shortcomings of limited data, the complexity of the problem, and the difficulty in numerically forecasting wet snow avalanches. Thus, while these models can provide additional tools for avalanche forecasting professionals, they are only tools. Avalanche forecasting and decisions about closures and safety, will continue to rely on human forecasters using various tools and conventional techniques (McClung, 2002).

6. ACKNOWLEDGEMENTS

This work would not have been possible without the efforts of the Westwide Avalanche Network which archived and maintained data. The Bridger Bowl Ski Patrol collected data for 32 years and answered our many questions. Special thanks are also due Derek Sonderegger and Dr. James Robison-Cox for assistance with statistical concepts and computations. MINITAB® is a registered trademark of Minitab Inc.

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