STORM AND WEATHER FACTORS RELATED TO DRY SLAB AVALANCHE ACTIVITY

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ABSTRACT: Storm cycle factors affect slab avalanche response primarily in terms of loading in starting zones. Wind velocity and supply of transportable snow, relative to terrain, control redistribution and thus potential loading of avalanche slopes. Snow metamorphism in near-surface layers may affect the degree of involvement of old snow in slab avalanches and the rate of bonding between the slab and old snow surface. Early season snow conditions and general loading rate during the season may also affect avalanche response. We evaluated empirical factors that combine wind velocity with new snow amount, describe the potential for near-surface grain growth and provide indices of between-storm snow condition. The importance of different factors was rated in terms of explaining deviance in avalanche activity indices. Avalanche activity indices included maximum size, number of releases and sum of sizes of released avalanches. Ranking and scores for the different factors resulted from classification and regression tree analyses carried out on avalanche observations from Alta, Utah and Mammoth Mountain, California. Time lagged conventional factors describing snowfall and derived wind-drift parameters ranked highest in all tests. Snow drift factors segregated into prominent wind directions showed moderate importance. Among the non-storm factors, the starting snow depth of a particular year ranked highest showing the importance of interannual variability. This was followed by the accumulated vapor pressure difference, which we formulated to describe the potential for near-surface grain growth. The average snow depth increase and other factors followed in importance.

Key Words: avalanche, avalanche forecasting, snow accumulation, snow cover stability

1. INTRODUCTION

Records of weather and storm variables and avalanche observations contain interrelationships between variables that can be discovered and that can lead to improved indices relating to different levels and types of avalanche activity. While traditionally this process has been largely based on knowledge, experience and intuition (LaChapelle, 1980), recent progress has been made in applying advanced analytical techniques to improve forecasts of avalanche hazard (e.g., Buser et al., 1987; McClung and Tweedy, 1994; Schweizer and Föhn, 1996).

Since Atwater's (1954) article listing critical factors leading to avalanches, much effort has focused on determining a limited set of index parameters, derived from weather observations and measurements from snow plots, which reduce the complexity of information considered by the forecaster. This development has led primarily to statistical, expert and hybrid models for assessing avalanche hazard over large regions. A major

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problem in achieving any sort of progress has been the development of data sets with verifiable response variables describing actual hazard or avalanche activity. Avalanches are recorded least frequently when and where the greatest number of naturally triggered releases occur: during storms deep in the backcountry of large mountain ranges. Addressing this issue, avalanche observations, snow cover tests and other records have been used to hindcast avalanche hazard levels for developing data to test models of regional hazard (Föhn and Schweizer, 1995 *as cited in* Schweizer and Föhn, 1996).

Ski resorts and other organizations in the U.S responsible for controlling public access and use of avalanche prone areas face similar tasks at smaller spatial scales. However, in this case the job is to forecast locally specific probabilities for avalanche activity. Many operations of this sort have neither the resources, nor the records to motivate development of complex relational models to aid forecasters. Rather, in this era of slim profit margins and decreasing government resources in the U.S. there have been trends to incrementally develop and incorporate analytical tools that function more to help input, output and communications, in relation to a human forecaster (Ueland, 1996; Tremper et al, 1996, e.g.). Moreover, day-to-day exposure to local avalanche terrain and long term experience in its response to storms will likely never be replaced by avalanche forecasting models. Still there is motivation to develop to new ideas that simplify analysis of snow conditions, or make more efficient the recognition of unusual situations.

The main objective of this study was to rank and score weather and snow cover parameters in terms of their value in explaining deviance in avalanche activity at two ski areas in the western U.S.. Stated another way, we sought to quantitatively evaluate weather and snow cover factors that could affect snow stability and lead to avalanches. This study derived some new parameters in an attempt to evaluate the effects of storm direction, snow processes between storms and differences of snow loading between years. These were tested along with conventional factors and parameters used previously.

2. METHODS

We used basic weather observations, snow measurements and avalanche records from study plots at Alta, Utah and Mammoth Mountain, California. Alta ski area lies in the Wasatch Mountains, which experiences intermountain climate. Snow climate conditions leading to avalanching can vary from deep alpine to moderate / shallow alpine with one or the other usually dominant in a given winter (LaChapelle, 1965). Hence the role of depth hoar can vary from season to season. Mammoth Mountain lies along the crest of the Sierra Nevada in California, which experiences a strong maritime effect with deep stable snow and surface avalanching (LaChapelle, 1965). The two ski areas have active and rigorous avalanche control programs, so avalanche observers have recorded the vast majority of significant avalanches. All reported avalanches were considered in our study, whether triggered by storm activity, explosives or ski cutting. Often a delay occurred between when unstable slabs formed and when instability was detected by explosive release or ski cutting. This was simply due to the expediencies of avalanche control work. Processing of the records attempted to mitigate the delay, or lag, between weather forming the unstable snow slabs and the artificial avalanche by time shifting some of those occurrence records back into the storm cycle.

2.1 *Weather Data Processing*

Weather and snow measurements included an elementary set measured at most snow plots once per day in the western U.S.: total snow depth from a stake, new snow depth and precipitation (water equivalent) from snow boards, average wind speed and direction, and maximum and minimum air temperatures. We tested set of short-term, or storm variables, in addition to the daily measurements. As with previous studies (Judson and Erickson, 1973; Bois et al., 1975; Bovis, 1977; Obled and Good, 1980; and others) we compiled sums of snowfall depth and water equivalent for 1, two and three day periods. Wind speed was averaged over one to three day periods as well.

Previous studies have used a snow drift parameter, derived as the product of wind speed and either snowfall depth or precipitation (Judson and Erikson, 1973; Föhn et al., 1977; Davis et al., 1996, e.g.). Tabler et al. (1990) showed that the mass flux of snow drifting with an unlimited snow supply was approximately proportional to the forth power of the wind speed, confirming an expression derived by Pomeroy (1988). We derived factors for snow drifting during storms based on the product of 24hr snowfall, which we assumed to be an index of the snow supply, and wind speed to the forth power.

Two factors were derived; one using snowfall depth and the other using water equivalent (precipitation). We tested these factors summed over one day, two days and three days. Previous studies have used sums of new snow depth over two and more days. One aim in testing these variables was to find out whether new snow depth and water equivalent are interchangeable. Also included in the analyses were snowdrift factors related to wind direction, where direction was divided into eight categories of 45°, centered on the directions north, northeast, east, and so forth. Perla (1970) discussed the importance of wind direction to avalanche release in Little Cottonwood Canyon and Judson and Erikson (1973) tested various combinations of wind and snow, finding that precipitation intensity modified by wind speed and sum of wind speeds resolved to an optimum direction were important. Obled and Good (1980) considered wind direction segregated into direction class and accumulated over three days. Here we test a snowdrift parameter, combined as above using 24hr values of snowfall depth and average wind speed, was mapped directly into one of the direction-related bins. Adjacent direction bins were assigned half the value and the rest set to zero.

Snow stability is also related to the conditions of the old surface snow underlying the new slab. For example, recent research has demonstrated that faceted crystals near the surface of a snow cover can affect avalanche release and size (Birkeland et al., 1998a). Faceted crystals can grow in the presence of large gradients of vapor pressure, driven by large diurnal temperature gradients (Birkeland et al., 1998b). The grain size of the old snow surface can affect the rate at which new snow becomes bonded to the old. While the processes controlling bonding are not well understood (Colbeck, 1997), it seems clear that the rate of bond formation is inversely proportional to the grain size. Accordingly, new snow will bond more slowly to an old snow surface, other factors being the same, if the grains of the old surface are large. We derived an index to describe grain growth. The main factors controlling grain growth are the temperature, the vapor flux and the initial size of the grains (Colbeck, 1982). A temperature gradient gives rise to a gradient in vapor pressure, and the warmer the average temperature, the steeper the gradient. To formulate an index we calculated the difference between the saturation vapor pressure at the daily minimum temperature and at the average of the daily maximum and minimum air temperatures. This value was summed every day between avalanche days. During avalanche days the value was held constant, and after the avalanche cycle the sum was reset to the value of that day.

Three parameters were derived from the daily total snow depth. Attempting to account for snow strengthening during periods between avalanches, we summed the daily settlement, provided that the snow pack did settle, between avalanche days. Obled and Good (1980) also used this parameter. The settlement value remained constant when snow was accumulating, or avalanching. The factor was reset after avalanche days and the value was restarted at zero. Previous work with the Alta data set (Davis et al., 1996) showed that the accuracy of classifying different levels of avalanche activity could be improved by dividing the seasonal records into years with thin snow at the beginning of avalanche control work from years starting with a substantial snow pack. The former were characterized by greater avalanche activity, given certain storm characteristics, and sometimes called "depth hoar years" (Perla, 1970). Attempting to account for interannual differences, we included the depth at the start of the snow season, a parameter held constant for the year. Blattenberger and Fowles (1994) evaluated a factor something like this; they used snow depth over some low threshold. The seasonal rate of snow loading was computed by the least squares method as the slope of depth increase from the beginning of the season the day in question. This factor changes most in the early part of the year.

Table 1 summarizes the weather and snow related factors tested.

Table 1. List of weather and snow factors.

1. total snow depth
2. 24hr new snow depth
3. 48hr new snow depth
4. 72hr new snow depth
5. 24hr total precipitation
6. 48hr total precipitation
7. 72hr total precipitation
8. 24hr average wind speed
9. 48hr average wind speed
10. 72hr average wind speed
11. (24hr snowfall depth)x(24hr wind speed)^4
12. (48hr snowfall depth)x(48hr wind speed)^4
13. (72hr snowfall depth)x(72hr wind speed)^4
14. (24hr total precip.)x(24hr wind speed)^4
15. (48hr total precip.)x(48hr wind speed)^4
16. (72hr total precip.)x(72hr wind speed)^4
17. west: (24hr snowfall depth)x(24hr wind speed)^4

18. northwest: (24hr snowfall depth)x(24hr wind speed)^4
19. north: (24hr snowfall depth)x(24hr wind speed)^4
20. northeast: (24hr snowfall depth)x(24hr wind speed)^4
21. east: (24hr snowfall depth)x(24hr wind speed)^4
22. southeast: (24hr snowfall depth)x(24hr wind speed)^4
23. south: (24hr snowfall depth)x(24hr wind speed)^4
24. southwest: (24hr snowfall depth)x(24hr wind speed)^4
25. maximum air temperature
26. minimum air temperature
27. degree days
28. cumulative vapor pressure difference
29. cumulative settlement
30. starting snow depth of year
31. average snow depth increase from beginning of year

2.2 *Avalanche Data Processing*

We compiled and processed avalanche records to build a matrix consisting of daily values of the 31 parameters listed above, the sum of avalanche sizes, the maximum size class, and the specification of avalanche day or not (1 and 0 respectively). Visually inspected plots of weather and avalanche variables guided further processing of the combined avalanche and weather data. We selectively eliminated long periods with no new snow or avalanches, reducing the number of "no action" days until days with avalanche days composed about 20 to 30 percent of the data. Effectively this eliminated about 13 percent of the record from Alta and 18 percent of the record from Mammoth, mostly during springtime. Cumulative variables were adjusted accordingly.

Next, we subjectively shifted the records of explosive avalanche release from the period of no new snow, immediately after storm cycles, back into the period of the storm. Previous results (Davis et al., 1995) showed that the majority of severe errors occurred due to avalanches released by control work days after storms cleared. The great majority of the shifts were one day backwards. For a few we felt comfortable with a 2-day shift. Where we shifted avalanche records to days with their own avalanches, we summed the records. Otherwise the shift replaced a day with no avalanche observations. The Alta data set totaled 1895 days, spanning the period of winters from 1983 through 1994. There were 532 days with avalanches (unshifted). We shifted 137 daily avalanche records. The Mammoth data set totaled 890 days, spanning the period 1989 to 1998, with two years missing. There were 160 days with avalanches, of which we shifted 47.

2.3 *Classification and Regression Trees*

We presumed that a set of tests using a robust method for determining relationships between avalanche activity and the index parameters should provide a useful way to rank and score the index parameters. Binary tree models provide a pragmatic and effective alternative to multiple linear regression models, classification algorithms and hybrid techniques. We selected classification and regression trees to perform these analyses primarily because the methodology is essentially non-parametric (Breiman et al., 1993). This test is not a "black box"; the theory is well documented and the method has seen a wide variety of applications in the physical and biological sciences. The tree models are particularly effective where the data contain hierarchical or nonlinear relationships. These models are pragmatic because the results are easily interpretable by people with a wide range of statistical understanding.

Not only can these models be used for prediction where appropriate, but they are also very effective tools for uncovering, interpreting and describing structure within a data set. This interpretation may be extended to the process level where physical relationships exist. Although inferential statistics are not yet well developed for the relatively new tree based models, there are some simple metrics for assessing model performance. One of the strengths of the method is the ability to overfit a given model for exploratory purposes, while retaining a more conservative model for predictive applications. The conservative model is obtained by pruning an over-fit tree back to a statistically defensible size though cross-validation or cost-complexity measures. Over-fitting the model allows one to uncover odd or rarely observed relationships in the data. In this mode the decision trees are really an exploratory tool for data analysis. This is the application for which we have used the trees in this study.

In using classification trees, the relations between predictors and responses are not particularly sensitive to statistical distributions of either the dependent or independent variables, so transformations of the data into new scalar, arbitrary,

or "experienced-based", class intervals are not required. The construction of regression trees requires the assumption of Gaussian distribution in scalar data, but this is loosely enforced due to the observation that the final tree structure is "surprisingly insensitive" to the splitting rule and hence the distributions of variables (Breiman et al., 1993).

In general, the algorithm uses a data set to grow a decision tree by recursively partitioning the data into increasingly homogeneous subsets until each subset contains a small number of cases. The algorithm then selectively prunes (recombines) decision branches of the tree until a stopping rule, or desired level of complexity, is satisfied (Breiman et al., 1993). Another way of describing this process is that first the algorithm finds out how almost every case is different from the rest. Then by pruning it finds the similarities in the differences. The method can be applied where one has a set of independent (predictor) variables (x) and a single dependent (response) variable (y). Classification trees must be used where the response is a discrete member of a finite set, class or category. In this set of analyses we used the *Gini index of diversity* to define subset impurity, defining the splitting rule, and we limited the depth of the final trees to 100 or less layers. Regression trees are used where the response variable is numeric or continuous. We again limited the depth of the final trees to 100 and used a hierarchical least squares rule to split nodes.

Classification trees with nominal response data results in decision structure similar to:

if

(wind speed < 12 m s^{-1}) & (wind direction $\in$ {N, NW})

then

maximum avalanche size class = 2

where wind speed and wind direction are members of x, and the maximum avalanche size class is the dependent variable y. Regression trees with ratio scale response variables take the form:

if

(new snow depth < 200 mm) & (air temperature < -5C)

& (wind direction $\in$ {SW, W})

then

sum of avalanche sizes = 63 (± some deviance)

where new snow depth, air temperature and wind direction are members of x, and the sum of avalanche sizes is the dependent variable y.

Accuracy of classification trees can be expressed as the probability of correct classification for a particular category, which for over-fit and very large trees is higher than is reasonable if the application is to predict outcomes, but not unreasonable if the application is to explore structures in the data. Average accuracy of response classes comprises one of our metrics in this study. The accuracy of regression trees is expressed as the coefficient of determination (R^2), using the relationship between tree deviance and total set deviance. The coefficient of nondetermination for a given tree is the sum of squared differences of all members of each terminal node from the predicted nodal value, summed for all terminal nodes, and then divided by the sum of squared differences of the entire data set from the grand mean of the response variable. The R^2 is simply one minus the coefficient of nondetermination.

We used successive tests to assess the relative merits of the derived factors in comparison to each other and to the conventional parameters. A test was assumed valid if a reasonable degree of explanation of the deviance in avalanche activity could be achieved. Importance of independent variables, expressed as scores, depends on how effectively a variable can a split cases. This is based not only on whether a variable gives the best split for a node, but also whether it gives the second or third best, and so forth. The values of importance result from comparison of the relative misclassification cost that the use of each variable brings. All of the parameters in Table 1 were used to grow classification trees on maximum avalanche size and avalanche day, and regression trees were constructed for sum of avalanche sizes. We selectively eliminated various classes of conventional and derived parameters to see both how the ranking and scoring of the remaining variables changed and to assess the change in classification accuracy. We removed variables that seemed to duplicate the information, such as new snow water equivalent or new snow depth. We eliminated parameters that described multi-day averages or sums. Finally we added back the derived parameters one at a time to assess their relative value in explaining deviance in avalanche day or not, maximum size class and sum of sizes.

3. RESULTS

3.1 *Classification and Regression Tree Accuracy*

The analyses using all factors from Table 1 showed probabilities for correct classification for trees with maximum depth 100 (rather over-fit) ranging from 0.14 to 0.98 depending on avalanche activity variable. The probability of correct classification for maximum size class ranged from 0.70 to 0.94 at Alta and 0.14 to 0.95 at Mammoth Mountain. The average classification accuracy for maximum size at Alta was 0.81 and at Mammoth 0.68. The average classification accuracy for avalanche size classes 2, 3 and 4 was 0.84 for Alta and 0.86 for Mammoth. Table 2 summarizes the results for classification accuracy of maximum size class and avalanche day for Alta and Mammoth Mountain. The probability for correct classification of an avalanche day at Alta using all factors was 0.97, and at Mammoth 0.98. The probability of correct classification of non-avalanche days was higher. The coefficient of determination, R^2, in predicting the sum of avalanche sizes using all factors was 0.84 for the Alta data and 0.88 for the Mammoth data. These tests formed the baseline accuracy against which all subsequent tests were compared.

Table 2. Binary tree accuracy – maximum size class. Values show the probability or correct classification.

Alta			
Size Class	All Factors	No Snowfall Depth	Derived Factors Only
2	0.94	0.93	0.9
3	0.87	0.82	0.81
4	0.70	0.68	0.64
5	0.73	0.73	0.55
Mammoth			
Size Class			
2	0.85	0.90	0.82
3	0.95	0.86	0.95
4	0.79	0.71	0.67
5	0.14	0.71	0.29

Factors based on snowfall water equivalent had slightly higher scores than those based on snowfall depth at both Alta and Mammoth. Table 2 also shows the effects of removing factors based on snowfall depth from the test on classification accuracy at both areas. We saw an improvement in probability of correct classification of the maximum size class 5 of about 0.09 at Alta and 0.57 at Mammoth, The averaged classification accuracy for all sizes decreased 0.02 for Alta but increased 0.12 for Mammoth. This result indicates that use of many correlated variables as predictors can sometimes increase the ambiguity in determining the best splits. Table 2 shows results of analyses with only the derived factors (14-27 and 30-34 in Table 1); the accuracy decreased somewhat for most of the avalanche size classes, with the exception of class 5 avalanches at Mammoth. The average classification accuracy using only the derived variables was comparable with the analyses using all factors.

3.2 *Ranks and Scores of and Time-Lagged and Derived Factors*

Time-based, or lagged, parameters derived from snowfall depth or new snow water equivalent dominated the rankings and scores. The results with individual lagged factors of the conventional type, such as 2-d and 3-d snowfall depth, were similar to previous results by many other researchers. Snowfall depth and water equivalent tended to rank in the top five parameters, with wind lower in the middle of the rankings, and temperatures generally even lower. Of the derived factors, snow and wind measurements combined in the snowdrift parameters for two and three days scored the highest for all three of the avalanche activity indices. These factors ranked in the top five in every test using them, and had showed scores only slightly lower than the two and 3-day snowfall water equivalent and depth. In tests using only derived factors (Table 2) the snow drift parameters ranked above the rest. Table 3 shows the list of independent variables and their ranking in analyses for maximum size class, avalanche day or not, and sum of sizes for Alta. Table 4 shows the same for Mammoth Mountain.

Factors describing conditions between storms and between years showed some value in explaining deviance in the avalanche observations. These derived factors were most important to explaining deviance in maximum avalanche size, relative to the other two avalanche activity indices. Rankings were somewhat similar between the two data sets.

Table 3. Classification-tree scores for derived factors from tests with Alta data. Values describe scores of importance in terms of reduced misclassification accuracy due using the parameter for either primary or surrogate splitting decisions.

Derived Factor	*Max. Size Class*	*Aval. Day*	*Sum of Sizes*	*Total*
(48hr total precip.)x(48hr wind speed)^4	91	77	33	201
(48hr snowfall depth)x(48hr wind speed)^4	77	78	36	191
(72hr total precip.)x(72hr wind speed)^4	79	64	31	174
(24hr total precip.)x(24hr wind speed)^4	72	57	38	167
(72hr snowfall depth)x(72hr wind speed)^4	84	27	25	136
(24hr snowfall depth)x(24hr wind speed)^4	34	59	33	126
starting snow depth of year	21	19	38	78
cumulative vapor pressure difference	29	26	21	76
average snow depth increase from beginning of year	20	25	24	69
degree days	28	21	15	64
west: (24hr snowfall depth)x(24hr wind speed)^4	18	15	19	52
cumulative settlement	20	16	14	50
southwest: (24hr snowfall depth)x(24hr wind speed)^4	16	8	11	35
Total	589	492	338	

The starting depth of snow for the year ranked highest of this group of factors, showing moderate importance to the coefficient of determination of sum of sizes at Alta, and showing moderate importance to probability of correct classification of maximum avalanche size at Mammoth Mountain. The accumulated vapor pressure difference was next down in the rankings of this group (Tables 3 and 4) and was most important to classification of maximum avalanche size in both data sets. Proceeding downward in the rankings, the average snow depth increase from the beginning of the year was next, followed by degree days and cumulative settlement between storms. In tests where time-lagged factors were eliminated, the between-storm derived factors ranked in the top five of every test, with similar relative ranking in their scores as described above. The snow drift parameters related to direction showed moderate importance compared to the other factors. At both Alta and Mammoth Mountain the west (270°±22.5°) component of snow drift ranked highest, with the southwest (225°±22.5°) somewhat lower (Tables 3 and 4).

3.3 Tree Structure and Terminal Nodes

The trees were over fit to the extent that terminal nodes containing rare events resulted from splits between only a few cases. This was the situation with avalanches of the class 4 and class 5 sizes, for example. At Alta there were 47 avalanches described in the size class 4 category and 11 in size class 5 during the period of record. At Mammoth Mountain there were 24 avalanches with size class 4 and 7 with size class 5. We found that the derived factors played a more important role in the splits for maximum size class for both test sites (Table 3 and 4). By derived we mean factors other than the conventional daily variables and lagged conventional variables (i.e. 14-27 and 30-34 from Table 1). We also found that derived factors play a decidedly more important role in the splits of rare events. At Alta, about half of all splits determining classification of class 4 or class 5 avalanches used derived factors as the primary decision, of as high-ranking surrogates. The majority of splits classifying avalanches with sizes 4 and 5 at Mammoth Mountain were determined by derived factors. In both data sets the most important derived factors were one of the snow drift parameters. The most important non-storm factor was the accumulated vapor pressure difference.

4. DISCUSSION

These results represent several years of careful analysis and reanalysis of two comprehensive data sets. We have refined the techniques of exposing data structure and correlation between meteorologically based independent variables and indices of avalanche activity using binary decision trees. We have also refined the data sets themselves to present a set of logical dependent

Table 4. Classification-tree scores for derived factors from tests with Mammoth Mountain data. Values describe scores of importance in terms of reduced misclassification accuracy due using the parameter for either primary or surrogate splitting decisions.

Derived Factor	*Max. Size Class*	*Aval. Day*	*Sum of Sizes*	*Total*
(24hr total precip.)x(24hr wind speed)^4	90	86	63	239
(48hr snowfall depth)x(48hr wind speed)^4	98	77	46	221
(24hr snowfall depth)x(24hr wind speed)^4	81	70	61	212
(48hr total precip.)x(48hr wind speed)^4	97	92	21	210
(72hr total precip.)x(72hr wind speed)^4	76	66	29	171
(72hr snowfall depth)x(72hr wind speed)^4	44	23	27	94
west: (24hr snowfall depth)x(24hr wind speed)^4	30	13	50	93
starting snow depth of year	41	22	20	83
southwest: (24hr snowfall depth)x(24hr wind speed)^4	16	11	54	81
cumulative vapor pressure difference	29	26	21	76
average snow depth increase from beginning of year	26	25	24	75
degree days	28	21	15	64
cumulative settlement	20	16	14	50
Total	676	548	445	

variables that are coherent in time with observed storm characteristics. One should keep in mind that the results are critically linked to three main factors: 1) the avalanche activity we are modeling applies to natural and artificial release; 2) all observations are at ski areas where skiing and control activity considerably alters the local snow stability compared to surrounding "natural" conditions; 3) the study sites represent best-case scenarios where a full suite of independent variables are collected on a regular basis.

It should be noted that the objective of the study was to evaluate the relationship between meteorologically based independent variables and avalanche activity, not to produce a forecasting method applicable either to a ski area or its surroundings. The results should be interpreted as "here are the factors that appear to be linked to avalanche activity at these ski areas and this is the manner in which they interact". This statement is really the root of the study and it should be emphasized. Artificial release provides a conservative estimate of potential activity. Natural or skier releases will likely be much lower even in the same terrain in the absence of artificial control. This relationship means that results from ski areas can be used in local or even regional forecasting outside of the ski area bounds only if forecasters and users realize the obvious nature and problems associated with this type of extrapolation. Indeed, many local and regional forecasts in mountainous areas of the United States are critically linked to results of nearby ski area control activity. The fact that ski area activity often reduces deep slab instability and magnitude of individual events also confounds forecasting for local and regional activity, but the error this time may be that greater instability in the "natural" snowpack is undetected at the ski area. It may be that these two factors are compensating, but the information necessary to assess the full relationship is not available due to limited backcountry observations.

We have quantitatively compared conventional and derived parameters in terms of determining how indices of avalanche activity were different in response to storm and between-storm conditions, and how these differences compare. In doing so we have also demonstrated how binary decision trees can uncover the relationships and interaction between the independent variables and observed avalanche activity. Three derived parameters showed particular value in identifying structure in the data. Of these the wind drift parameter was the most important of the storm related factors. This simply confirms what is already well known, but provides a metric that has some basis to physical process. The two other derived parameters relate to conditions of the existing snow cover, not the slab formed by the storm. The starting depth of snow for the year was useful in separating general avalanche activity response to a given storm from one year to the next. Without multiple years of data, this factor

would not show any importance. It seems commonly understood by experienced forecasters that years starting with thin snow tend to produce more, but not necessarily larger avalanches, than years with an early thick snow cover.

The accumulated difference in vapor pressure difference was also important, notably in its value in separating the maximum avalanche size on different days and especially in distinguishing between the larger events. We believe this also has a basis in physical process in that it provides an index of grain growth in the near-surface layers of snow. Originally we thought this index would work two ways. If the index accumulated rapidly then maybe this was a signal that the snow was loosing strength. In this case we would expect some increased importance in distinguishing maximum sizes. If the index accumulated slowly, but over a long time, then maybe the grains were growing large and rounded, so the textural mismatch might make for poor bonding between the slab and snow surface. In this case we might expect more releases and hence increased importance in the sum of sizes. If the index increased at some intermediate rate we might expect that both processes were competing, with no net effect on bonding (Colbeck, personal communication). While this index deserves some future attention, the results appear to show that this parameter makes some indication of surface weakening.

5. CONCLUSIONS

We have evaluated 31 conventional, time lagged and derived factors of weather and snow conditions as they relate to avalanche activity indices maximum size, avalanche day and sum of avalanche sizes. Tests with derived factors by themselves have slightly lower overall accuracy in explaining deviance in avalanche activity indices than tests using all or most of the factors, showing that conventional and lagged conventional factors cannot be ignored.

Storm related factors dominated the scored of all tests, with those factors using snowfall water equivalent slightly more important than those using depth. Snowfall water equivalent and snowfall depth appeared more or less interchangeable, and we found that elimination of one or the other from classification tree analyses increased the probability of correctly classifying larger avalanches. The snow drift parameter based on snowfall water equivalent and wind speed to the forth power was the most important of the derived variables. A similar factor segregated into predominant directions was much less important, but identified directions most associated with avalanches.

Between-storm factors improved classification and regression accuracy, primarily the probability to correctly classify maximum avalanche size class. Moreover, derived factors in general were important factors in decision splits for rare events, such as large avalanches. Our tests show that starting snow depth of the year was surprisingly the most important of the non-storm derived factors. It appeared mostly in the splits for moderate size avalanches and moderate sums of sizes of releases. The accumulated vapor pressure difference ranked second of this type of factor and scored high in decisions classifying maximum avalanches sizes 4 and 5. Other factors showed modest importance.

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