MARCH WET AVALANCHE PREDICTION AT

BRIDGER BOWL SKI AREA, MONTANA

by

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ABSTRACT

Wet avalanches are a safety concern for all ski areas because they are difficult to control artificially and the shift from safe to dangerous wet snow conditions can happen very quickly. Forecasting for wet avalanche conditions in intermountain ski areas, such as Bridger Bowl, Montana, can be especially difficult because intermountain snow climates can exhibit wet avalanche characteristics of either maritime or continental snow climates. Various statistical models have been developed for avalanche prediction; however, most are tailored specifically for dry avalanche forecasting. Archived meteorological, snowpack and avalanche data for the month of March from 1968 to 2001 (1996 data unavailable) were used to develop 68 possible predictor variables related to temperature, snowpack settlement, and precipitation characteristics. The original Bridger Bowl dataset was divided into a 'new snow' and an 'old snow' dataset. A 'new snow' day has newly fallen snow that is less than 48 hours old; an 'old snow' day has newly fallen snow that is more than 48 hours old. The two datasets were used to determine whether the factors that influence 'old snow' and 'new snow' wet avalanche occurrence differ. Hypotheses were developed and tested to determine which 'old snow' and 'new snow' variables behaved significantly different on days with wet avalanches compared to days with no wet avalanches. The 33 'old snow' significant variables and the 22 'new snow' significant variables were analyzed with binomial logistic regression to produce one prediction model for 'old snow' wet avalanche conditions and another prediction model 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. This model has a 75% success rate for calculating accurate wet avalanche probabilities for 'old snow' days. The 'new snow' model uses the prediction day minimum temperature as well as the three day cumulative new snow water equivalent as predictor variables. This model has a 72% success rate for calculating accurate wet avalanche probabilities for 'new snow' days.

INTRODUCTION

At ski areas with a significant avalanche hazard, one of the main purposes of the ski patrol is to ensure safe skiing conditions throughout the season by the taking measures to reduce skier exposure to avalanche danger. As spring approaches, snow conditions can change rapidly and wet snow avalanches become a hazard for ski areas in all snow climates (maritime, intermountain and continental). Ski patrollers face the difficult task of identifying that critical moment when ski slopes are transitioning from a stable wet snow situation to a dangerous one. Wet avalanche conditions are particularly problematic because they are difficult to control artificially. Dry snow avalanche hazards are often successfully mitigated by the use of explosives. However, the physical properties of wet snow suppress the propagation of the shock wave essential to trigger wet snow avalanches (Armstrong, 1976). The timing of the onset of dangerous wet snow conditions is difficult to determine as well. Whereas dry snow avalanche hazards can develop relatively slowly and 'weak layers' can be tracked throughout the majority of the ski season, wet snow avalanche hazards can develop in hours or even minutes. Difficulties with control and knowledge regarding when wet snow conditions will become dangerous make wet avalanches a serious hazard for inbound skiers who can be seriously injured by the debris. This is a particularly important issue at Bridger Bowl Ski Area where the majority of natural or skier-triggered wet slides start in expert ski areas and can run out onto heavily used intermediate and beginner level ski slopes below.

Bridger Bowl is in the Bridger Range in the intermountain snow climate of southwest Montana, approximately 19km northeast of Bozeman, Montana (Fig. 1). This is a predominantly east facing ski area but north, west and south aspects are also present. The elevation ranges from 1,860m at its base to 2,652m at the top of the ridge above the ski area.

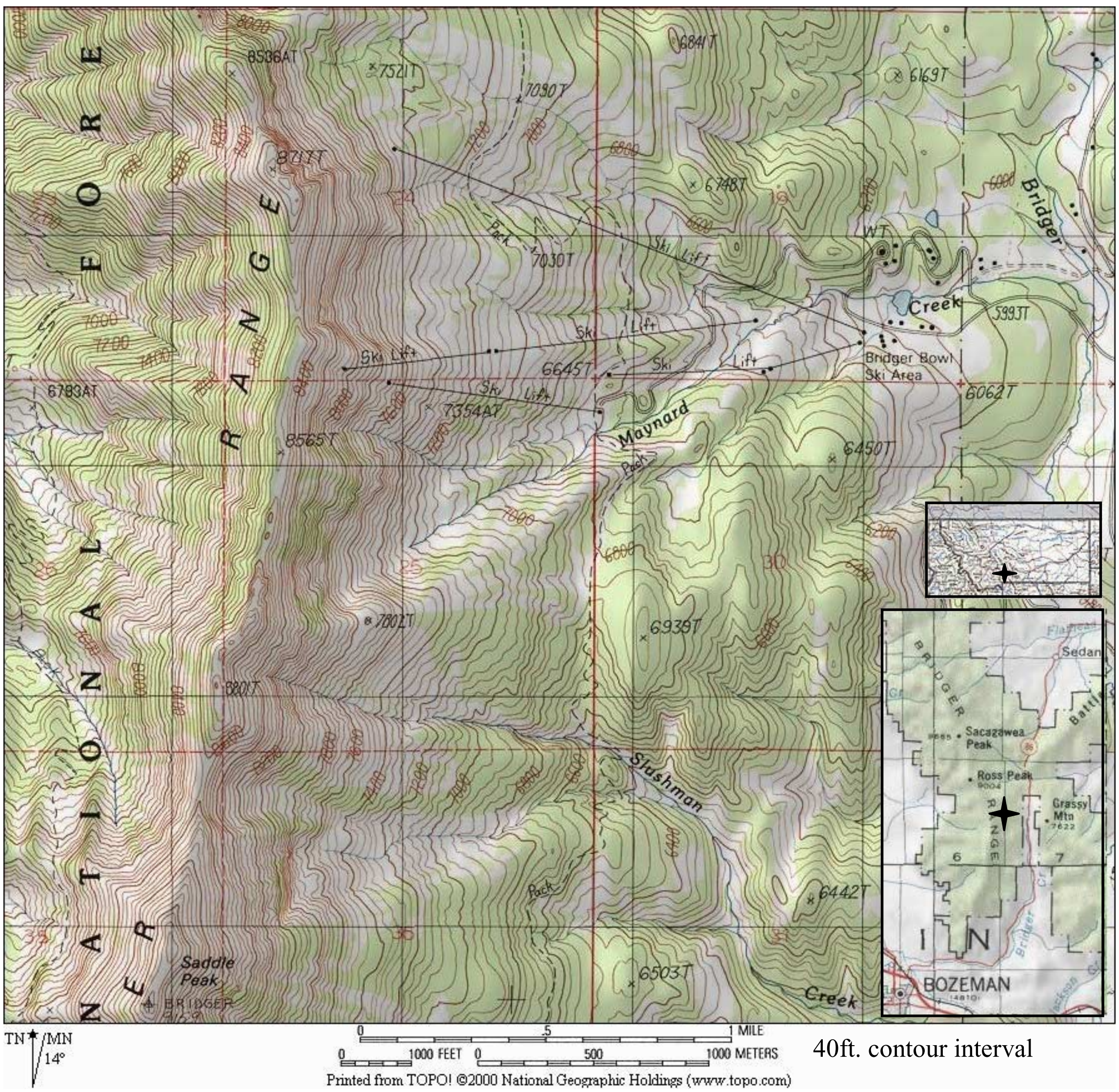

Figure 1. Site Location Map

The main ski area lies directly below the ridge with a dramatic cliff band that runs along its entirety from north to south. This cliff band creates a particularly challenging situation for ski patrollers because it is the starting zone for many of the wet slides that can run out onto intermediate and beginner ski slopes below. Decisions regarding when to close the upper mountain are difficult for patrollers because the shift from safe to dangerous wet snow stability can be very subtle, and the consequences for not recognizing that shift in time, or for underestimating the traveling distance of a natural or artificially released wet avalanche can be severe.

The uncertainties involving wet snow hazards are related to wet snow metamorphic processes and how those processes influence snow strength. Wet snow is different from dry snow in two fundamental ways: the amount of liquid water within the snow matrix and the way in which heat is transferred throughout the snowpack (McClung and Schaerer, 1993). Wet snow is considered saturated "when liquid water can be squeezed out by hand with moderate pressure" (Colbeck et al., 1990, p.4). More specifically, saturated wet snow has liquid water that occupies about 14% of the pore volume, or 7% of the total volume, and has liquid water present in continuous paths throughout the pore spaces (Colbeck, 1982). In dry snow, liquid water cannot be squeezed out by hand with moderate pressure, the liquid saturation is less than 14% of the pore volume, or less than 7% of the total volume, and air occupies interconnected paths throughout the pore spaces (Colbeck, 1982; Colbeck et al., 1990).

The second fundamental difference between dry and wet snow is the heat transfer processes that drive snow metamorphism. Crystal metamorphism is slower in dry snow because the interconnected paths of air present in dry snow do not move heat as efficiently as the interconnected paths of liquid water present in wet snow. In dry snow, heat transfer is driven by the vapor flux imposed by the temperature gradient within the snowpack (McClung and Schaerer, 1993). When large temperature gradients are present, water vapor moves from areas of higher vapor pressure around the smaller grains to areas of lower vapor pressure found around larger grains where the vapor will condense resulting in the growth of large snow crystal at the expense of the small snow crystals (McClung and Schaerer, 1993). Metamorphism in wet snow is driven by heat advection associated with the continuous paths of liquid water within the snow matrix. Snow strength increases as liquid water initially infiltrates into the snowpack and freezes. As more liquid water is introduced however, heat is transferred from the liquid to the snow and metamorphism increases at a very rapid rate (Kattelmann, 1984). Because the radius of curvature is inversely proportional to melting temperature, small grains have a lower melting temperature and disappear quickly leaving only large crystals with fewer bond-to-bond contacts (Colbeck, 1979). The result is a snowpack that has lost much of its mechanical strength.

Wet avalanche conditions create safety hazards for ski areas in all three snow climates. Wet avalanches in maritime snow climates are often direct action releases resulting from rain on snow events that are common throughout the ski season (McClung and Schaerer, 1993). Ski areas in continental climates have wet avalanches almost exclusively in the spring when solar insolation plays a larger role in melting the snowpack. Because intermountain snow climates exhibit both maritime and continental climate characteristics, wet avalanches can release for a variety of reasons such as rain on snow (rare at Bridger Bowl), increased incoming solar radiation, warm air advection, or a combination of all three (Roch, 1949; LaChapelle, 1966; Armstrong and Armstrong, 1987; Mock and Kay, 1992). Patrollers working in intermountain snow climates must learn to recognize the wet avalanche hazards associated with both maritime and continental snow climates.

A number of statistical methods have been applied to develop avalanche forecasting models. Most of these models have been tailored to predict dry snow avalanches in continental climates, but a handful of studies have examined wet snow avalanche prediction separately with varying success. Perla (1970) used univariate analysis to determine which meteorological and snowpack variables correlated most with a 'hazard probability' for all avalanche types (without separating dry avalanches from wet avalanches) for the Alta Highway and Village in Utah (intermountain snow climate (Mock and Birkeland, 2000)). Judson and Erickson (1973) used univariate analysis to develop a two-parameter storm index to predict the number of expected avalanches (without distinguishing dry avalanches from wet avalanches) on 23 avalanche paths in Berthoud Pass, Colorado (continental snow climate (Mock and Birkeland, 2000)). Multivariate discriminant analysis was then used to produce eight refined three-variable models that predicted the probability of avalanche occurrence on eight avalanche paths in Berthoud Pass with an average success rate of 75%. Multivariate discriminant analysis was also used by Bovis (1977) to create forecasting models for both dry snow avalanche conditions and wet snow avalanche conditions for the San Juan Mountains in southern

Colorado (continental snow climate (Mock and Birkeland, 2000)). Eleven wet avalanche forecasting models were developed with two to four predictor variables and averaged an 85% success rate for correctly classifying wet avalanche days and an 80% success rate for correctly classifying days with no wet avalanches.

A 1977 article by Fohn et al. compares the success rates of four statistical models developed on data collected in Weissfluhjoch/Davos, Switzerland (intermountain snow climate (personal communications M. Schneebeli, 2004)). The first model created 10 components via principal component analysis that were then subjected to a discriminant factor analysis that categorized each day into a 'dry avalanche day' a 'wet avalanche day' or a 'non avalanche day'. The finished model used seven predictor variables and had an 80% success rate for correctly classifying each day as a 'dry avalanche day', 'wet avalanche day,' or 'non-avalanche day'. The second model incorporated forward and backward step-wise discrimination in the model selection process. Four to seven variables were identified that had a 60-70% success rate for dry avalanche prediction only. The third model used the same variables as the second model and a similar step-wise discrimination process, but employed principal component analysis to develop elaborate variables prior to the step-wise discrimination process. The results of the third model showed a 60-70% success rate for dry avalanches only. The fourth model separated the avalanche season into early season avalanches and late season avalanches. The model was developed using a combination of principal component analysis, dynamic clustered analysis and linear or quadratic discrimination. Each avalanche day was classified into one of nine 'situational' groups and calculated the probability of an avalanche day based on which group the forecast-day falls into. This final model had a 70-80% success rate. Judson and King (1985) developed a model for early and late season stability forecasting in the Colorado Front Range (continental snow climate (Mock and Birkeland, 2000)) using probability theory and a statistical sequential analysis to evaluate existing snowpack stability. Rather than predicting the probability of an avalanche occurrence, this model gave predictions in terms of the probability for low, moderate or high snowpack stability and had a 90% success rate when forecasts were compared to observed data.

A model based on classification and regression tree (CART) analysis was pursued by Davis et al. (1999) to determine the relationship between weather and snowpack variables and the occurrence of dry snow avalanches at Alta Ski Area, Utah (intermountain snow climate (Mock and Birkeland, 2000)) and Mammoth Ski Area, California (maritime snow climate (Mock and Birkeland, 2000)). Both models used 31 input variables and had a maximum of 100 decision 'tree-branches'. The Alta model had a 97% success rate and the model for Mammoth had a 98% success rate for correctly classifying non avalanche days (success rate for avalanche days unreported). Merindol et al., (2002) used the nearest neighbor statistical approach for avalanche prediction. Five predictor variables were subjected to a principal component analysis prior to the nearest neighbor analysis resulting in a model with a 60% success rate for correctly predicting days without avalanches and a 15% success rate for correctly predicting avalanche days. Wet avalanches were not separated from dry avalanches in this model.

Advances in computer technology have allowed for Geographical Information System (GIS) software to be incorporated into avalanche prediction models. McCollister et al. (2002) developed an avalanche forecasting tool for Jackson Hole Ski Area (intermountain snow climate (Mock and Birkeland, 2000)) using nearest neighbors and GIS to provide the user with a probabilistic forecast and a graphical display of analogous nearest neighbor days using new snow, wind speed and wind direction as predictor variables. This tool can be used for wet snow avalanches given the appropriate inputs, however this has not yet been done.

Out of the eight studies described above, only three (Bovis, 1977; Fohn et al., 1977; and Judson and King, 1985) considered wet avalanches when developing their models. Bovis (1977) was the only study to design prediction models specifically for wet avalanches, and these models were developed for a highway corridor in a continental climate. A study on wet snow hypothesis testing and modeling at a ski area in the intermountain snow climate is needed.

Bridger Bowl was selected as the focus of this study because it is within the intermountain snow climate and has an excellent dataset with which to test wet avalanche hypotheses and develop a wet avalanche prediction model. One of the objectives of this study is to use Bridger Bowl's weather, snowpack and avalanche data from 1968-2001 (1996 data unavailable) for the month of March (when wet avalanches are most common at Bridger Bowl) to develop and test hypotheses regarding possible wet avalanche predictor variables that relate to temperature, snowpack settlement, precipitation, and wind characteristics. Since wet avalanches in intermountain snow climates can occur after precipitation events or after a succession of warm days and/or nights, hypotheses will also be tested on whether the factors that drive wet avalanche formation are different for ‘new snow’ and ‘old snow’ conditions. In this case, a ‘new snow’ day has measured newly fallen snow that is less than 48 hours in age and an ‘old snow’ day has measured newly fallen snow that is greater than 48 hours in age.

The second objective of this study is to develop two wet avalanche prediction models, one model for ‘new snow’ wet avalanche conditions and one model for ‘old snow’ wet avalanche conditions. Variables that are determined to be statistically significant during the hypothesis testing phase will be further analyzed with binomial logistic regression to determine which variable arrangements provide the best predictive success for the ‘new snow’ and ‘old snow’ wet avalanche prediction models. The final models should use predictor variables that require data that are readily available and these variables should be easily calculated and/or estimated by the user.

This study is unique in that it focuses specifically on wet avalanche prediction for ski area purposes in the intermountain snow climate. The 32-year Bridger Bowl dataset provides a substantial amount of information on which sound statistical analysis can be performed. The statistical methods are rigorous and have a probabilistic approach to wet avalanche prediction rather than a deterministic, or ‘yes/no’ approach. Finally, this study is the first to examine wet old snow and wet new snow avalanche conditions.

METHODS

Data

Data Quality

The Bridger Bowl meteorological, snowpack and avalanche data come from two sources. The 1968 to 1995 records 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) (F. Johnson personal communication, 2002). Wind data were not available for Bridger Bowl. Seven hundred millibar daily average wind direction and velocity data from 1968-2001 were acquired from the National Weather Service's NCEP/NCAR Reanalysis Project database (NCEP/NCAR, 2004).

Since 1968, meteorological and snowpack data have been observed and recorded by Bridger Bowl patrol each morning during the ski season at the Alpine weather station located on the north side of the Bridger Bowl Ski Area at approximately 2260m in elevation (Mock and Birkeland, 2000). The Alpine weather station is a standardized study plot with typical weather and snowpack instruments including snow board, snow stake, recording weighing mechanical precipitation gage, and maximum/minimum mercury thermometers. Weather and snowpack data include 24 hour maximum temperature, 24 hour minimum temperature, total snowpack depth, 24 hour new snow depth, 24 hour new snow water equivalent (SWE), and 24 hour rain totals. Temperature data are recorded to the nearest 1°F, snow depth measurements are recorded to the nearest 1.0 inch, and SWE measurements are recorded to the nearest 0.01 inch. Avalanche data have been collected by patrol since 1968 as well. This dataset uses the U.S. avalanche recording scale, 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 of interest. Wet slab avalanches make up 31% of the total number of wet avalanches and wet loose avalanches make up the remaining 69%.

The Bridger Bowl weather, snowpack and avalanche database is one of longest and most complete records available (K. Birkeland personal communication, 2004), however there are problems that need to be kept in mind when interpreting the results. Fortunately, the Alpine weather station has remained in its original location and the same data collection routines have continued since 1968. However over the years, the spruce trees that surround the weather station have grown and have caused unknown changes in the records due to the shelter they now provide.

The avalanche dataset is also of concern. Questions that arise regarding this dataset are; 'Is Bridger Bowl patrol correctly identifying and labeling wet avalanches?' and 'Are all of the wet avalanches being recorded?' Colbeck (1982, 1990) and others have defined wet snow in the funicular regime, as snow with a liquid water content (as percentage of the total volume) of about 7% or greater. Snow is considered 'very wet' when liquid water can be "pressed out by moderately squeezing the snow in the hands, but there is an appreciable amount of air confined within the pores" (Colbeck, 1990, p.4).

This corresponds to a liquid water content of approximately 8-15%. Snow with a liquid water content greater than 15% is termed ‘slush’ snow and is “flooded with water and contains a relatively small amount of air” in the pores (Colbeck, 1990, p.4). A wet snow avalanche then, is one that has free water as the primary cause of release. Interviews with Bridger Bowl patrol confirm that the liquid water content is never measured to make a wet avalanche determination, but they will often use the ‘squeeze test’ (Colbeck et al., 1990) to do so. The way in which patrollers have identified wet avalanches in the past is subjective. Patrollers may have decided an avalanche is wet by observing its flow characteristics. Compared to dry avalanches, wet avalanches are relatively slow moving because there is a great deal of friction between the moving snow and the sliding surface (McClung and Schaerer, 1993). There is rarely a dust cloud of suspended material in a wet slide. Ski patrollers may look at the starting zones for clues too. Most wet slides start as point releases. Often the snow around the starting zone looks and feels wet. They may look at the bed/sliding surface. Usually the sliding surface looks and/or feels wet. During the slide, wet snow will gouge the soft sliding surface, “causing scoring or the formation of grooves and entrainment of rocks, dirt, and other material…Wet snow will follow terrain features much more readily than dry snow” (McClung and Schaerer, 1993, p. 108).

When there is concern about wet snow conditions at Bridger Bowl, patrollers are assigned a route on the mountain and continually ski this route to observe the changes occurring within the snowpack. Patrollers look for increasing ski, boot and pole penetration into the snow as a sign that the snow is losing cohesion. Patrollers may perform ‘squeeze tests’ (Colbeck, 1990) or try to make ‘snow doughnuts’ or ‘snow pinwheels’ by throwing snowballs onto the snow surface along their route to observe increasing water content. The snow temperature is taken at 20cm below the snow surface in areas of concern to track increasing snow temperature. They also look for increased melting around rocks, trees, cirques and bowls. Melt rates are advanced where radiation is absorbed by rocks and trees and re-radiated as longwave energy, and in areas where there is increased reflection and re-absorption such as cirques and bowls. When patrollers are observing wet snow conditions and an avalanche releases during wet snow conditions there is enough evidence to suggest that the slide is wet. A dry snow avalanche could be misclassified if its downslope motion creates enough friction and heat that the debris begins to melt. Once the motion stops, the warmed debris can refreeze and have a similar appearance to wet snow avalanche debris (McClung and Schaerer, 1993). Given the subjective nature of what is considered a ‘wet’ avalanche or ‘dry’ avalanche, there is a possibility that a number of the avalanches labeled as ‘wet’ in the Bridger Bowl records may not be technically ‘wet’. However, given the defining characteristics of wet avalanches and the experience of the Bridger Bowl ski patrol, there are likely “very few, if any [misclassified wet avalanches] in the records” (K. Birkeland personal communication, 2004).

Because it is impossible to know for certain if there are misidentified wet avalanches in the dataset, all of the data were retained in the study and no attempts were made to discard outliers. A cursory quality control check was performed on the entire dataset. Three points of data were removed because they had recordation errors. For example, March 24, 1971 was deleted from the dataset because the total snowpack depth was recorded as 0cm while the total snowpack depth on March 23rd was 228.6cm and the total snowpack depth on March 25th was 241.3cm. The reader should also be aware that the avalanche dataset includes both natural and artificially released avalanches. Naturally releasing 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. Model results given in the discussion section should not be interpreted as the probability of a wet avalanche release, but as the probability of avalanches identified as wet by Bridger patrol.

The other concern regarding the avalanche dataset is how consistent patrollers were in recording each and every wet avalanche that released in March. Patrollers admit that some wet avalanches may go unrecorded, especially towards the end of March when the ski season is coming to an end. A more thorough avalanche dataset may provide better results, however compared to most meteorological, snowpack and avalanche datasets, Bridger Bowl's is considered to be one of the most thorough and consistent records available (K. Birkeland personal communication, 2004; Mock and Birkeland, 2000).

The discussion regarding the dataset problems is not intended to discount the capabilities of the Bridger patrol, but is to make the reader aware of the possible unknowns that exist in this dataset. Bridger Bowl is very fortunate. Over half of its patrol staff has 10 to 20+ years of patrolling experience *at* Bridger Bowl. The patrollers know the mountain extremely well and are very qualified to distinguish dry avalanches from wet avalanches.

Data Restriction

The Bridger Bowl dataset was restricted to all days in March from 1968-2001 because wet avalanches occur most frequently in the spring, particularly in March, in intermountain snow climates. April data were omitted because the weather, snowpack and avalanche data were not consistently recorded each day and the final April date on which Bridger Bowl Ski Area closes operation varies from year to year (Fig. 2).

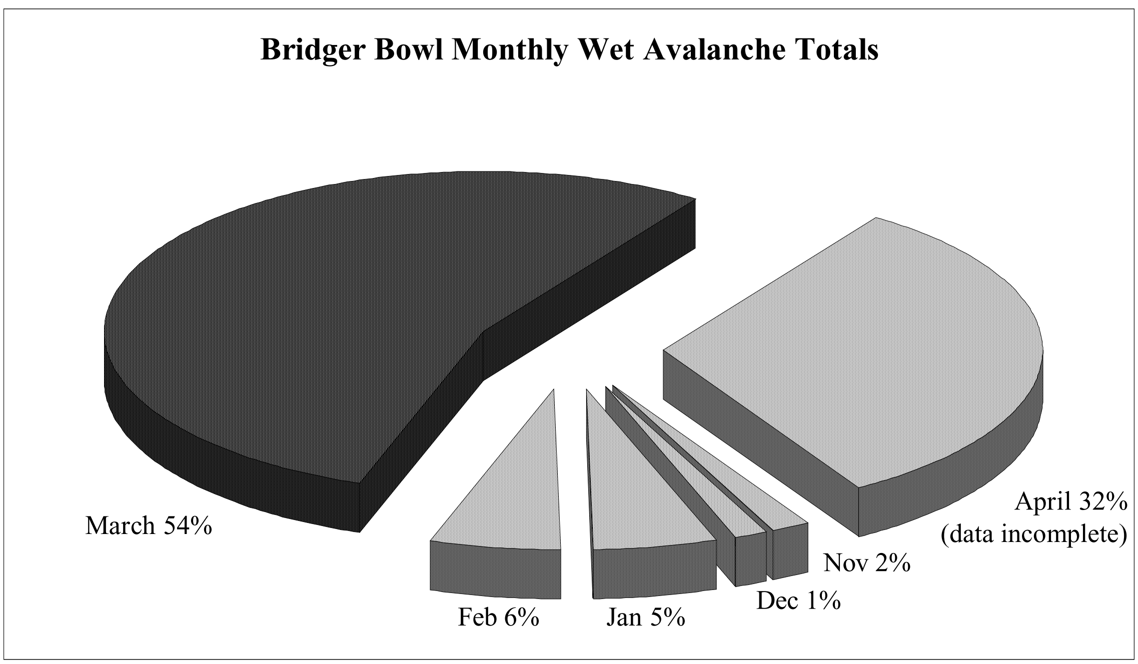

Figure 2. Bridger Bowl Monthly Wet Avalanche Distribution 1968-2001

The dataset was modified so that the presence or absence of a recorded wet avalanche became 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 have a binomial response equal to '1'. Days with no recorded wet avalanches are labeled as either 'no-wet-avalanche days' or 'days with no wet avalanches' and have a binomial response of '0'. 'No-wet-avalanche days' may have had recorded dry avalanches or no recorded avalanches at all, but given that there are no recorded wet avalanches they are termed 'no-wet-avalanche days'. Because wet avalanches in intermountain climates have been observed to release primarily after precipitation events followed by increased solar insolation, or after a succession of warm days and/or nights, there is reason to believe that the factors which drive wet avalanche formation are different for new snow conditions and old snow conditions. To test this idea, the original Bridger Bowl dataset containing all days in March from 1968-2001 was divided into a 'new snow' dataset and an 'old snow' dataset where a 'new snow' day has measured newly fallen snow that is less than 48 hours in age and an 'old snow' day has measured newly fallen snow that is greater than 48 hours in age.

Variable Description

The predictor variables used in this study were created to represent the processes that influence wet avalanche formation such as temperature change, changes in snowpack depth, new snow accumulation, new snow water equivalent, snow density, snow albedo, and relative humidity. Similar variables were found to be contributory factors to wet and dry avalanche conditions by Perla (1970), Fohn et al. (1977), Bovis (1977), Judson and King (1985), Davis et al. (1999), and Merindol et al. (2002). Old snow wet avalanche conditions may develop more slowly than new snow wet avalanche conditions. More time and greater amounts of energy are required to melt the numerous and strong bonds that develop in old snow. In contrast, new snow will retain liquid water more readily because there are more pores that are smaller in size within the new snow matrix. As more liquid water is retained, metamorphism will occur at a rapid rate leading to the quick development of cohesionless snow conditions.

To test whether important patterns emerge over time, a ‘time lag’ was built into each variable. 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 days prior’ variables were the oldest significant variables, with only a few exceptions. This study limits the number of preceding or leading days to three. The variables are defined within each dataset in terms of ‘prediction day’ (0), ‘one day prior’ (-1), ‘two days prior’ (-2), and ‘three days prior’ (-3). ‘Prediction day’ always refers to the day the model is predicting for, usually the current day, and is the day that the ‘one day prior’, ‘two days prior’ and ‘three days prior’ variables lead up to. A ‘prediction day’ may or may not have recorded wet avalanches. ‘One day prior’ always refers to the day that is one day prior to the ‘prediction day’; ‘two days prior’ always refers to the day that is two days prior to the ‘prediction day’; and ‘three days prior’ always refers to the day that is three days prior to the ‘prediction day’. Figure 3 serves as an example for the time-lag concept. Suppose that today, the day wet avalanche probability is being predicted for, is Monday. Any variable with an observation taken on this day is given a ‘0’ subscript. Sunday is considered one day prior to the prediction day and any observation taken on this day is given a ‘-1’ subscript. Saturday is two days prior to the prediction day and observations taken on this day are given subscript of '-2'. Friday is three days prior to the prediction day and observations taken on this day are given a '-3' subscript.

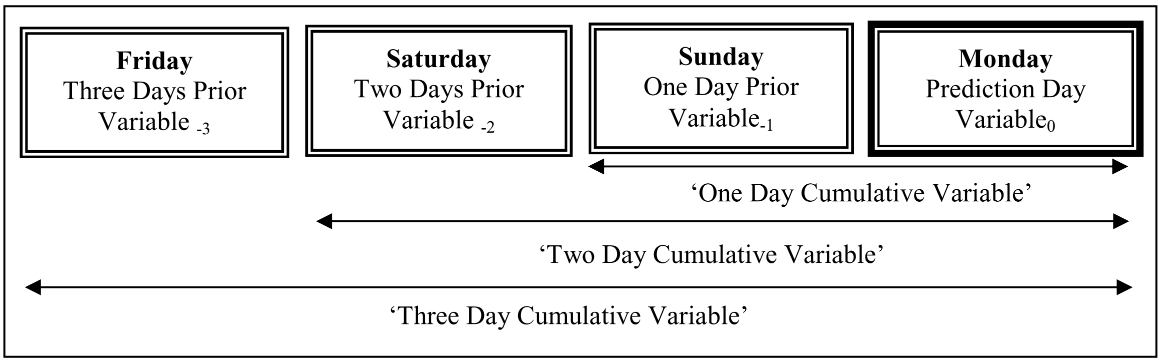

Figure 3. Predictor Variables With Time-Lag Example

The variables are either single-day measurements or cumulative day measurements. For example, the maximum temperature variables listed in Table 1 are $MaxT_0$, $MaxT_{-1}$, $MaxT_{-2}$, $MaxT_{-3}$, $AvgMaxT_{0,-1}$, $AvgMaxT_{0,-1,-2}$, $AvgMaxT_{0,-1,-2,-3}$. $MaxT_0$, $MaxT_{-1}$, $MaxT_{-2}$, and $MaxT_{-3}$ are single day measurements, that is $MaxT_0$ is the maximum temperature recorded for the prediction day; $MaxT_{-1}$ is the maximum temperature recorded one day prior to the prediction day; $MaxT_{-2}$ is the maximum temperature recorded two days prior to the prediction day; and $MaxT_{-3}$ is the maximum temperature recorded three days prior to the prediction day. $AvgMaxT_{0,-1}$, $AvgMaxT_{0,-1,-2}$, and $AvgMaxT_{0,-1,-2,-3}$ are cumulative day measurements. The subscripts indicate what 'prior' days are included in the cumulative variable. For example, $AvgMaxT_{0,-1}$ is the averaged maximum temperature of the prediction day and the one day prior observations.

The 68 variables used in the analysis (Table 1) can be grouped into three basic categories; temperature variables, snowpack settlement variables, and precipitation variables. Each variable will be briefly defined below, more complete definitions can be found in Appendix A ("Definitions").

Table 1. General Hypotheses

Predictor Variable	Hypothesis
Day of Year	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ As Day of Year increases, more solar radiation (energy) is available for snow melt.
Maximum Temperature: $MaxT_0$, $MaxT_{-1}$, $MaxT_{-2}$, $MaxT_{-3}$, $AvgMaxT_{0,-1}$, $AvgMaxT_{0,-1,-2}$, $AvgMaxT_{0,-1,-2,-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Warmer maximum temperatures indicate increased available energy for snow melt.
Minimum Temperature: $MinT_0$, $MinT_{-1}$, $MinT_{-2}$, $MinT_{-3}$, $AvgMinT_{0,-1}$, $AvgMinT_{0,-1,-2}$, $AvgMinT_{0,-1,-2,-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Warmer minimum temperatures reduces the amount of energy required to warm the snowpack to 0°C prior to melt.
Average Temperature: $AvgT_0$, $AvgT_{-1}$, $AvgT_{-2}$, $AvgT_{-3}$, $AvgAvgT_{0,-1}$, $AvgAvgT_{0,-1,-2}$, $AvgAvgT_{0,-1,-2,-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Warmer average temperatures indicate increased available energy for snow melt.
Degree Day (Maximum Temperature): $DDMaxT_0$, $DDMaxT_{0,-1}$, $DDMaxT_{0,-1,-2}$, $DDMaxT_{0,-1,-2,-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ The degree day number using maximum temperature is directly proportional to snowmelt depth (Rango and Marinec 1995). Increased degree day values indicates increased snowmelt depth.
Degree Day (Average Temperature): $DDAvgT_0$, $DDAvgT_{0,-1}$, $DDAvgT_{0,-1,-2}$, $DDAvgT_{0,-1,-2,-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ The degree day number using average temperature is directly proportional to snowmelt depth (Rango and Marinec 1995). Increased degree day values indicates increased snowmelt depth.
Maximum Temperature Range: $MaxT_0$-$MaxT_{-1}$, $MaxT_0$-$MaxT_{-2}$, $MaxT_0$-$MaxT_{-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Positive values indicate warming leading up to the prediction day. Higher values increase the probability of wet snow conditions.
Minimum Temperature Range: $MinT_0$-$MinT_{-1}$, $MinT_0$-$MinT_{-2}$, $MinT_0$-$MinT_{-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Positive values indicate less cooling leading up to the prediction day. Higher values reduce the amount of energy required to raise the snow temperature to 0°C prior to melt.

Table 1. Continued

Predictor Variable	**Hypothesis**
Average Temperature Range: $AvgT_0$-$AvgT_{-1}$, $AvgT_0$-$AvgT_{-2}$, $AvgT_0$-$AvgT_{-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Positive values indicate warming leading up to the prediction day. Higher values increase the probability of wet snow conditions.
Day-Time Temperature Range: $MaxT_0$-$MinT_0$, $MaxT_{-1}$-$MinT_{-1}$, $MaxT_{-2}$-$MinT_{-2}$, $MaxT_{-3}$-$MinT_{-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Positive values indicate ambient air temperature has increased during the day and energy available to melt snow has increased.
Overnight Temperature Range: $MaxT_{-1}$-$MinT_0$, $MaxT_{-2}$-$MinT_{-1}$, $MaxT_{-3}$-$MinT_{-2}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Warming (-) or minimal cooling (+) will reduce the amount of energy required to heat the snow to 0°C the following day.
Change in Total Snowpack Depth: HS_0-HS_{-1}, HS_0-HS_{-2}, HS_0-HS_{-3}	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ (-) values indicate a decrease in total snow depth. Greater decreases are a response to free water in the snowpack.
Total Snowpack Settlement: $Stl_{0,-1}$, $Stl_{0,-1,-2}$, $Stl_{0,-1,-2,-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Similar to 'Change in Total Snowpack Depth' variable, but 'Settlement' excludes new snow depths. (-) values indicate a decrease in total snow depth. Greater settlement is a response to free water in the snowpack.
Age of New Snow: HNA_0, HNA_{-1}, HNA_{-2}, HNA_{-3}	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ The age of new snow will determine whether new or old snow wet avalanche conditions will be of concern and whether new and old snow have different wet avalanche predictors.
New Snow Depth: HN_0, $HN_{0,-1,}$, $HN_{0,-1,-2}$, $HN_{0,-1,-2,-3}$	H_0: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ H_a: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ Daily new snow depth will not be a significant predictor of wet snow conditions because it does not describe how the new snow responds to warming conditions.
New Snow Water Equivalent: HNW_0, $HNW_{0,-1,}$, $HNW_{0,-1,-2}$, $HNW_{0,-1,-2,-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ Larger snow water equivalent values increase the percent liquid water within the snow matrix. Increased percent liquid water decreases the amount of energy required to shift snow into the funicular regime.
New Snow Density: HND_0, $HND_{0,-1,}$, $HND_{0,-1,-2}$, $HND_{0,-1,-2,-3}$	H_0: $\mu_{0old} = \mu_{1old}$; $\mu_{0new} = \mu_{1new}$; $\mu_{1old} = \mu_{1new}$ H_a: $\mu_{0old} \neq \mu_{1old}$; $\mu_{0new} \neq \mu_{1new}$; $\mu_{1old} \neq \mu_{1new}$ As new snow density increases, albedo decreases, water content increases, melt depth increases and wetting front accelerates.

Temperature Variables Temperature variables describe the daily temperatures and the change in temperature leading up to the prediction day. The 'day' of year variable (Table 1) is considered a surrogate variable for available radiation. If January 1st is equal to day 1 of a year, then March 1st is equal to day 60 (or day 61 in a leap year). Maximum temperature variables (Table 1) include single day and cumulative day measurements. Single day measurements are maximum temperatures recorded for the prediction day, one day prior to the prediction day, two days prior to the prediction day and three days prior to the prediction day ($MaxT_0$, $MaxT_{-1}$, $MaxT_{-2}$, $MaxT_{-3}$ respectively). The cumulative day measurements are the average maximum temperatures ($AvgMaxT_{0,-1}$, $AvgMaxT_{0,-1,-2}$, $AvgMaxT_{0,-1,-2,-3}$) calculated by averaging the maximum temperature recorded on the prediction day and one day prior ($AvgMaxT_{0,-1}$); the prediction day, one day prior, and two days prior ($AvgMaxT_{0,-1,-2}$); and the prediction day, one day prior, two days prior and three days prior ($AvgMaxT_{0,-1,-2,-3}$). The minimum temperature variables ($MinT_0$, $MinT_{-1}$, $MinT_{-2}$, $MinT_{-3}$, $AvgMinT_{0,-1}$, $AvgMinT_{0,-1,-2}$, $AvgMinT_{0,-1,-2,-3}$) and the average temperature variables ($AvgT_0$, $AvgT_{-1}$, $AvgT_{-2}$, $AvgT_{-3}$, $AvgAvgT_{0,-1}$, $AvgAvgT_{0,-1,-2}$, $AvgAvgT_{0,-1,-2,-3}$) use the same definitions applied to the maximum temperature variables (Table 1).

Two sets of degree day variables (Table 1) are tested using maximum temperature in the calculations ($DDMaxT_0$, $DDMaxT_{0,-1}$, $DDMaxT_{0,-1,-2}$, $DDMaxT_{0,-1,-2,-3}$) and average temperature in the calculations ($DDAvgT_0$, $DDAvgT_{0,-1}$, $DDAvgT_{0,-1,-2}$, $DDAvgT_{0,-1,-2,-3}$). Linsley et al. (1958) defines a degree day as a departure of one degree per day in the daily maximum or average temperature from 0°C. For example, $DDMaxT_0$

is the difference between the prediction day's maximum temperature and 0°C. $DDMaxT_{0,-1}$ is the difference between the prediction day's maximum temperature and 0°C *plus* the difference between the one day prior maximum temperature and 0°C. The same concept is extended to $DDMaxT_{0,-1,-2}$ and $DDMaxT_{0,-1,-2,-3}$. The degree day variables related to average temperature ($DDAvgT_0$, $DDAvgT_{0,-1}$, $DDAvgT_{0,-1,-2}$, $DDAvgT_{0,-1,-2,-3}$) use the same calculations as the degree day maximum temperature variables.

The last group of temperature variables describe different types of temperature changes occurring over various time periods (Table 1). Maximum temperature range variables ($MaxT_0$-$MaxT_{-1}$, $MaxT_0$-$MaxT_{-2}$, $MaxT_0$-$MaxT_{-3}$), minimum temperature range variables ($MinT_0$-$MinT_{-1}$, $MinT_0$-$MinT_{-2}$, $MinT_0$-$MinT_{-3}$) and average temperature range variables ($AvgT_0$-$AvgT_{-1}$, $AvgT_0$-$AvgT_{-2}$, $AvgT_0$-$AvgT_{-3}$) are all calculated the same way. For example, $MaxT_0$-$MaxT_{-1}$ is simply the difference between the prediction day maximum temperature and the one day prior maximum temperature; $MaxT_0$-$MaxT_{-2}$ is the difference between the prediction day maximum temperature and the two days prior maximum temperature; and $MaxT_0$-$MaxT_{-3}$ is the difference between the prediction day maximum temperature and the three days prior maximum temperature. The day-time temperature range variables ($MaxT_0$-$MinT_0$, $MaxT_{-1}$-$MinT_{-1}$, $MaxT_{-2}$-$MinT_{-2}$, $MaxT_{-3}$-$MinT_{-3}$) use single day observations to calculate how much the air temperature increased or decreased each day. To calculate the day-time temperature change that occurred one day prior to the prediction day ($MaxT_{-1}$-$MinT_{-1}$) subtract the one day prior minimum temperature ($MinT_{-1}$) from the one day prior maximum temperature ($MaxT_{-1}$). The overnight temperature range variables ($MaxT_{-1}$-$MinT_0$, $MaxT_{-2}$-$MinT_{-1}$, $MaxT_{-3}$-$MinT_{-2}$) use single day measurement to calculate how much the air temperature increased or decreased each night. These variables are calculated by subtracting the previous day's maximum temperature from the next day's minimum temperature.

<u>Snowpack Settlement Variables</u> Snowpack settlement variables are intended to describe how the snowpack responds to temperature changes and loading. Two types of snowpack change are tested; the total change in snowpack depth and total snowpack settlement. The key difference is the total change in snowpack depth variable accounts for the addition of new snowfall and the settlement variable excludes new snowfall from its calculations (Table 1). The total change in snowpack depth variables (HS_0-HS_{-1}, HS_0-HS_{-2}, HS_0-HS_{-3}) describe how much the total depth of the snowpack has increased or decreased over one day, two day and three day time intervals. The total snowpack settlement variables ($Stl_{0,-1}$, $Stl_{0,-1,-2}$, $Stl_{0,-1,-2,-3}$) exclude new snowfall amounts and therefore represent only those processes that will decrease the snowpack depth. One day settlement ($Stl_{0,-1}$) is calculated by subtracting the one day prior total snow depth (HS_{-1}) and the prediction day new snow totals (HN_0) from the prediction day total snow depth (HS_0), ($Stl_{0,-1} = HS_0 - HS_{-1} - HN_0$). Settlement that has occurred over the two days leading up to the prediction day is calculated with the following equation: $Stl_{0,-1,-2} = HS_0 - HS_{-2} - HN_0 - HN_{-1}$. Three-day settlement uses the equation: $Stl_{0,-1,-2,-3} = HS_0 - HS_{-3} - HN_0 - HN_{-1} - HN_{-2}$.

Precipitation Variables The precipitation variables describe the age, depth, snow water equivalent, and density of the newly fallen snow as well as the accumulated totals and day-to-day changes leading up to the prediction day (Table 1). The age of new snow variables (HNA_0, HNA_{-1}, HNA_{-2}, HNA_{-3}) describe how old (in days) the newly fallen snow is on the prediction day (HNA_0), one day prior (HNA_{-1}), two days prior (HNA_{-2}), and three days prior (HNA_{-3}) to the prediction day. For example, if it is snowing on the prediction day, the new snow is 0 days old. If the most recent snowfall occurred one day prior to the prediction day, the new snow is 1 day old and if the most recent snowfall occurred two days prior to the prediction day, the new snow is 2 days old, and so forth. New snow depth variables (HN_0, $HN_{0,-1,}$, $HN_{0,-1,-2}$, $HN_{0,-1,-2,-3}$) are cumulative variables except for the prediction day (HN_0) measurement. The one-day cumulative snowfall variable ($HN_{0,-1}$) is the sum of the prediction day new snow depth (HN_0) and the one day prior new snow depth (HN_{-1}) ($HN_{0,-1} = HN_0+HN_{-1}$). The two-day cumulative new snowfall variable ($HN_{0,-1,-2}$) is calculated using the following equation: $HN_{0,-1,-2} = HN_0+HN_{-1}+HN_{-2}$. The three-day cumulative new snowfall variable ($HN_{0,-1,-2,-3}$) uses the equation: $HN_{0,-1,-2} = HN_0+HN_{-1}+HN_{-2}+HN_{-3}$. The new snow water equivalent variables (HNW_0, $HNW_{0,-1,}$, $HNW_{0,-1,-2}$, $HNW_{0,-1,-2,-3}$) are calculated the same way, except the new snow water equivalent measurement are used in place of the new snow depth measurements. The cumulative new snow density variables (HND_0, $HND_{0,-1,}$, $HND_{0,-1,-2}$, $HND_{0,-1,-2,-3}$) follow the same concept of the new snow total and new snow water equivalent measurements, but require a few more calculations. The prediction day new snow density is determined by multiplying the prediction day new snow water equivalent by 1000kg/m^3 (the density of liquid water) and dividing the product by the prediction day new snow depth ($HND_0 = (HNW_0*1000kg/m^3) \div HN_0$). One day cumulative new snow density is calculated by multiplying the cumulative one day snow water equivalent by 1000kg/m^3, dividing the product by the one day prior new snow depth and adding the total to the prediction day new snow density ($HND_{0,-1} = HND_0 + (HNW_{-1} * 1000kg/m^3) \div HN_{-1}$). The two day cumulative new snow density is the prediction day new snow density plus the one day prior new snow density and two days prior new snow density ($HND_{0,-1,-2} = HND_{0,-1} + (HNW_{-2} * 1000kg/m^3) \div HN_{-2}$). The three day cumulative new snow density calculations follow the same pattern, ($HND_{0,-1,-2,-3} = HND_{0,-1,-2} + (HNW_{-3}*1000kg/m^3) \div HN_{-3}$).

Rainfall was not used as a predictor variable because rain is a relatively rare occurrence at Bridger Bowl (only 15 days out of the 1046 total number of days in the dataset had recorded rain totals).

Wind Variables Unfortunately, wind direction and speed data were not archived at Bridger Bowl. Wind direction and wind speed data at the 700mb level were downloaded from the National Weather Service NCEP/NCAR Reanalysis Project database (NCEP/NCAR, 2004) (Table 1). Wind speed data were eventually dropped from the analysis because wind velocities at the 700mb level were not considered representative of the wind speeds occurring near the snow surface. The wind direction data were eventually dropped from the analysis because the NCEP/NCAR wind direction data were extrapolated over a 2.5 x 2.5 (latitude/longitude) degree grid. The large area over which the wind direction data are averaged reduces the affects of topography, thus making the data not representative of the true wind direction at Bridger Bowl Ski Area. To assess wind effectively local wind sensors are needed near the ground. The high variability caused by complex mountain terrain makes this approach impractical.

Null and alternative hypotheses as well as a brief statement for support are provided in Table 1. These will be examined in further detail in the discussion section.

Hypothesis Testing Methods

The study is divided into two phases; the hypothesis testing phase and the model development phase. There are two main hypotheses being tested. The first hypothesis will test which meteorological and snowpack predictor variables are significant in predicting old snow and new snow wet avalanche conditions, and whether there are unique predictor variables for old and new snow wet avalanche conditions. For each variable in the old snow dataset and new snow dataset this hypothesis asks: 'Is the mean or median for no-wet-avalanche avalanche days (μ_0) equal to the mean or median for wet avalanche days (μ_1) at $\alpha = 0.05$ significance level?' (Table 1). The null hypothesis is accepted when the means or medians test results give a p-value that is greater than 0.05, which shows that the means or medians are not significantly different from one another (H_0: $\mu_0 = \mu_1$). In other words, the wet avalanche days and days with no wet avalanches have the same means and therefore the variable will not be a significant predictor in the model selection phase to come. The alternative hypothesis is accepted when the means or medians test results give a p-value that is less than or equal to 0.05, which shows that the means or medians are significantly different from one another (H_1: $\mu_0 \neq \mu_1$). In other words, the wet avalanche days and days with no wet avalanches have different means for the variable of interest and should be further tested in the model selection phase of the study.

The second hypothesis test will determine whether the significant variables from the old snow dataset have different means or medians than the same variables from the new snow dataset. For each significant variable (determined by the first hypothesis test), this hypothesis question asks: 'Is the mean or median for old snow wet avalanche days (μ_{1old}) equal to the mean or median for new snow wet avalanche days (μ_{1new}) at $\alpha = 0.05$ significance level?' (Table 1). The null and alternative hypotheses are accepted on the same basis as described in the first hypothesis test. Acceptance of the null hypothesis shows that old snow wet avalanche day means or medians are not significantly different than new snow wet avalanche day means or medians (H_0: $\mu_{1old} = \mu_{1New}$). Acceptance of the alternative hypothesis shows that old snow and new snow wet avalanche day means or medians are significantly different ($\mu_{1Old} \neq \mu_{1New}$) and that even though the variable being tested is a significant predictor for both old snow and new snow wet avalanche conditions, it behaves uniquely depending on the age of the snow.

Before these hypotheses can be tested, the appropriate means or medians test must be determined by testing each variable in the old snow dataset and new snow dataset for normality and equal variance at the $\alpha = 0.05$ significance level. The Anderson-Darling Normality Test was used to test each variable for normality. The null hypothesis for this test states that the data are normally distributed (p-value > 0.05), and the alternative hypothesis states that the data are not normally distributed (p-value $\leq$ 0.05). See Appendix B for results ("Old Snow Hypothesis Testing Results", "New Snow Hypothesis Testing Results" and "Old and New Snow Wet Avalanche Day Hypothesis Testing Results").

Each variable from the old and new snow datasets were then tested for equal variance. An F-Test was used to determine equal variance for variables that were normally distributed (Minitab, Inc., 2000). Levene's Test for equal variance was used for variables with nonparametric, or non-normal distributions (Minitab, Inc., 2000). The null hypothesis for both tests states that the data do not have significantly different variance (p-value > 0.05), and the alternative hypothesis states that the data have significantly different variance (p-value $\leq$ 0.05). See Appendix B for results ("Old Snow Hypothesis Testing Results", "New Snow Hypothesis Testing Results" and "Old and New Snow Wet Avalanche Day Hypothesis Testing Results").

Many variables were found to have nonparametric distributions and/or unequal variance. Ideally, the 2-Sample T-Test with pooled (equal) variance is used to test for equal means because it tends to produce the narrowest confidence intervals for the means; however, this test is restricted to variables with normal distributions and equal variance (Minitab, Inc., 2000). If necessary, up to three transformations were attempted for each variable to correct distribution and variance problems. The Box-Cox Transformation procedure is one method of estimating the best-fit 'lambda', where lambda (λ) is the estimated exponent for each variable being transformed (Minitab, Inc., 2000). When a Box-Cox Transformation is performed using MiniTab statistical software, the user is given a 95% confidence interval for lambda with an 'optimal' estimate of lambda and two closely competing values for lambda denoted as 'lower alternate' and 'upper alternate'. The first transformation attempt used a recognizable or 'common' lambda value such as 0.5, 2 or zero that fell within the given 95% confidence interval (0.5 is the square-root of the variable, 2 is the square of the variable and zero is the log transformation of the variable). If this transformation did not correct the variable's non-normality or unequal variance, a second transformation was performed using the estimated 'optimal' lambda. If the 'optimal' transformation did not correct the variable's distribution and variance problems a final transformation was attempted using one of the two estimated competing values of lambda. See Appendix B for the transformation accepted for each variable ("Old Snow Hypothesis Testing Results", "New Snow Hypothesis Testing Results" and "Old and New Snow Wet Avalanche Day Hypothesis Testing Results").

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 null hypotheses for each test states that the data do not have significantly different means or medians (p-value > 0.05), and the alternative hypothesis states that the data have significantly different means or medians (p-value ≤ 0.05).

There were several instances where variables continued to have nonparametric distributions and unequal variances even after the three transformation attempts. The Kolomogorov-Smirnov test could be performed to test the distributions of these variables, however this is considered to be a test with poor statistical efficiency (Neter et al., 1996). Instead, the variables' means were tested using the most normally distributed form of the variable in a 2-Sample T-Test with unequal variance. This decision was based on the fact that the 2-Sample T-Test is a very robust test and can produce reliable results for nonparametric data especially when the datasets are large (Neter et al., 1996).

Model Development Methods

After the significant old snow and new snow variables were identified, binomial logistic regression was used to build an 'old snow wet avalanche probability model' and a 'new snow wet avalanche probability model'. Only those variables that are determined to be significant old snow and new snow predictors during the hypothesis testing phase will be used in the model selection phase of this study. The purpose of this phase of the study is to determine which significant old snow and new snow variables best predict the probability of spring-time wet avalanche conditions at Bridger Bowl.

The intent is to build two wet avalanche prediction models for old and new snow conditions that are easy-to-use. They should provide dependable and practical results that can be readily understood by any user. To do this, the variables included in the model should not require additional calculations that the user may not be immediately familiar with. Only variables whose values are readily known, or have only one unknown meteorological or snowpack factor that can be easily estimated through daily forecasts are included in the final models. More complicated variables that would require the user to estimate more than one meteorological or snowpack factor were discarded only when a more straight-forward variable that had comparable predictive success was available. For example, suppose the new snow density variables (HND_0, $HND_{0,-1}$, $HND_{0,-1,-2}$, $HND_{0,-1,-2,-3}$) and the new snow water equivalent variables (HNW_0, $HNW_{0,-1}$, $HNW_{0,-1,-2}$, $HNW_{0,-1,-2,-3}$) were found to be good new snow wet avalanche predictors. The new snow density variables require the user to estimate the new snowfall and new snow water equivalent totals for each prediction day, while the new snow water equivalent variables only require the use to estimate the SWE for each prediction day. If the new snow water equivalent variables had comparable predictive success they would be chosen in favor of the new snow density variables because they are easier for the user to calculate.

Correlation Testing

Before the model selection process could begin, correlation tests were performed on all old snow and new snow significant variables. The purpose of the correlation testing was to identify those variables that are too correlated with one another to be included in the same model. Strongly correlated variables essentially explain the same changes in the response and contribute a limited amount of unique information to the model. The result of having strongly correlated variables in the same model is a decrease in the overall strength of its predictive capability because the correlated variables increase the complexity of the model while contributing little predictive power (Neter et al., 1996). The Pearson product moment correlation coefficient (r) was used to measure the degree of linear relationship, or correlation, between two variables. The correlation coefficient can have a value between –1 and 1. Negative values indicate that the two variables being tested are inversely related with one another, while positive values indicate that the two variables are directly related with one another (Neter et al., 1996). Two variables with a Pearson coefficient of 1 or –1 are perfectly correlated with one another and can be considered identical predictor variables. Any two variables with a Pearson product correlation coefficient between 0.5 to 1.0 and –0.5 to -1.0 was noted and caution was used during the final model building process to prevent highly correlated variables from being in the same model. Tables 9 and 10 in the discussion section provide the old snow and new snow correlation test results.

Variable Selection Criteria

Old snow and new snow variables that were selected for the final model building phase were chosen based on their p-values, odds ratios, percent concordant pairs and the ease in which the variable can be calculated and/or estimated by the model user. P-values less than or equal to 0.05 indicate that the variable's coefficient is significantly different than zero at the $\alpha = 0.05$ significance level. The odds ratio value is an indicator of the variable's effect on the model results. For example, a variable with an odds ratio of 2 means that the odds of the prediction model calculating a wet avalanche outcome (binomial response equal to 1) is two-fold for each incremental increase in the variable's value. The odds ratio can take on any value, positive or negative. As it approaches 1.0 the variable will have a decreasing effect on the model results (Minitab, Inc., 2000). The percent concordant pairs value is a measure of association between the observed response and the predicted probabilities. If, for example, the model predicts a greater probability for wet avalanche conditions (predicted probability) on a wet avalanche day (observed response) the model has given an accurate or ‘concordant’ response. If, however, the model predicts a higher probability for wet avalanche conditions on an observed no-wet-avalanche day the model has given an inaccurate or ‘discordant’ response. The greater percent concordant pairs the greater the model’s predictive accuracy (Minitab, Inc., 2000).

RESULTS

The following results describe the Bridger Bowl datasets and variables used in this study prior to statistical treatment. Hypothesis testing and model selection outcomes are presented in the discussion section. 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 and are therefore labeled as 'wet avalanche days' (Table 2). The remaining 974 days may have had recorded dry avalanches, or no avalanches at all, but because no wet avalanches were recorded, these days are labeled as either 'no-wet-avalanche days' or 'days with no wet avalanches'. The original dataset was divided into a 'new snow dataset' and an 'old snow dataset' (Table 2). The 'new snow dataset' is made up of 704 'new snow' days, where a 'new snow' day has measured newly fallen snow that is less than or equal to 48 hours in age. Thirty-nine days in the new snow dataset had recorded wet avalanche occurrences and 665 days were days with no wet avalanches. The 'old snow dataset' contains 342 'old snow' days, where an 'old snow' day has measured newly fallen snow that is more than 48 hours old. This dataset has 33 wet avalanche days and 309 day with no wet avalanches. Although there are nearly twice as many days in the new snow dataset than the old snow dataset, the number of wet avalanche days differs by just six days between the two datasets. The new snow dataset and old snow dataset were used in the hypothesis testing phase of the study (results presented in discussion section). For model selection and testing purposes, the new and old snow datasets were divided into 'training' and 'testing' datasets (Table 2). 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 (results presented in the discussion section).

Table 2. Dataset Descriptive Statistics

Dataset	**Total Days**	**Total Wet Avalanche Days**	**Total No-Wet-Avalanche Days**
Original Dataset	1,046	72	974
New Snow Dataset	704	39	665
Training Dataset	562	28	534
Testing Dataset	142	11	131
Old Snow Dataset	342	33	309
Training Dataset	273	27	246
Testing Dataset	69	6	63

Basic descriptive statistics for all 68 variables used in the analysis are given in Tables 3 (Original Dataset), 4 (Old Snow Dataset) and 5 (New Snow Dataset). For each table, 'N' provides the total number of observations for each variable in the dataset. 'N' may vary due to missing data in the records or recordation errors that were deleted from the dataset. The minimum, maximum, mean and standard deviation for each variable are also provided in tables. See Appendix A for a list of variable definitions.

Table 3. Original Dataset – Predictor Variable Descriptive Statistics

Variable	N	Minimum	Mean	Maximum	St. Dev.
Day of Year	1046	57	75	91.0	9.2
$MaxT_0$°C	1038	-20.0	1.8	20.0	5.8
$MaxT_{-1}$°C	1039	-20.0	1.7	19.4	5.8
$MaxT_{-2}$°C	1040	-20.0	1.7	19.4	5.8
$MaxT_{-3}$°C	1032	-20.0	1.7	19.4	5.8
$AvgMaxT_{0,-1}$°C	1032	-18.6	1.7	16.2	5.3
$AvgMaxT_{0,-1,-2}$°C	1026	-15.2	1.7	15.5	5.0
$AvgMaxT_{0,-1,-2,-3}$°C	1021	-13.4	1.7	14.9	4.7
$MinT_0$°C	1037	-26.1	-7.8	5.6	5.1
$MinT_{-1}$°C	1038	-26.1	-7.9	5.6	5.2
$MinT_{-2}$°C	1038	-26.1	-8.0	5.6	5.2
$MinT_{-3}$°C	1039	-26.1	-8.0	5.6	5.1
$AvgMinT_{0,-1}$°C	1030	-25.3	-7.9	3.9	4.7
$AvgMinT_{0,-1,-2}$°C	1023	-24.6	-7.9	2.2	4.3
$AvgMinT_{0,-1,-2,-3}$°C	1017	-23.7	-8.0	1.8	4.1
$AvgT_0$°C	1037	-22.8	-3.0	10.6	5.1
$AvgT_{-1}$°C	1038	-22.8	-3.1	10.6	5.1
$AvgT_{-2}$°C	1038	-22.8	-3.2	10.6	5.1
$AvgT_{-3}$°C	1039	-22.8	-3.2	10.6	5.1
$AvgAvgT_{0,-1}$°C	1030	-21.1	-3.1	9.0	4.7
$AvgAvgT_{0,-1,-2}$°C	1023	-19.9	-3.1	7.6	4.4
$AvgAvgT_{0,-1,-2,-3}$°C	1017	-18.3	-3.1	7.2	4.2
$DDMaxT_0$°C	1038	-20.0	1.8	20.0	5.8
$DDMaxT_{0,-1}$°C	1032	-37.2	3.4	32.3	10.6
$DDMaxT_{0-1,-2}$°C	1026	-45.6	5.0	46.6	15.0
$DDMaxT_{0,-1,-2,-3}$°C	1021	-53.4	6.6	59.4	18.9
$DDAvgT_0$°C	1037	-22.8	-3.0	10.6	5.1
$DDAvgT_{0,-1}$°C	1030	-42.3	-6.2	17.9	9.4
$DDAvgT_{0,-1,-2}$°C	1023	-59.7	-9.4	22.8	13.2
$DDAvgT_{0,-1-2,-3}$°C	1017	-73.1	-12.6	29.0	16.7
$MaxT_0$-$MaxT_{-1}$°C	1032	-17.3	0.1	22.2	4.8
$MaxT_0$-$MaxT_{-2}$°C	1031	-18.3	0.2	17.8	6.2
$MaxT_0$-$MaxT_{-3}$°C	1032	-22.2	0.2	18.9	6.8
$MinT_0$-$MinT_{-1}$°C	1030	-16.8	0.1	17.7	4.4
$MinT_0$-$MinT_{-2}$°C	1029	-20.2	0.2	21.1	5.7
$MinT_0$-$MinT_{-3}$°C	1030	-23.9	0.2	23.3	6.1
$AvgT_0$-$AvgT_{-1}$°C	1030	-12.9	0.1	12.2	3.9
$AvgT_0$-$AvgT_{-2}$°C	1029	-19.0	0.2	18.6	5.4
$AvgT_0$-$AvgT_{-3}$°C	1030	-23.1	0.2	21.1	6.0
$MaxT_0$-$MinT_0$°C	1038	0.0	9.6	27.7	4.2
$MaxT_{-1}$-$MinT_{-1}$°C	1039	0.0	9.6	27.7	4.2
$MaxT_{-2}$-$MinT_{-2}$°C	1039	0.0	9.6	27.7	4.2
$MaxT_{-3}$-$MinT_{-3}$°C	1030	0.5	9.6	27.7	4.1
$MaxT_{-1}$-$MinT_0$°C	1031	-4.4	9.5	28.8	5.3
$MaxT_{-2}$-$MinT_{-1}$°C	1032	-4.4	9.6	28.8	5.3
$MaxT_{-3}$-$MinT_{-2}$°C	1033	-4.4	9.6	28.8	5.4

Table 3. Continued

Variable	N	Minimum	Mean	Maximum	St. Dev.
HS_0-HS_{-1} cm	1040	-38.1	0.8	91.4	8.8
HS_0-HS_{-2} cm	1040	-45.7	1.7	91.4	12.6
HS_0-HS_{-3} cm	1040	-45.7	2.6	91.4	15.0
$Stl_{0,-1}$ cm	1037	-43.1	-4.0	28.0	4.8
$Stl_{0,-1,-2}$ cm	1033	-55.8	-7.9	27.9	7.4
$Stl_{0,-1,-2,-3}$ cm	1029	-76.1	-11.8	22.9	9.6
HNA_0 days	1046	0.0	1.5	16.0	2.4
HNA_{-1} days	1046	0.0	1.6	16.0	2.4
HNA_{-2} days	1046	0.0	1.6	16.0	2.4
HNA_{-3} days	1046	0.0	1.6	16.0	2.4
HN_0 cm	1042	0.0	4.8	109.2	8.6
$HN_{0,-1}$ cm	1038	0.0	9.7	116.8	13.1
$HN_{0,-1,-2}$ cm	1034	0.0	14.6	124.4	16.7
$HN_{0,-1,-2,-3}$ cm	1030	0.0	19.4	132.0	19.9
HNW_0 cm	1030	0.0	0.4	8.8	0.7
$HNW_{0,-1}$ cm	1021	0.0	0.7	9.1	1.0
$HNW_{0,-1,-2}$ cm	1015	0.0	1.1	9.3	1.3
$HNW_{0,-1,-2,-3}$ cm	1010	0.0	1.5	10.2	1.5
HND_0 kg/m^3	1026	0.0	36.8	268.4	49.2
$HND_{0,-1}$ kg/m^3	1013	0.0	52.3	266.7	51.0
$HND_{0,-1,-2}$ kg/m^3	1003	0.0	62.0	266.7	50.0
$HND_{0,-1,-2,-3}$ kg/m^3	994	0.0	68.1	266.7	47.9

Table 4. Old Snow Dataset – Predictor Variable Descriptive Statistics

Variable	N	Minimum	Mean	Maximum	St. Dev.
Day of Year	342	57	73	91.0	9.1
$MaxT_0$°C	337	-15.0	5.5	20.0	5.4
$MaxT_{-1}$°C	338	-20.0	3.7	17.2	6.0
$MaxT_{-2}$°C	341	-20.0	2.4	17.2	6.3
$MaxT_{-3}$°C	340	-17.2	2.2	15.6	6.1
$AvgMaxT_{0,-1}$°C	334	-13.9	4.6	16.2	5.4
$AvgMaxT_{0,-1,-2}$°C	333	-15.0	3.8	15.5	5.2
$AvgMaxT_{0,-1,-2,-3}$°C	331	-13.2	3.4	14.9	5.0
$MinT_0$°C	337	-23.3	-5.4	5.6	4.9
$MinT_{-1}$°C	338	-26.1	-7.1	3.3	5.5
$MinT_{-2}$°C	340	-26.1	-8.1	3.3	5.4
$MinT_{-3}$°C	340	-26.1	-7.9	2.2	5.4
$AvgMinT_{0,-1}$°C	334	-24.2	-6.3	3.9	4.9
$AvgMinT_{0,-1,-2}$°C	332	-23.4	-7.0	2.2	4.7
$AvgMinT_{0,-1,-2,-3}$°C	330	-22.1	-7.2	1.8	4.5
$AvgT_0$°C	337	-19.2	0.0	10.6	4.8
$AvgT_{-1}$°C	338	-22.8	-1.7	8.4	5.4
$AvgT_{-2}$°C	340	-22.8	-2.9	8.4	5.5
$AvgT_{-3}$°C	340	-20.9	-2.9	7.8	5.3
$AvgAvgT_{0,-1}$°C	334	-19.1	-0.9	9.0	4.9

Table 4. Continued

Variable	N	Minimum	Mean	Maximum	St. Dev.
$AvgAvgT_{0,-1,-2}$°C	332	-19.2	-1.6	7.6	4.8
$AvgAvgT_{0,-1,-2,-3}$°C	330	-17.7	-1.9	7.2	4.6
$DDMaxT_{0}$°C	337	-15.0	5.5	20.0	5.5
$DDMaxT_{0,-1}$°C	334	-27.8	9.1	32.3	10.7
$DDMaxT_{0-1,-2}$°C	333	-45.0	11.4	46.6	15.7
$DDMaxT_{0,-1,-2,-3}$°C	331	-52.8	13.5	59.4	19.9
$DDAvgT_{0}$°C	337	-19.2	0.0	10.6	4.8
$DDAvgT_{0,-1}$°C	334	-38.1	-1.7	17.9	9.7
$DDAvgT_{0,-1,-2}$°C	332	-57.6	-4.7	22.8	14.3
$DDAvgT_{0,-1-2,-3}$°C	330	-70.6	-7.6	29.0	183
$MaxT_{0}$-$MaxT_{-1}$°C	334	-16.7	1.9	22.2	4.3
$MaxT_{0}$-$MaxT_{-2}$°C	336	-13.9	3.1	17.8	5.7
$MaxT_{0}$-$MaxT_{-3}$°C	335	-14.6	3.4	18.9	6.4
$MinT_{0}$-$MinT_{-1}$°C	334	-11.2	1.7	17.7	3.8
$MinT_{0}$-$MinT_{-2}$°C	335	-10.6	2.7	21.1	4.9
$MinT_{0}$-$MinT_{-3}$°C	335	-10.6	2.5	23.3	5.5
$AvgT_{0}$-$AvgT_{-1}$°C	334	-9.2	1.8	12.2	3.3
$AvgT_{0}$-$AvgT_{-2}$°C	335	-10.9	3.0	18.6	4.6
$AvgT_{0}$-$AvgT_{-3}$°C	335	-11.4	3.0	21.1	5.3
$MaxT_{0}$-$MinT_{0}$°C	337	1.1	10.9	27.7	4.0
$MaxT_{-1}$-$MinT_{-1}$°C	338	1.1	10.8	27.7	4.0
$MaxT_{-2}$-$MinT_{-2}$°C	340	1.1	10.5	25.0	4.3
$MaxT_{-3}$-$MinT_{-3}$°C	340	1.1	10.1	25.0	4.1
$MaxT_{-1}$-$MinT_{0}$°C	334	-1.1	9.0	23.4	4.9
$MaxT_{-2}$-$MinT_{-1}$°C	337	-2.2	9.5	24.6	5.1
$MaxT_{-3}$-$MinT_{-2}$°C	338	-1.7	10.3	24.6	5.1
HS_{0}-HS_{-1} cm	340	-38.1	-3.4	2.6	3.9
HS_{0}-HS_{-2} cm	340	-38.1	-6.6	2.6	5.7
HS_{0}-HS_{-3} cm	340	-35.6	-7.3	27.9	8.2
$Stl_{0,-1}$ cm	340	-38.1	-3.4	2.6	3.9
$Stl_{0,-1,-2}$ cm	340	-38.1	-6.9	2.6	6.0
$Stl_{0,-1,-2,-3}$ cm	340	-50.8	-10.9	7.7	8.1
HNA_{0} days	342	2.0	4.2	16.0	2.6
HNA_{-1} days	342	1.0	3.2	15.0	2.6
HNA_{-2} days	342	0.0	2.2	14.0	2.6
HNA_{-3} days	342	0.0	2.0	13.0	2.5
HN_{0} cm	342	0.0	0.0	0.0	0.0
$HN_{0,-1}$ cm	342	0.0	0.0	0.0	0.0
$HN_{0,-1,-2}$ cm	342	0.0	3.1	66.0	6.7
$HN_{0,-1,-2,-3}$ cm	341	0.0	6.9	66.0	10.1
HNW_{0} cm	342	0.0	0.0	0.0	0.0
$HNW_{0,-1}$ cm	342	0.0	0.0	0.0	0.0
$HNW_{0,-1,-2}$ cm	337	0.0	0.2	3.8	0.6
$HNW_{0,-1,-2,-3}$ cm	334	0.0	0.5	3.8	0.8
HND_{0} kg/m^3	342	0.0	0.0	0.0	0.0
$HND_{0,-1}$ kg/m^3	342	0.0	0.0	0.0	0.0
$HND_{0,-1,-2}$ kg/m^3	337	0.0	24.7	266.7	45.8
$HND_{0,-1,-2,-3}$ kg/m^3	333	0.0	42.3	266.7	54.1

Table 5. New Snow Dataset – Predictor Variable Descriptive Statistics

Variable	**N**	**Minimum**	**Mean**	**Maximum**	**St. Dev.**
Day of Year	704	57	76	91.0	9.2
$MaxT_0$°C	701	-20.0	0.0	17.2	5.1
$MaxT_{-1}$°C	701	-17.2	0.7	19.4	5.5
$MaxT_{-2}$°C	698	-15.6	1.3	19.4	5.6
$MaxT_{-3}$°C	700	-20.0	1.4	19.4	5.7
$AvgMaxT_{0,-1}$°C	698	-18.6	0.4	15.0	4.8
$AvgMaxT_{0,-1,-2}$°C	693	-15.2	0.7	14.8	4.5
$AvgMaxT_{0,-1,-2,-3}$°C	690	-13.4	0.8	14.2	4.4
$MinT_0$°C	700	-26.1	-9.0	2.2	4.8
$MinT_{-1}$°C	700	-26.1	-8.3	5.6	5.0
$MinT_{-2}$°C	698	-24.4	-7.9	5.6	5.0
$MinT_{-3}$°C	699	-25.6	-8.0	5.6	5.0
$AvgMinT_{0,-1}$°C	696	-25.3	-8.7	1.7	4.4
$AvgMinT_{0,-1,-2}$°C	691	-24.6	-8.4	1.8	4.1
$AvgMinT_{0,-1,-2,-3}$°C	687	-23.7	-8.3	1.4	3.8
$AvgT_0$°C	700	-22.8	-4.5	7.8	4.5
$AvgT_{-1}$°C	700	-20.9	-3.8	10.6	4.8
$AvgT_{-2}$°C	698	-20.0	-3.3	10.6	4.9
$AvgT_{-3}$°C	699	-22.8	-3.3	10.6	5.0
$AvgAvgT_{0,-1}$°C	696	-21.1	-4.2	6.0	4.2
$AvgAvgT_{0,-1,-2}$°C	691	-19.9	-3.9	5.3	4.0
$AvgAvgT_{0,-1,-2,-3}$°C	687	-18.3	-3.7	5.1	3.8
$DDMaxT_0$°C	701	-20.0	0.0	17.2	5.1
$DDMaxT_{0,-1}$°C	698	-37.2	0.7	30.0	9.5
$DDMaxT_{0-1,-2}$°C	693	-45.6	2.0	44.4	13.6
$DDMaxT_{0,-1,-2,-3}$°C	690	-53.4	3.3	56.6	17.4
$DDAvgT_0$°C	700	-22.8	-4.5	7.8	4.5
$DDAvgT_{0,-1}$°C	696	-42.3	-8.3	11.9	8.5
$DDAvgT_{0,-1,-2}$°C	691	-59.7	-11.6	15.9	12.1
$DDAvgT_{0,-1-2,-3}$°C	687	-73.1	-15.0	20.4	15.3
$MaxT_0$-$MaxT_{-1}$°C	698	-17.3	-0.7	13.3	4.8
$MaxT_0$-$MaxT_{-2}$°C	695	-18.3	-1.3	16.7	5.9
$MaxT_0$-$MaxT_{-3}$°C	697	-22.2	-1.4	16.8	6.5
$MinT_0$-$MinT_{-1}$°C	696	-16.8	-0.7	15.5	4.4
$MinT_0$-$MinT_{-2}$°C	694	-20.2	-1.1	19.5	5.7
$MinT_0$-$MinT_{-3}$°C	695	-23.9	-1.0	21.7	6.1
$AvgT_0$-$AvgT_{-1}$°C	696	-12.9	-0.7	10.9	4.0
$AvgT_0$-$AvgT_{-2}$°C	694	-19.0	-1.2	16.2	5.2
$AvgT_0$-$AvgT_{-3}$°C	695	-23.1	-1.2	18.5	5.8
$MaxT_0$-$MinT_0$°C	701	0.0	9.0	25.0	4.2
$MaxT_{-1}$-$MinT_{-1}$°C	701	0.0	9.0	25.0	4.1
$MaxT_{-2}$-$MinT_{-2}$°C	699	0.0	9.2	27.7	4.1
$MaxT_{-3}$-$MinT_{-3}$°C	699	0.5	9.4	27.7	4.1
$MaxT_{-1}$-$MinT_0$°C	697	-4.4	9.7	28.8	5.5
$MaxT_{-2}$-$MinT_{-1}$°C	695	-4.4	9.6	28.8	5.5

Table 5. Continued

Variable	N	Minimum	Mean	Maximum	St. Dev.
$MaxT_{-3}$-$MinT_{-2}$°C	695	-4.4	9.3	28.8	5.4
HS_0-HS_{-1} cm	700	-33.1	2.9	91.4	9.8
HS_0-HS_{-2} cm	700	-45.7	5.7	91.4	13.0
HS_0-HS_{-3} cm	700	-45.7	7.4	91.4	15.2
$Stl_{0,-1}$ cm	697	-43.1	-4.3	28.0	5.2
$Stl_{0,-1,-2}$ cm	693	-55.8	-8.4	27.9	7.9
$Stl_{0,-1,-2,-3}$ cm	689	-76.1	-12.3	22.9	10.2
HNA_0 days	704	0.0	0.3	1.0	0.4
HNA_{-1} days	704	0.0	0.8	16.0	1.9
HNA_{-2} days	704	0.0	1.3	16.0	2.3
HNA_{-3} days	704	0.0	1.4	16.0	2.4
HN_0 cm	700	0.0	7.2	109.2	9.7
$HN_{0,-1}$ cm	696	0.0	14.4	116.8	13.7
$HN_{0,-1,-2}$ cm	692	0.0	20.2	124.4	17.3
$HN_{0,-1,-2,-3}$ cm	689	0.0	25.5	132.0	20.6
HNW_0 cm	688	0.0	0.5	8.8	0.8
$HNW_{0,-1}$ cm	679	0.0	1.1	9.1	1.1
$HNW_{0,-1,-2}$ cm	678	0.0	1.5	9.3	1.3
$HNW_{0,-1,-2,-3}$ cm	676	0.0	1.9	10.2	1.5
HND_0 kg/m^3	684	0.0	55.3	268.4	51.2
$HND_{0,-1}$ kg/m^3	671	0.0	79.0	266.7	42.6
$HND_{0,-1,-2}$ kg/m^3	666	0.0	80.9	266.7	40.5
$HND_{0,-1,-2,-3}$ kg/m^3	661	0.0	81.1	266.7	38.4

In order to better understand why the statistical approach described in the methods section was chosen, the distribution of several variables from the original dataset prior to transformation is provided in Figures 4 through 8. Each ‘Descriptive Statistics’ figure provides a list of descriptive statistics on the right and several descriptive graphs to the left including a histogram with the variable’s normality curve overlaid to assess its normality; a boxplot that summarizes information about the shape, dispersion and center of the variable; a 95% confidence interval for the mean (Mu or μ); and a 95% confidence interval for the variable’s median. See Appendix A for the descriptive statistics for all 68 variables in the original dataset (“Descriptive Statistics”).

The following explanation refers to Figure 4, but is applicable to Figures 5 through 8 as well as the remaining variables in Appendix A. Starting with the statistics listed on the right hand side (Fig. 4), the 'Anderson-Darling Normality Test' is commonly used to test a variable's distribution for normality. A-squared refers to the Anderson Darling statistic, which in this case, describes how well the data fits a normal distribution. The smaller the A-squared value, the more normally distributed the data are (Minitab, Inc., 2000). A p-value less than or equal to 0.05 indicates there is sufficient evidence that the data are not normally distributed and a p-value greater than 0.05 indicates that evidence exists for the normal distribution of the data. When all of the observations in the '$MaxT_0$' distribution are summed and divided by the total number of observations (N), the result is the mean. The standard deviation is one way to measure how spread out, or scattered, the data are. Squaring the standard deviation will provide the variance of the distribution. If the distribution of the data are not symmetric, the skewness value will be less than or greater than zero, depending on whether the data are skewed to the left (-) or to the right (+). The distribution of the prediction day maximum temperature ($MaxT_0$) from the original dataset appears to be almost normally distributed, but is slightly skewed to the left, therefore the skewness value is just below zero. The Kurtosis value describes how much the distribution's peakedness departs from that of a normal distribution. Distributions with sharper peaks, thinner shoulders and fatter tails than normally distributed data generally have positive Kurtosis values. Distributions with flatter peaks, fatter shoulders and thinner tails than normally distributed data, are generally given a negative Kurtosis value (MiniTab Inc., 2000). Minimum and maximum values are given next. When the data are plotted from its minimum value to its maximum value, the first 25% of the data are less than or equal to the 1^{st} quartile value. The first 50% of the data are less than or equal to the 2^{nd} quartile, or median, which is the value in the very center of the distribution. The first 75% of the data are less than or equal to the 3^{rd} quartile. The remaining 25% of the data are greater than or equal to the 3^{rd} quartile value and less than or equal to the maximum value. The 95% confidence interval for Mu (μ or mean) is bounded by the upper and lower values provided. This can be interpreted as 'we can be 95% confident that the true Mu (μ or mean) is captured within the lower and upper bounds of this interval'. The 95% confidence intervals for sigma (standard deviation) and the median are interpreted in the same manner. The first graph to the left of the column statistics is a histogram of the prediction day maximum temperature variable ($MaxT_0$) (Fig. 4) with its normality curve overlaid. If the data were normally distributed, all of the shaded columns would fit within the normality curve. The height of each column shows the relative frequency of each value on the X-axis. The box plot directly below the histogram uses the same scale and represents the same distribution in a different format. Here, the box with the 'whiskers' extending left and right represents the inner quartile range, or inner 50%, of the '$MaxT_0$' distribution. The 'whiskers' represent the outer 50% of the '$MaxT_0$' distribution. The left edge of the box is the 1^{st} quartile value and the right edge of the box is the 3^{rd} quartile value. Several outliers exist and are noted by the asterisks (*) beyond the whiskers. The mean and median of the '$MaxT_0$' distribution are captured within the inner quartile and their 95% confidence intervals are plotted in the diagonally-lined box plots. The true '$MaxT_0$'

mean lies within the diagonally-line 95% confidence interval for Mu box and the best estimate for the mean lies on the box's center line. The true 'MaxT_0' median lies within the diagonally-lined 95% confidence interval for median box and its best estimate is marked by the box's center line. Both plots share the same scale, 1.0^0C to 2.0^0C. Since 'MaxT_0' is only minimally skewed, the 95% confidence interval boxes for the mean and median are fairly in-line with one another.

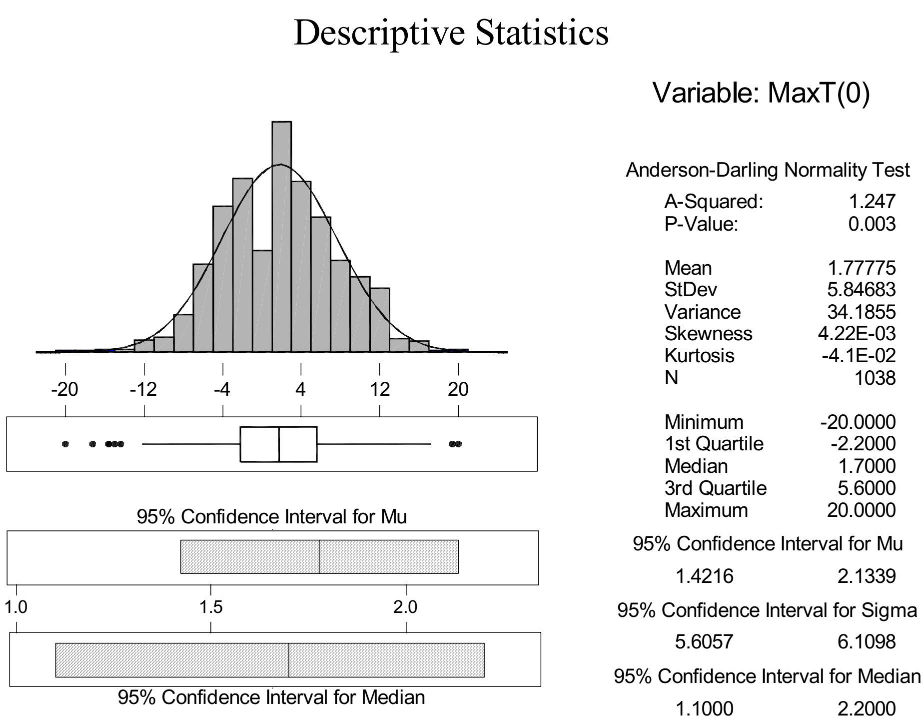

Figure 4. Original Dataset – Prediction Day Maximum Temperature Descriptive Statistics

The distribution of the 'day' of year variable is non-normal and this is evident by the gray bars extending beyond the black normal distribution curve (Fig. 5). In some cases when a wet avalanche day occurred on March 1st (day 60), days 57-59 were needed to calculate certain 'pre-day' variables, but because this did not occur frequently the number of days plotted in the histogram drop off quickly for days prior to day 60. The number of days greater than day 90 (March 31st) drop off quickly as well because March 31st becomes day 91 in a leap year. The lack of asterisks (*) in the box plot below the histogram indicate that no outliers exist for this variable. The relative symmetry of this distribution is evident in the way the 95% confidence interval boxes for the mean and median line up.

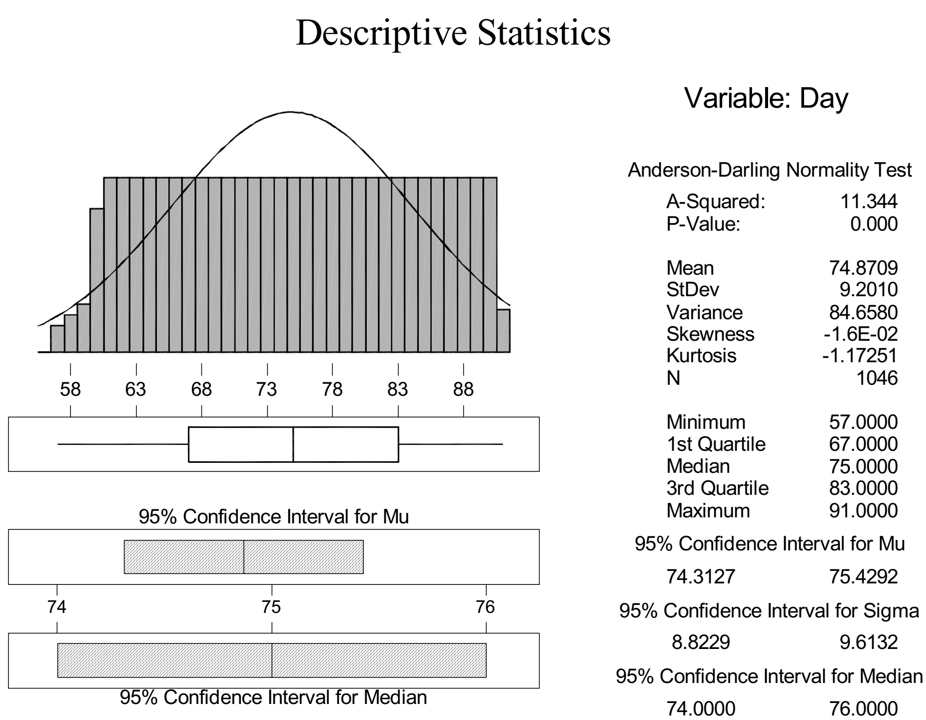

Figure 5. Original Dataset - 'Day' of Year Descriptive Statistics

The prediction day minimum temperature ($MinT_0$) distribution from the original dataset is more skewed, this time to the right (Fig. 6). This right-sided shift of the data have created a longer left side tail with outliers marked on the box plot below. The increased skewness has increased the range for the mean and median 95% confidence intervals and has reduced the overlapping of the boxes.

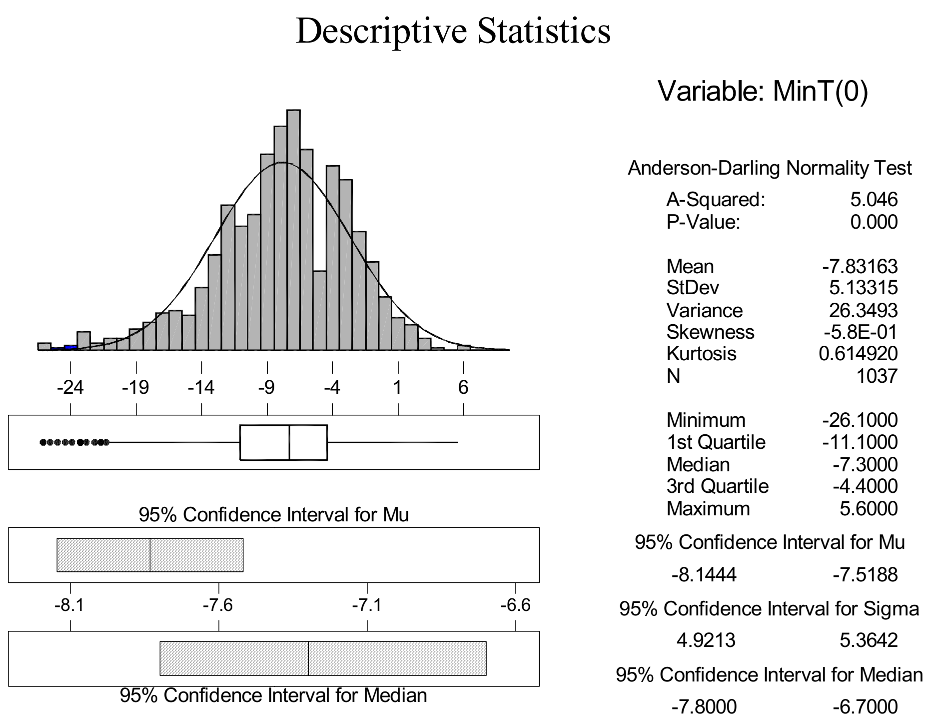

Figure 6. Original Dataset – Prediction Day Minimum Temperature Descriptive Statistics

The distribution for the overnight temperature range prior to the prediction day ($MaxT_{-1}$-$MinT_0$) (Fig. 7) is nearly opposite of the prediction day minimum temperature distribution described above (Fig. 6). This data are skewed to the left of its normal distribution curve and has a long right hand tail with outliers noted in the right hand side of the box plot below. As before, the mean 95% confidence interval box is skewed in the direction of the outliers while the median confidence interval box is in the direction of the most frequent observations.

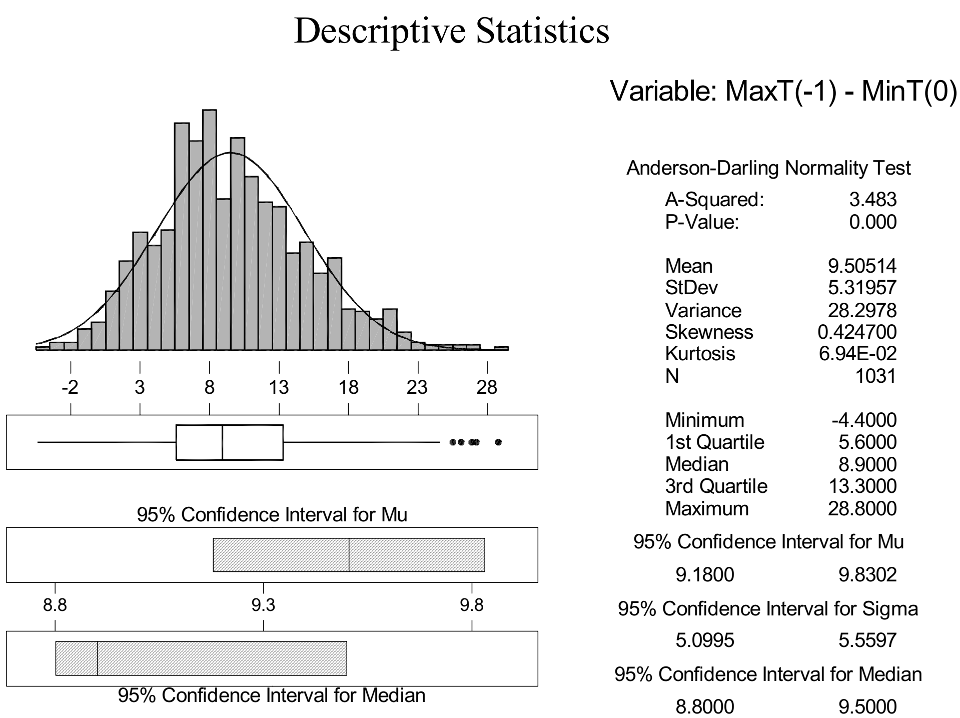

Figure 7. Original Dataset – Prediction Day Overnight Temperature Range Descriptive Statistics

The distribution for the cumulative new snow water equivalent (SWE) over the three days leading up to and including the prediction day ($HNW_{0,-1,-2,-3}$) is the most highly skewed of the examples provided above (Fig. 8). This is evident in the shortened left whisker and elongated right whisker with far reaching outliers that extend beyond in the box plot below the histogram. The skewness has also pushed the 95% confidence interval boxes for the mean and median to opposite ends of the range.

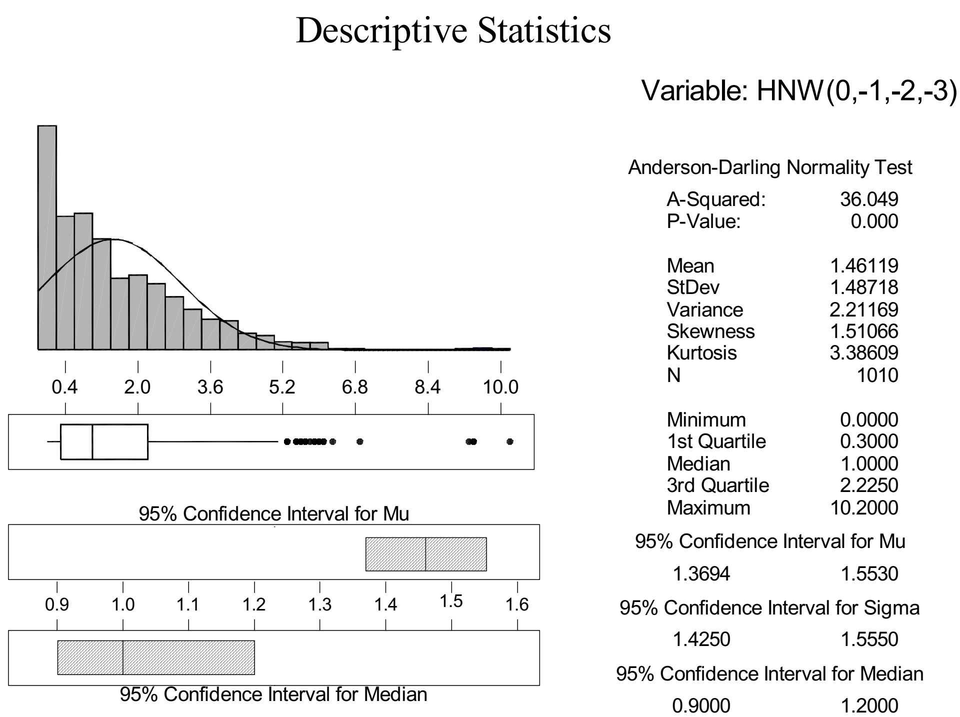

Figure 8. Original Dataset – Three Day Cumulative New SWE Descriptive Statistic

Figures 4 through 8 illustrate that the data in the original dataset are not always normally distributed, and statistical tests of wet avalanche occurrence in March cannot be made with the data in its current state because wet avalanche days are not distinguished from days with no wet avalanches.

Figures 9 and 10 show the distribution of the prediction day maximum temperature (Fig. 9) and the distribution of the prediction day minimum temperature (Fig. 10) from the original dataset, this time as they relate to observed wet avalanche days in the dataset. The light bars in Figure 9 represent the prediction day maximum temperature frequency (this is the same distribution shown in Figure 4, but with the upper and lower tails removed). The black bars represent the number of wet avalanches that occurred at a given temperature. For example, there were approximately 90 days with a maximum temperature of 1°C recorded in the original dataset. At this same temperature, roughly 32 wet avalanches released and were recorded. The black triangles represent the proportion, given as percentages, of days at a given temperature that had recorded wet avalanche occurrence. Using 1°C maximum temperature as an example, there were 90 days in the dataset with this maximum temperature, six of those 90 days produced a total of 32 wet avalanches. The six wet avalanche days make up 7% of the 90 days with a maximum temperature of 1°C. Since 1968, wet avalanches have been recorded on days with a maximum temperature ranging from -8°C to 15°C. The highest frequencies tend to occur between -1°C and 12°C, and the proportion of wet avalanche days tend to increase as the maximum temperature increases, but the temperature thresholds are not clear and the proportion pattern is not strong.

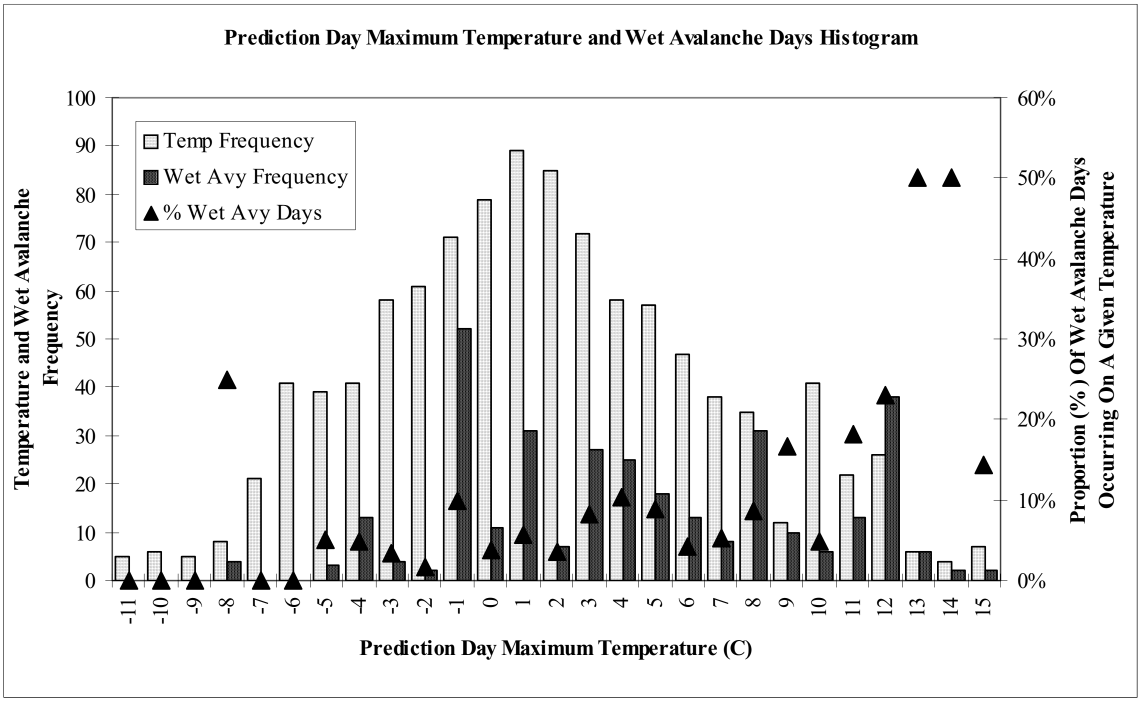

Figure 9. Original Dataset – Prediction Day Maximum Temperature and Wet Avalanche Day Distribution

The interpretation for the prediction day minimum temperature and wet avalanche day distributions (Fig. 10) is the same as that described for Figure 9. In the past, wet avalanches have been recorded on days with minimum temperatures ranging from -20°C to 3°C. Most of these avalanches released when minimum temperatures were between -9°C and 3°C. The proportion of wet avalanche days tends to rise sharply as the minimum temperature increases from -10°C to -9°C and drop off sharply from 3°C to 4°C.

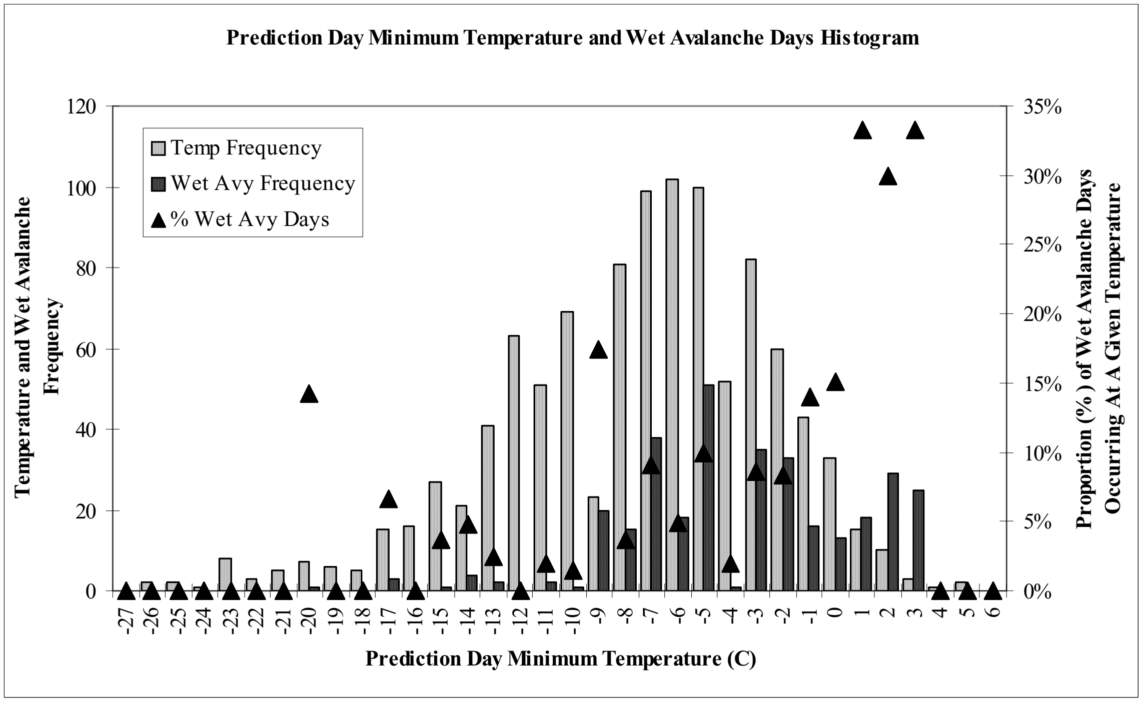

Figure 10. Original Dataset – Prediction Day Minimum Temperature and Wet Avalanche Day Distribution.

Plotting the wet avalanche days separately in Figures 9 and 10 provides a great deal more information about the prediction day maximum and minimum variables than the simple plots given in the "Descriptive Statistics" figures above. However, the ranges for both temperature variables are fairly wide and it is impossible to determine for certain if and how new snow wet avalanche distributions may vary from old snow wet avalanche distributions. To see more clearly the patterns and associations for each variable, more statistical tests are needed. These tests were described in the methods section and results are presented in the discussion section.

DISCUSSION

Data Analysis – Hypothesis Testing

Old Snow Dataset Hypothesis Testing Results

The results of the appropriate means (2-Sample T-Test) or medians (Mann-Whitney) tests for the significant old snow variables determined for the first hypothesis question (H_0: $\mu_{0old} = \mu_{1old}$ vs. H_1: $\mu_{0old} \neq \mu_{1old}$) are provided in Table 6. The means and medians are in their original non-transformed state for comparison purposes. See Appendix A for variable definitions ("Definitions") and Appendix B for means and medians tests for all of the old snow variables ("Old Snow Hypothesis Testing Results").

Table 6. Old Snow Dataset – Hypothesis Testing Results, Significant Variables Only

Variable	**Test**	**Wet Avalanche Day Mean or Median**	**No-Wet-Avalanche Day Mean or Median**	**Wet Avalanche Day – No-Wet-Avalanche Day**	**P-Value**
Day	Mann-Whitney	Day 78	Day 72	6 days	0.007
$MaxT_0$*	2-Sample T-Test	9.1°C	5.1°C	4.0°C	0.000
$MaxT_{-1}$	Mann-Whitney	7.2°C	3.3°C	3.9°C	0.001
$MaxT_{-2}$	Mann-Whitney	4.4°C	2.2°C	2.2°C	0.042
$AvgMaxT_{0,-1}$	Mann-Whitney	8.9°C	4.5°C	4.4°C	0.000
$AvgMaxT_{0,-1,-2}$*	2-Sample T-Test	6.8°C	3.5°C	3.3°C	0.000
$AvgMaxT_{0,-1,-2,-3}$	Mann-Whitney	6.8°C	3.0°C	3.8°C	0.001
$MinT_0$	Mann-Whitney	-1.1°C	-5.0°C	3.9°C	0.000
$MinT_{-1}$*	2-Sample T-Test	-4.2°C	-7.4°C	3.2°C	0.001
$MinT_{-2}$*	2-Sample T-Test	-5.7°C	-8.4°C	2.7°C	0.007
$AvgMinT_{0,-1}$*	2-Sample T-Test	-3.5°C	-6.6°C	3.1°C	0.000
$AvgMinT_{0,-1,-2}$*	2-Sample T-Test	-4.2°C	-7.2°C	3.0°C	0.000
$AvgMinT_{0,-1,-2,-3}$*	2-Sample T-Test	-4.8°C	-7.4°C	2.6°C	0.001
$AvgT_0$*	2-Sample T-Test	3.2°C	-0.3°C	3.5°C	0.000
$AvgT_{-1}$*	2-Sample T-Test	1.3°C	-2.0°C	4.3°C	0.000
$AvgT_{-2}$*	2-Sample T-Test	-0.6°C	-3.1°C	2.5°C	0.009

Table 6. Continued

Variable	**Test**	**Wet Avalanche Day Mean or Median**	**No-Wet-Avalanche Day Mean or Median**	**Wet Avalanche Day – No-Wet-Avalanche Day**	**P-Value**
$AvgAvgT_{0,-1}$*	2-Sample T-Test	2.2°C	-1.2°C	3.4°C	0.000
$AvgAvgT_{0,-1,-2}$*	2-Sample T-Test	1.3°C	-1.9°C	3.2°C	0.000
$AvgAvgT_{0,-1,-2,-3}$*	2-Sample T-Test	0.6°C	-2.2°C	2.8°C	0.000
$DDMaxT_{0}$*	2-Sample T-Test	9.1°C	5.1°C	4.0°C	0.000
$DDMaxT_{0,-1}$*	2-Sample T-Test	15.9°C	8.4°C	7.5°C	0.000
$DDMaxT_{0,-1,-2}$*	2-Sample T-Test	20.5°C	10.4°C	10.1°C	0.000
$DDMaxT_{0,-1,-2,-3}$*	2-Sample T-Test	23.8°C	12.4°C	11.4°C	0.001
$DDAvgT_{0}$*	2-Sample T-Test	3.2°C	-0.3°C	3.5°C	0.000
$DDAvgT_{0,-1}$*	2-Sample T-Test	4.5°C	-2.4°C	6.9°C	0.000
$DDAvgT_{0,-1,-2}$*	2-Sample T-Test	3.9°C	-5.6°C	9.5°C	0.000
$DDAvgT_{0,-1,-2,-3}$*	2-Sample T-Test	2.4°C	-8.7°C	11.1°C	0.000
HS_{0}-HS_{-1}	Mann-Whitney	-5.1cm	-2.5cm	-2.6cm	0.002
HS_{0}-HS_{-2}	Mann-Whitney	-10.2cm	-5.1cm	-5.1cm	0.000
HS_{0}-HS_{-3}	Mann-Whitney	-10.2cm	-7.6cm	-2.6cm	0.000
$Stl_{0,-1}$	Mann-Whitney	-5.1cm	-2.5cm	-2.6cm	0.002
$Stl_{0,-1,-2}$	Mann-Whitney	-10.2cm	-5.1cm	-5.1cm	0.000
$Stl_{0,-1,-2,-3}$	Mann-Whitney	-15.2cm	-7.9cm	-7.3cm	0.000

All 2-Sample T-Tests used pooled sample variance
* Variable was transformed – see Appendix B for λ value

Old Snow Temperature Variables The 'day' of year variable is a proxy for available incoming radiation. The difference between the old snow 'day' of year median for wet avalanche days and days with no wet avalanches (Table 6) is somewhat misleading. A histogram of wet avalanche days and 'day' of year better illustrates the pattern of wet avalanche release (Fig. 11). Wet avalanche occurrence tends to increase as the day of year increases. The results agree with the a priori hypothesis that as the day of the year increases and moves closer to the summer solstice, the amount of energy available to melt snow and create wet avalanche conditions increases. The slight drop in wet avalanche activity at the end of the month may reflect the fact that most of the unstable wet snow has already released and the remaining snowpack has become well-drained.

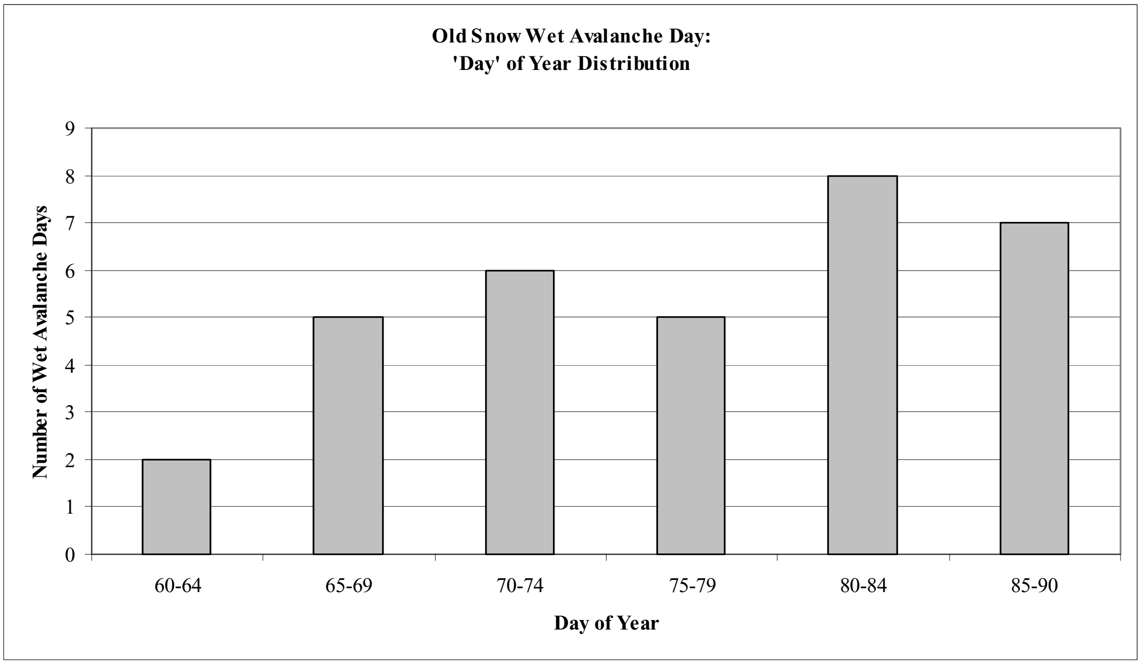

Figure 11. Old Snow Dataset – Wet Avalanche Day ‘Day’ of Year Distribution

Changes in the prediction day, one day prior, and two days prior maximum temperatures ($MaxT_0$, $MaxT_{-1}$, $MaxT_{-2}$) are interesting in that there is a 3°C and 2°C daily increase in the maximum temperature leading up to a wet avalanche day where as the increase in temperature leading up to a day with no wet avalanches is only approximately 1°C and 2°C increase per day (Table 6). The difference between the maximum temperatures leading up to a wet avalanche day and a day with no wet avalanches range from 2°C and 4°C. One day prior, two days prior and three days prior average maximum temperatures ($AvgMaxT_{0,-1}$, $AvgMaxT_{0,-1,-2}$, $AvgMaxT_{0,-1,-2,-3}$) for wet avalanche days are all well above 0°C and are at least 3°C warmer than the one day prior, two days prior, and three days prior average maximum temperatures for no-wet-avalanche days. These changes in temperature agree with previous studies that describe temperature as a component of the radiation regime and an index of the energy available to melt snow (Armstrong, 1976; Kattelmann, et al., 1998). Warmer temperatures and periods of prolonged heating (in this case, three days including the prediction day) increase the probability of deep wet snow instability (McClung and Schaerer, 1993). A prolonged period of warming is especially important for wet snow instability in old snow (Table 6). As snow densifies with age, permeability decreases, which in turn reduces the ability of liquid water to transmit through the snowpack (Colbeck, 1979). This can result in the liquid water pooling above a dense layer, which can quickly lead to cohesionless wet snow.

Old snow prediction day, one day prior, and two days prior minimum temperature variables ($MinT_0$, $MinT_{-1}$, $MinT_{-2}$) follow similar changes in temperature for wet avalanche days and no-wet-avalanche days, but wet avalanche days are approximately 3°C to 4°C warmer each day and reach -1°C by the prediction day whereas no-wet-avalanche prediction day minimum temperatures only reach –5°C on average (Table 6). Average minimum temperature variables ($AvgMinT_{0,-1}$, $AvgMinT_{0,-1,-2}$, $AvgMinT_{0,-1,-2,-3}$) have similar temperature changes as well, increasing less than 1°C per day, but wet avalanche day temperatures are on average about 3°C warmer each day than days with no wet avalanches. The warmer minimum temperatures occurring on and leading up to wet avalanche days likely results from warm cloudy nights that minimize radiative cooling of the snowpack. The loss of heat through cooling creates what Cline

(1997) and others have termed a ‘heat deficit’ in the snowpack. Before snowmelt can begin on a given day, “any energy deficit from the previous night (resulting in either refreezing of meltwater, cooling of the snowpack, or both) must first be satisfied” (Cline, 1997, p.44). Mild temperatures at night reduce the amount of energy needed to satisfy the ‘heat deficit’ in the snowpack the following day before melting can take place. Cloudy nights will capture longwave radiation emitted by the snowpack and transmit some of the radiation back into the snowpack. Because snow is so opaque to the thermal infrared wavelength, radiation emitted by one grain is absorbed by the neighboring grain resulting in the warming of subsurface snow while only the very topmost grains will lose heat to space (Brandt and Warren, 1993). Successive 24 hour periods with warm minimum temperatures is an important element to old snow wet avalanche conditions because it provides for a relatively warm snowpack temperature regime which requires only minimal amounts of heat to be consumed during the day to raise the temperature of the snow to 0°C which will create conditions for rapid melt and subsequent percolation of free water (Armstrong, 1976).

Old snow average and averaged average temperature variables ($AvgT_0$, $AvgT_{-1}$, $AvgT_{-2}$, $AvgAvgT_{0,-1}$, $AvgAvgT_{0,-1,-2}$, $AvgAvgT_{0,-1,-2,-3}$) are nearly 0°C or above for each day leading up to and including the prediction day on wet avalanche days, but are below 0°C for days with no wet avalanches (Table 6). Warm average and averaged average temperatures ranging from –0.6°C to 3.2°C can result from a variety of conditions such as mild maximum temperatures and warm minimum temperatures, warm maximum and minimum temperatures, or a combination of the above. Mild maximum temperatures and warm minimum temperatures often form under cloudy conditions. Under low cloud conditions, sunlight can penetrate through the clouds to warm the snow cover, but the longwave radiation emitted by the snow cover cannot escape through the clouds creating a 'greenhouse effect' (McClung and Schaerer, 1993). Obled and Harder (1978) found that incoming global radiation can be two times as great for a surface with a low albedo to longwave radiation, such as snow, because of reflection and back scattering between the snow surface and clouds. Warm average and averaged temperatures can also form under very warm maximum temperatures and very cool minimal temperatures indicating clear sky conditions and intense radiation during the day. Average temperatures are not necessarily required to be above zero for wet snow conditions to be present. Temperature is only a portion of the total energy input at the snow surface, which includes downward solar radiation, downward thermal infrared radiation, turbulent exchange of sensible and latent heat, and conduction of heat through the snow (Brandt and Warren, 1993).

> "Incident solar, shortwave, radiation penetrates to considerable depth in snow, whereas the cooling by emission of thermal infrared and longwave radiation to space only occurs at the very upper surface of the snowpack… Shortwave heating at depth with longwave cooling at the surface causes a temperature gradient to support a conductive heat flux upward toward the surface" (Brandt and Warren, 1993, p.99).

Ambach and Howorka (1966) found that average temperature is proportional to the daily free water content of the snow cover. It follows then, that as the average daily temperature increase, the daily mean free water content of the snowcover increases and the probability of wet avalanche conditions increase as well. As before, successive 24 hour periods with warm average temperatures will allow for a relatively warm snowpack temperature regime that requires only minimal amounts of heat to be consumed during the day to raise the temperature of the snow to 0°C (Armstrong, 1976).

The degree day variables ($DDMaxT_0$, $DDMaxT_{0,-1}$, $DDMaxT_{0,-1,-2}$, $DDMaxT_{0,-1,-2,-3}$) are one way to describe how far the maximum temperature departed from 0°C during the day and each successive prior day describes how great the cumulative departure was from 0°C (Rango and Martinec, 1995). The mean cumulative degree day value for wet avalanche days is nearly twice that of no-wet-avalanche days (Table 6). This is supported by findings described by Rango and Martinec (1995) that degree days are directly proportional to snowmelt depth. The degree day value increases as the snow becomes wet, and the decreasing albedo enhances the heat gain from the increasing solar radiation penetration, which in turn, increases the depth of snow melt. Successive 24 hour periods with increasing degree day values will enhance the snow melt process. Older wet snow with higher density has a lower albedo and a higher liquid water content, so each degree day becomes more melt-efficient (Rango and Martinec, 1995).

The degree day variables using average temperature ($DDAvgT_0$, $DDAvgT_{0,-1}$, $DDAvgT_{0,-1,-2}$, $DDAvgT_{0,-1,-2,-3}$) is a common alternative to using maximum temperature in the degree day calculations. It describes how far the average temperature departed from 0°C and in the case of the one day prior and two days prior variables, the cumulative departure from 0°C (Rango and Martinec, 1995). On average, the difference between wet avalanche day and no-wet-avalanche day degree day values range from 3.5°C to 11.1°C (Table 6). Wet avalanche day degree day variable means are all positive on wet avalanche days and all negative for days with no wet avalanches. The results agree with the findings in Rango and Martinec (1995) discussed above.

Old Snow Snowpack Settlement Variables The one day, two day and three day change in total snow depth (HS_0-HS_{-1}, HS_0-HS_{-2}, HS_0-HS_{-3}) for wet avalanche days is nearly twice as great as the change on days with no wet avalanches (Table 6). On average, the total snow depth decreases by 5cm between the one day prior and the wet avalanche prediction day, and about 10cm between two days prior and the prediction day as well as three days prior and the prediction day. The change in total snow depth variables take into account the addition of new snow, the overall settlement of the snowpack and other factors such as ablation that might contribute to the overall change in total snow depth. The rapid decreases in HS_0-HS_{-1}, HS_0-HS_{-2}, and HS_0-HS_{-3} that lead up to observed wet avalanches indicate snow settlement, which is a response to the presence of free water within the snowpack (Armstrong, 1976).

One day, two day and three day cumulative settlement variables ($Stl_{0,-1}$, $Stl_{0,-1,-2}$, $Stl_{0,-1,-2,-3}$) are similar to the one day, two day and three day total snow depth change variables described above, except new snowfall amounts are subtracted so that the settlement variable represents only those factors that lead to the decrease in total snowpack depth such as melt, densification and ablation (see Appendix A for variable definitions). Because old snow is defined as those days with no new recorded snowfall for at least 48 hours prior to the prediction day, this settlement variable is very similar to the total change in snow depth variable. Settlement rates are two times as great on wet avalanche days than they are on days with no wet avalanches. On average, the snowpack settles 5cm one day prior to an observed wet avalanche day; 10cm over the two days prior to a wet avalanche day; and 15cm over the three days leading up to a wet avalanche day. The snowpack responds to the presence of water by settling (Armstrong, 1976) and rapid settlement rates are associated with wet avalanche activity (McClung and Schaerer, 1993). In general, settlement increases densification and strength, however "local concentrations of water content can produce important decreases in strength. Such decreases raise the chance of slip or glide, which adversely affect stability" (McClung and Schaerer, 1993). As density increases, the snow albedo decreases and energy is absorbed more efficiently, which allows for wet unstable conditions to develop rapidly (McClung and Schaerer, 1993).

Old Snow Dataset Summary Old snow wet avalanche conditions have 33 significant predictor variables, 27 of which are temperature and snowpack settlement related and six variables are related to snowpack settlement (Table 6). It was found that prediction day, one day prior and two day prior variables were significant for all temperature related variables and in many cases, the third day prior to the prediction day was significant as well. All temperature variables showed relatively strong temperature increases that lead up to the wet avalanche day. All maximum temperature related variables were well above 0°C, minimum temperature related variables were all within -6°C of freezing and warmed near freezing on the prediction day; all average temperature related variables remained just slightly below or above 0°C over the prediction day, one day prior, two days prior and three days prior time period. Total snow depth change variables and total snow settlement variables were all similar and averaged 5cm to 10cm of snow depth change over the variables' time period.

New Snow Dataset Hypothesis Testing Results

New snow hypothesis testing results show eleven fewer significant variables than the old snow hypothesis testing results (Table 6 and Table 7). The results of the appropriate means (2-Sample T-Test) or medians (Mann-Whitney) tests for the significant new snow variables determined for the first hypothesis question are provided in Table 7. The means and medians are in their original non-transformed state for comparison purposes. See Appendix A for variable definitions ("Definitions") and Appendix B for means and medians tests for all of the new snow variables ("New Snow Hypothesis Testing Results").

Table 7. New Snow Dataset – Hypothesis Testing Results, Significant Variables Only

Variable	**Test**	**Wet Avalanche Day Mean or Median**	**No-Wet-Avalanche Day Mean or Median**	**Wet Avalanche Day – No-Wet-Avalanche Day**	**P-Value**
$MinT_0$	Mann-Whitney	-7.6°C	-8.9°C	1.3°C	0.005
$AvgMinT_{0,-1}$*	2-Sample T-Test	-7.3°C	-8.8°C	1.5°C	0.036
$AvgT_0$*	2-Sample T-Test	-2.9°C	-4.6°C	1.7°C	0.005
$DDAvgT_0$*	2-Sample T-Test	-2.9°C	-4.6°C	1.7°C	0.005
$MaxT_0$-$MaxT_{-2}$	2-Sample T-Test	0.5°C	-1.4°C	1.9°C	0.049
$MinT_0$-$MinT_{-1}$	Mann-Whitney	1.1°C	-1.1°C	2.2°C	0.013
$MinT_0$-$MinT_{-2}$	Mann-Whitney	1.1°C	-1.1°C	2.2°C	0.005
$MinT_0$-$MinT_{-3}$*	Mann-Whitney	1.9°C	-1.1°C	3.0°C	0.005
$AvgT_0$-$AvgT_{-1}$	2-Sample T-Test	0.8°C	-0.8°C	1.6°C	0.016
$AvgT_0$-$AvgT_{-2}$	2-Sample T-Test	0.9°C	-1.3°C	2.2°C	0.012
$AvgT_0$-$AvgT_{-3}$	2-Sample T-Test	0.8°C	-1.3°C	2.1°C	0.029
$MaxT_{-1}$-$MinT_0$	2-Sample T-Test	7.3°C	9.9°C	-2.6°C	0.001
$Stl_{0,-1}$	Mann-Whitney	-5.1cm	-2.6cm	2.5cm	0.008
$Stl_{0,-1,-2}$	Mann-Whitney	-10.2cm	-7.5cm	2.7cm	0.003
$Stl_{0,-1,-2,-3}$	Mann-Whitney	-15.3cm	-10.2cm	5.1cm	0.018
$HN_{0,-1,-2}$	Mann-Whitney	21.7cm	15.2cm	6.5cm	0.003

Table 7. Continued

Variable	Test	Wet Avalanche Day Mean or Median	No-Wet-Avalanche Day Mean or Median	Wet Avalanche Day – No-Wet-Avalanche Day	P-Value
$HN_{0,-1,-2,-3}$	Mann-Whitney	32.4cm	20.3cm	12.1cm	0.002
$HNW_{0,-1}$	Mann-Whitney	1.3cm	0.8cm	0.5cm	0.010
$HNW_{0,-1,-2}$	Mann-Whitney	1.9cm	1.2cm	0.7cm	0.000
$HNW_{0,-1,-2,-3}$	Mann-Whitney	2.6cm	1.5cm	1.1cm	0.000
$HND_{0,-1}$	Mann-Whitney	93.1kg/m^3	74.5 kg/m^3	18.6kg/m^3	0.023
$HND_{0,-1,-3}$	Mann-Whitney	93.1kg/m^3	75.9kg/m^3	17.2 kg/m^3	0.029

All 2-Sample T-Tests used pooled sample variance, except '$AvgT_0$' and '$DDAvgT_0$' used unpooled sample variance.
* Variable was transformed – see Appendix B for λ value

New Snow Temperature Variables New snow prediction day minimum and one day average minimum temperatures ($MinT_0$, $AvgMinT_{0,-1}$) are significantly different for wet avalanche days and no-wet-avalanche days (Table 7). Mean values for prediction day minimum ($MinT_0$) and one day average temperatures ($AvgMinT_{0,-1}$) are nearly the same on wet avalanche days at –7.6°C and –7.3°C respectively and were approximately 1.5°C warmer than mean prediction minimum and one day average minimum temperatures on no-wet-avalanche days at –8.9°C and –8.8°C respectively. The slightly warmer minimum temperatures on wet avalanche days help to reduce the amount of 'heat deficit' in the snowpack that needs to be compensated for the following day before melting can take place (Cline, 1997).

New snow prediction day average temperature ($AvgT_0$) and the prediction day degree day variable ($DDAvgT_0$) are on average 1.7°C warmer on wet avalanche days than for days with no wet avalanches, but both remain below 0°C (Table 7). These mild average temperatures may form under cloudy conditions, or under sunny conditions that develop after a new snowfall event. Cloudy conditions required for snowfall will reradiate some outgoing longwave radiation and keep minimum temperatures warm. Warm minimum temperatures and mild maximum temperatures explain the subfreezing average temperatures. Rango and Martinec (1995, p.664) state “snowmelt by radiation can take place at temperatures slightly below 0°C and that there may be melt taking place on days when the average temperature is ≤0°C”. Wet snow instability under new snow conditions is driven by the fine-grained snow crystals and lack of bonds within the new snow matrix. The fine-grained snow crystals tend to retain liquid water more readily because of increased surface tension associated with the increased surface area within the new snow matrix. As more liquid water is retained within a new snow layer, the bonds that do exist within the snow matrix are quickly melted resulting in cohesionless new snow.

The difference between the prediction day maximum temperature and the two days prior maximum temperature ($MaxT_0$-$MaxT_{-2}$) is approximately 2°C greater on wet avalanche days than it is on days with no wet avalanches (Table 7). The $MaxT_0$-$MaxT_{-2}$ for wet avalanche days is 0.5°C while the mean for no-wet-avalanche days is –1.4°C. The positive value occurring on wet avalanche days indicates that in the past, the prediction day maximum temperature is slightly warmer than two days prior maximum temperature. The negative value for the days with no wet avalanches indicates that in the past the minimum temperature on the prediction day is 1.4°C cooler on average than the two days prior maximum temperature.

The differences between wet avalanche day and no-wet-avalanche day minimum temperature range variables ($MinT_0$-$MinT_{-1}$, $MinT_0$-$MinT_{-2}$, and $MinT_0$-$MinT_{-3}$) are approximately 2°C and 3°C with all wet avalanche day temperature ranges positive and all ranges negative for days with no wet avalanches (Table 7). Both wet avalanche day and no-wet-avalanche day temperature ranges change very little if at all. The key difference is that the positive values for wet avalanche days indicate warming occurs prior to a wet avalanche day and there is a reduction in the amount of energy that is required to raise the snowpack temperature to 0°C before melt. Days with no wet avalanches have negative temperature ranges indicating that the prediction day is cooler than each preceding day, which means that each day, more energy is required for the snow to be warmed to 0°C.

The average temperature range variables ($AvgT_0$-$AvgT_{-1}$, $AvgT_0$-$AvgT_{-2}$, $AvgT_0$-$AvgT_{-3}$) provide very similar results (Table 7). Mean wet avalanche day ranges are roughly 2°C warmer than no-wet-avalanche day average temperature ranges. Wet avalanche day means approach 1°C while no-wet-avalanche day means are centered around -1°C. Wet avalanche day values are very stable suggesting that new snow wet avalanche conditions develop when mild conditions persist for several days. Days with no wet avalanche conditions are also very stable, with the mean average temperature increasing slightly between the $AvgT_0$-$AvgT_{-1}$ and $AvgT_0$-$AvgT_{-2}$ variables.

The overnight temperature range prior to the prediction day ($MaxT_{-1}$-$MinT_0$) as expected, is less for the night before a wet avalanche day (Table 7). The evening before a wet avalanche day cools approximately 7.3°C while the night before a day with no wet avalanches cools 9.9°C, a difference of 2.6°C.

<u>New Snow Snowpack Settlement Variables</u> An increased one day, two day and three day settlement rate ($Stl_{0,-1}$, $Stl_{0,-1,-2}$, $Stl_{0,-1,-2,-3}$) has occurred on wet avalanche days in the past (Table 7). On average, about 5cm of settlement occurs each day leading up to the wet avalanche day and only 3cm or 4cm usually occurs prior to a day with no wet avalanches. Settlement is one way in which the snowpack responds to the presence of free water (Armstrong, 1976) and is associated with increased wet avalanche activity (McClung and Schaerer, 1993). Settlement generally increases snow densification and strength, but "local concentrations of water content can produce important decreases in strength. Such decreases raise the chances of slip or glide, which adversely affect stability" (McClung and Schaerer, 1997, p.157).

<u>New Snow Precipitation Variables</u> Two and three day cumulative new snow depths prior to wet avalanche days ($HN_{0,-1,-2}$, $HN_{0,-1,-2,-3}$) were on average 6.5cm and 12cm greater than two and three day cumulative new snow depth prior to no-wet-avalanche days (Table 7). Average new snow accumulation rates for the $HN_{0,-1,-2}$ and $HN_{0,-1,-2,-3}$ variables are approximately 7.0 cm/day and 8.0 cm/day respectively for wet avalanche days and 5.0cm/day for days with no wet avalanches. Quickly accumulating new snow under relatively warm conditions has little time to form bonds and can loose cohesion at lower liquid water contents than older, more well bonded snow (McClung and Schaerer, 1993). Wet avalanche days have 0.5cm to 1.1cm more one day, two day and three day cumulative new snow water equivalent ($HNW_{0,-1}$, $HNW_{0,-1,-2}$, $HNW_{0,-1,-2,-3}$) values than no-wet-avalanche days (Table 7). This equates to a 0.6cm/day and 0.7cm/day

new snow water equivalent accumulation rate for wet avalanche days and a steady rate of 0.4cm/day for days with no wet avalanches.

Wet avalanche days have had average one and three day cumulative new snow densities ($HND_{0,-1}$, $HND_{0,-1,-2,-3}$) that are approximately 17.2kg/m^3 to 18.6 kg/m^3 greater than no-wet-avalanche days (Table 7). This is to be expected when one considers the higher new snowfall depths and greater new snow water equivalencies that have historically occurred on and leading up to wet avalanche days. As density increases, the snow albedo decreases, which allows for more absorption of solar radiation by the snowpack.

New Snow Dataset Summary New snow wet avalanche conditions have 22 significant predictor variables; 12 are temperature related, three are related to snowpack settlement, and the remaining seven are precipitation variables (Table 7). The distinction between new snow wet avalanche days and days with no wet avalanches lie in the slight differences in temperature where maximum, minimum and average temperatures as well as their multiple temperature ranges are only 1°C or 2°C warmer on wet avalanche days. The key difference seems to be larger than average, wetter than average and denser than average snowfalls that precipitate under slightly warmer conditions. New snow requires less time and energy for wet avalanche development primarily because new snow is finer-grained and retains water more easily. New snow also has fewer, smaller and weaker grain to grain contacts, and can fail at a lower water content than snow with greater initial strength, such as old snow (McClung and Schaerer, 1993).

Old Snow and New Snow Wet Avalanche Day
Hypothesis Testing Results

The results of the second hypothesis question provide information on if and how old snow wet avalanche conditions differ from new snow wet avalanche conditions (Table 8). Only those variables with significantly different old snow and new snow means or medians are included in this table. The means and medians are in their original non-transformed state for comparison purposes. See Appendix B for means and medians tests for all of the old snow and new snow wet avalanche day variables ("Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results").

Table 8. Old Snow vs. New Snow Wet Avalanche Days - Hypothesis Testing Results Significant Variables Only

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	P-Value
$MaxT_0$	2-Sample T-Test	9.1°C	1.1°C	8°C	0.000
$MaxT_{-1}$	2-Sample T-Test	6.9°C	0.4°C	6.5°C	0.000
$MaxT_{-2}$	2-Sample T-Test	4.5°C	0.5°C	4°C	0.004
$AvgMaxT_{0,-1}$	2-Sample T-Test	8.0°C	0.7°C	7.3°C	0.000
$AvgMaxT_{0,-1,-2}$	2-Sample T-Test	6.8°C	0.7°C	6.1°C	0.000
$AvgMaxT_{0,-1,-2,-3}$	2-Sample T-Test	6.0°C	0.8°C	5.2°C	0.000
$MinT_0$	**2-Sample T-Test**	**-2.8°C**	**-6.9C**	**4.1°C**	**0.000**
$MinT_{-1}$	2-Sample T-Test	-4.2°C	-7.8°C	3.6°C	0.001
$MinT_{-2}$	2-Sample T-Test	-5.7°C	-8.1°C	2.4°C	0.027
$MinT_{-3}$*	2-Sample T-Test	-6.3°C	-8.6°C	2.3°C	0.024
$AvgMinT_{0,-1}$‡	**2-Sample T-Test**	**-3.5°C**	**-7.3°C**	**3.8°C**	0.000
$AvgMinT_{0,-1,-2}$	2-Sample T-Test	-4.2°C	-7.6°C	3.4°C	0.000
$AvgMinT_{0,-1,-2,-3}$	2-Sample T-Test	-4.8°C	-7.9°C	3.1°C	0.000
$AvgT_0$	**2-Sample T-Test**	**3.2°C**	**-2.9°C**	**6.1°C**	**0.000**
$AvgT_{-1}$	2-Sample T-Test	1.3°C	-3.7°C	5°C	0.000
$AvgT_{-2}$	2-Sample T-Test	-0.6°C	-3.8°C	3.2°C	0.005
$AvgT_{-3}$	2-Sample T-Test	-1.4°C	-3.6°C	2.2°C	0.035
$AvgAvgT_{0,-1}$‡	2-Sample T-Test	2.2°C	-3.3°C	5.5°C	0.000
$AvgAvgT_{0,-1,-2}$*	2-Sample T-Test	1.3°C	-3.5°C	6.1°C	0.000
$AvgAvgT_{0,-1,-2,-3}$	2-Sample T-Test	0.6°C	-3.5°C	4.1°C	0.000
$DDMaxT_0$	2-Sample T-Test	9.1°C	1.1°C	8°C	0.000

Table 8. Continued

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	P-Value
$DDMaxT_{0,-1}$	2-Sample T-Test	15.9°C	1.5°C	14.4°C	0.000
$DDMaxT_{0,-1,-2}$	2-Sample T-Test	20.5°C	2.0°C	18.5°C	0.000
$DDMaxT_{0,-1,-2,-3}$	2-Sample T-Test	23.8°C	3.4°C	20.4°C	0.000
$DDAvgT_0$	**2-Sample T-Test**	**3.2°C**	**-2.9°C**	**6.1°C**	**0.000**
$DDAvgT_{0,-1}$‡	2-Sample T-Test	4.5°C	-6.6°C	11.1°C	0.000
$DDAvgT_{0,-1,-2}$*	2-Sample T-Test	3.9°C	-10.4°C	14.3°C	0.000
$DDAvgT_{0,-1,-2,-3}$	2-Sample T-Test	2.4°C	-14.1°C	16.5°C	0.000
$MaxT_0$-$MaxT_{-2}$	2-Sample T-Test	4.6°C	0.5°C	4.1°C	0.003
$MaxT_0$-$MaxT_{-3}$	2-Sample T-Test	5.7°C	-0.3°C	6.0°C	0.000
$AvgT_0$-$AvgT_{-2}$	2-Sample T-Test	3.7°C	0.9°C	2.8°C	0.010
$AvgT_0$-$AvgT_{-3}$	2-Sample T-Test	4.7°C	0.8°C	3.9°C	0.002
$MaxT_0$-$MinT_0$	2-Sample T-Test	11.8°C	7.8°C	4.0°C	0.000
$MaxT_{-1}$-$MinT_{-1}$	2-Sample T-Test	11.1°C	8.1°C	3.0°C	0.003
$MaxT_{-1}$-$MinT_0$‡	2-Sample T-Test	9.6°C	7.3°C	2.3°C	0.003
HS_0-HS_{-1}†	2-Sample T-Test	-5.1cm	0.2cm	-5.3cm	0.000
HS_0-HS_{-2}*‡	2-Sample T-Test	-9.9cm	4.4cm	-14.3 cm	0.000
HS_0-HS_{-3}*	2-Sample T-Test	-11.6cm	8.5cm	-20.1 cm	0.000
$HN_{0,-1,-2}$*	2-Sample T-Test	2.3cm	25.3cm	-23 cm	0.000
$HN_{0,-1,-2,-3}$*	2-Sample T-Test	6.9cm	33.0cm	-26.1 cm	0.000
HNW_0†	2-Sample T-Test	0.0cm	0.63cm	-0.63cm	NC
$HNW_{0,-1}$†	2-Sample T-Test	0.0cm	1.5cm	-1.5 cm	NC
$HNW_{0,-1,-2}$*	Mann-Whitney	0.0cm	1.9cm	-1.9 cm	0.000
$HNW_{0,-1,-2,-3}$	Mann-Whitney	0.1cm	2.6cm	-2.5 cm	0.000
HND_0†	2-Sample T-Test	0.00cm	61.7kg/m^3	-61.7kg/m^3	NC
$HND_{0,1}$†	2-Sample T-Test	0kg/m^3	95.7kg/m^3	-95.77kg/m^3	NC
$HND_{0,-1-,2,-3}$†	2-Sample T-Test	51.7kg/m^3	93.9kg/m^3	-42.27kg/m^3	0.001

Bold variables are significant predictors for both new and old snow wet avalanche conditions.
*Transformed Variables – See Appendix B for λ value
‡Variables that used unpooled sample variance in 2-Sample T-Test. All other variables used pooled sample variance in 2-Sample T-Test.
†Nonparametric variables that were tested using 2-Sample Tests with unequal variance.
NC p-value could not be calculated because all values for old snow variable equal zero. Difference between new and old snow variable is likely significant.

Old Snow and New Snow Wet Avalanche Day Temperature Variables Prediction day, one day prior and two day prior maximum air temperatures ($MaxT_0$, $MaxT_{-1}$, $MaxT_{-2}$) are significantly cooler for new snow wet avalanche days than old snow wet avalanche days (Table 8). New snow maximum temperatures remain just above 0°C one and two days prior to the prediction day and increase to just over 1°C on the prediction day. Because the new snow has had little time to form multiple strong bonds and retains liquid water more easily, less energy is required to create a cohesionless snowcover prone to release. Old snow wet avalanche days on the other hand are far warmer starting at 4.5°C three days prior to the prediction day and increasing steadily to 9.1°C by the prediction day. The greater increases in temperature suggests that more energy is required to melt the strong melt-freeze bonds that often develop in old snow during spring-time conditions.

One day, two day, and three day average maximum air temperature ($AvgMaxT_{0,-1}$, $AvgMaxT_{0,-1.-2}$, $AvgMaxT_{0,-1,-2,-3}$) means are similar to the prediction day, one day prior and two days prior maximum temperature variables discussed above (Table 8). New snow wet avalanche average maximum temperatures change very little and hover just above 0°C as the prediction day approaches, while old snow average maximum temperatures increase steadily from 6.0°C ($AvgMaxT_{0,-1,-2,-3}$) to 8.0°C ($AvgMaxT_{0,-1}$). The difference between old snow and new snow average maximum temperatures is considerable with differences ranging from approximately 5°C to 7°C. Again, the differences illustrate that old and new snow wet avalanche conditions do form under very different temperature regimes.

Old and new snow wet avalanche conditions show similar temperature changes in their prediction day, one day prior, two days prior, and three days prior minimum air temperatures ($MinT_0$, $MinT_{-1}$, $MinT_{-2}$, $MinT_{-3}$) but new snow minimum temperatures are on average 2.3°C to 4.1°C cooler than old snow minimum temperatures (Table 8).

Old and new snow averaged minimum air temperatures ($AvgMinT_{0,-1}$, $AvgMinT_{0,-1,-2}$, $AvgMinT_{0,-1,-2,-3}$) behave similarly to old and new snow averaged maximum temperatures, although the difference between the new and old snow avalanche day average minimum temperatures are not as extreme as they are for the average maximum temperatures (Table 8). New snow averaged minimum temperatures increase only 0.6°C over the three days period leading up to the prediction day while old snow averaged minimum temperatures increase 1.3°C over the three prior days. New snow averaged minimum temperatures are on average about 3°C to 4°C cooler than old snow averaged minimum temperatures.

The prediction day, one day prior, two days prior, and three days prior averaged air temperature variables ($AvgT_0$, $AvgT_{-1}$, $AvgT_{-2}$, $AvgT_{-3}$) have almost the identical patterns seen in the new and old snow minimum and maximum variables (Table 8). The mean new snow average temperature variables remain between –3.6°C and –3.8°C during the three days leading up to the prediction day and then warm to –2.9°C on the prediction day. Old snow average temperatures are generally about –1.4°C three days prior to the prediction day. The average temperature for each progressive day increases by about 1.9°C to reach an average temperature of 3.2°C on the prediction day. These temperature changes suggest that in the past, new snow wet avalanche conditions develop when the average temperature remains fairly constant for a few days before the prediction day with a slight warm-up on the prediction day itself – whereas old snow conditions display progressive warming over several days prior to the prediction day.

One day prior, two days prior and three days prior averaged average air temperature ($AvgAvgT_{0,-1}$, $AvgAvgT_{0,-1,-2}$, $AvgAvgT_{0,-1,-2,-3}$) means show the similar temperature change patterns seen in the averaged maximum and averaged minimum variables (Table 8). New snow averaged average temperatures remain constant at about –3.5°C over the three day period and old snow averaged temperatures increase steadily from 0.6°C to 2.2°C. Note again that new snow air temperatures remain below freezing and old snow air temperatures remain above 0°C.

The degree day variables using maximum air temperature for calculations ($DDMaxT_0$, $DDMaxT_{0,-1}$, $DDMaxT_{0,-1,-2}$, $DDMaxT_{0,-1,-2,-3}$) support the findings that old snow wet avalanche conditions have greater energy demands for formation than new snow wet avalanche conditions (Table 8). This is seen by the obvious difference in degree day means for old and new snow wet avalanche days. New snow wet avalanche day degree day totals range from just 1.1°C to 3.4°C while old snow degree day total range from 9.1°C to 23.8°C, a 8°C to 20.4°C difference.

A clear distinction can also be seen in the degree day variables using averaged air temperature ($DDAvgT_0$, $DDAvgT_{0,-1}$, $DDAvgT_{0,-1,-2}$, $DDAvgT_{0,-1,-2,-3}$) (Table 8). New snow degree day totals range from –2.9°C to –14.1°C and old snow degree day ratios are all positive ranging from 2.4°C to 4.5°C, a 6.1°C to 16.5°C difference.

The two day maximum air temperature range ($MaxT_0$-$MaxT_{-2}$), three day maximum temperature range ($MaxT_0$-$MaxT_{-3}$), two day average air temperature range ($AvgT_0$-$AvgT_{-2}$), and three day average air temperature range ($AvgT_0$-$AvgT_{-3}$) all provide similar results and support the patterns seen in the earlier variables (Table 8). New snow wet avalanche temperature ranges vary from –0.3°C to 0.9°C for all four variables indicating that the weather conditions change very little for the three days leading up to the prediction day. Old snow wet avalanche temperature ranges vary by about 2°C, and have a much warmer range of 3.7°C to 4.7°C suggesting a much stronger temperature increase and greater weather changes leading up to the prediction day.

The prediction day temperature range ($MaxT_0$-$MinT_0$) and the one day prior temperature range ($MaxT_{-1}$-$MinT_{-1}$) are 4°C to 3°C (respectively) greater for old snow wet avalanche days compared to new snow wet avalanche days. Again, the differences indicate that old snow wet avalanche conditions experience stronger temperature increases during the prediction day and the days preceding the prediction day.

The overnight temperature range prior to the prediction day ($MaxT_{-1}$-$MinT_0$) is 2.3°C less for new snow wet avalanche conditions than old snow wet avalanche conditions (Table 8). The difference in temperature range is likely the result of cloudier skies in new snow conditions, which retain more of the previous day's heat overnight. The higher day time temperatures seen in the mean maximum temperatures for old snow suggest clear sky conditions which would result in a greater loss of heat during the night and greater heat requirements the following day in order to melt the snow.

Old Snow and New Snow Wet Avalanche Day Snowpack Settlement Variables

The one day, two day and three day change in total snow depth (HS_0-HS_{-1}, HS_0-HS_{-2}, HS_0-HS_{-3}) reflect the basic division of this dataset (Table 8). Mean changes in snow depth are positive for new snow days because new snow is accumulating and mean changes in snow depth are negative for old snow days because no new snow is accumulating on the prediction day or one day prior. This also reflects the different temperature regimes in which old snow and new snow wet avalanche conditions develop. New snow conditions remain cool allowing snow to accumulate and not melt as readily while old snow conditions have much warmer temperatures that melt any new snow quickly.

Although the settlement variable was not found to behave significantly different on old snow days and new snow days, it is interesting to note that the cumulative two day settlement variable ($Stl_{0,-1,-2}$) shows that new snow settlement rates are approximately 0.5cm/day greater than old snow settlement rates. Recall that the settlement variable excludes the addition of new snowfall in the calculation so that this variable only represents the processes that will reduce the total depth of the snowpack. This difference in settlement rate is likely due to the fact that new snow snowpack is less dense than old snow snowpack, has fewer, smaller and weaker bonds within its matrix, and can therefore settle more rapidly than old snow. Rapid settlement is a precursor to wet avalanche activity (McClung and Schaerer, 1993), which may be one of the reasons why new snow wet avalanche conditions require less energy input in the form of heat for releases to occur. Cumulative two day settlement is the only significant predictor variable that does not behave significantly different for old snow and new snow wet avalanche conditions.

<u>Old Snow and New Snow Wet Avalanche Day Precipitation Variables</u> The cumulative two day and three days prior new snowfall amounts ($HN_{0,-1,-2}$, $HN_{0,-1,-2,-3}$) vary greatly between new and old snow wet avalanche days (Table 8). New snow mean

cumulative two day snowfall is about 25cm (8.4cm/day) and cumulative three day snowfall totals are 33cm (8.3cm/day) on average. Old snow cumulative two and three day snowfalls are just 2.3cm (0.8cm/day) and 6.9cm (1.7cm/day) respectively. The large difference in new snow accumulations is a product of the fundamental characteristics of the new and old snow datasets. Recall that new snow days can have recorded precipitation on prediction day, one day prior, two days prior and three days prior. By definition, old snow days can only have recorded precipitation two days prior and three days prior to the prediction day. The difference in accumulation totals may also be an artifact of the cooler new snow day air temperatures that help maintain accumulated new snow depths.

The prediction day, one day prior, two days prior and three days prior new snow water equivalent totals (HNW_0, $HNW_{0,-1}$, $HNW_{0,-1,-2}$, $HNW_{0,-1,-2,-3}$) also reflect the basic division of the new and old snow data (Table 8). Old snow days do not have new snowfall, and therefore no new snow water equivalent totals, on the prediction day, or one day prior to the prediction day. New snow water equivalent values are minimal for two days prior and three days prior to an old snow wet avalanche day because either no new snow fell or the snow had little water equivalent compared to the new snow that falls prior to a new snow wet avalanche day. New snow water equivalent prediction day, one day prior, two days prior and three days prior accumulations are on average about 0.6cm to 2.5cm greater for new snow days than old snow days.

The prediction day, one day prior and three days prior new snow density measurements (HND_0, $HND_{0,-1}$, $HND_{0,-1,-2,-3}$) are approximately 42kg/m^3 to 96kg/m^3

greater for new snow wet avalanche conditions than old snow wet avalanche conditions (Table 8). Because old snow conditions by definition do not have measurable new snowfall amounts on the prediction day or one day prior to the prediction day, the HND_0 and $HND_{0,-1}$ values are zero. The old snow three day new snow density is 45% lower than the new snow three day new snow density values. This is likely the result of little to no new snow falling three days prior to an old snow wet avalanche day, or the snow that fell was much less dense and had a lower snow water equivalent value than the snow that falls prior to a new snow wet avalanche day.

Old Snow and New Snow Wet Avalanche Day Summary New snow predictor variables tend to have fewer significant 'leading' day variables compared to old snow predictor variables suggesting that new snow wet avalanche conditions develop more quickly. Unlike the old snow temperature related variables, new snow temperature related variables showed relatively little change in the days leading up to the wet avalanche day. Settlement rates in new snow wet avalanche conditions were similar to those of old snow wet avalanche conditions. New snowfall characteristics were quite different however with new snow wet avalanche condition new snow totals, SWE totals and density values being much greater than those of old snow conditions.

The data suggest and literature supports the idea that old snow wet avalanche conditions require more time and energy to develop than new snow wet avalanche conditions (McClung and Schaerer, 1993). This is likely because old snow has had time to develop stronger grain-to-grain contacts and may have gone through more than one cycles of melt freeze before the avalanche day. Melt-freeze can create extraordinarily well-bonded grains and snow layers that require a large amount of energy for bond destruction (McClung and Schaerer, 1993). In addition, old snow is more likely to have formed drainage channels within its matrix so that a well-drained snowpack has formed. In order to overwhelm these flow channels, a great deal of free water must be created, and this requires a large amount of heat input.

Data Analysis – Model Design

Correlation Testing Results

The correlation test results (Table 9) show that the prediction day average temperature ($AvgT_0$) and prediction day degree using average temperature are perfectly correlated with one another (Pearson's r = 1). In other words, the two variables are identical. This occurred because the prediction day degree day variable uses the equation $DDAvgT_0 = AvgT_0 - 0°C$, which equals the prediction day average temperature, therefore $DDAvgT_0 = AvgT_0$. Since the prediction day average temperature is a more familiar concept, the prediction day degree day variable was dropped from the analysis. The old snow one day change in total snow depth variable ($HS_0 – HS_{-1}$) and the one day snowpack settlement variable ($Stl_{0.-1}$) also have perfect correlation. There is no new snowfall included in the $HS_0 – HS_{-1}$ variable because by definition, old snow days do not have recorded new snow on the prediction day or one day prior, therefore $HS_0 – HS_{-1} = Stl_{0,-1}$. Since total snow depth (HS) is measured at the Alpine weather station and $HS_0 – HS_{-1}$ does not require any additional calculations, the one day snowpack settlement variable ($Stl_{0,-1}$) was eventually dropped from the analysis. All remaining variables were retained for further analysis.

Table 9. Old Snow Dataset - Correlation Test Results

	Day	**$MaxT_0$**	**$MaxT_{-1}$**	**$MaxT_{-2}$**	**$AvgMaxT_{0,-1}$**	**$AvgMaxT_{0,-1,-2}$**	**$AvgMaxT_{0,-1,-2,-3}$**	**$MinT_0$**	**$MinT_{-1}$**	**$MinT_{-2}$**	**$AvgMinT_{0,-1}$**	**$AvgMinT_{0,-1,-2}$**	**$AvgMinT_{0,-1,-2,-3}$**	**$AvgT_0$**
$MaxT_0$	0.0													
$MaxT_{-1}$	0.0	0.2												
$MaxT_{-2}$	0.0	0.0	0.0											
$AvgMaxT_{0,-1}$	0.0	0.7	0.6	0.0										
$AvgMaxT_{0,-1,-2}$	0.0	0.7	0.6	0.3	0.9									
$AvgMaxT_{0,-1,-2,-3}$	0.0	0.6	0.5	0.2	0.8	0.9								
$MinT_0$	0.0	0.9	0.2	0.0	0.7	0.7	0.6							
$MinT_{-1}$	0.0	0.1	0.8	0.0	0.5	0.5	0.4	0.1						
$MinT_{-2}$	0.0	0.0	0.0	0.6	0.0	0.2	0.1	0.0	0.1					
$AvgMinT_{0,-1}$	0.0	0.7	0.6	0.0	0.9	0.8	0.7	0.7	0.7	0.0				
$AvgMinT_{0,-1,-2}$	0.0	0.6	0.6	0.3	0.8	0.9	0.8	0.6	0.6	0.4	0.9			
$AvgMinT_{0,-1,-2,-3}$	0.0	0.6	0.5	0.2	0.7	0.8	0.9	0.6	0.5	0.4	0.8	0.9		
$AvgT_0$	0.1	0.9	0.2	0.0	0.7	0.6	0.6	0.9	0.3	0.0	0.8	0.7	0.6	
$AvgT_{-1}$	0.0	0.2	0.9	0.0	0.6	0.6	0.5	0.1	0.9	0.0	0.6	0.6	0.5	0.2
$AvgT_{-2}$	0.0	0.0	0.0	0.7	0.0	0.2	0.1	0.0	0.0	0.9	0.0	0.4	0.4	0.0
$AvgAvgT_{0,-1}$	0.0	0.7	0.6	0.0	0.9	0.8	0.7	0.7	0.7	0.0	0.9	0.8	0.8	0.8
$AvgAvgT_{0,-1,-2}$	0.0	0.7	0.6	0.3	0.8	0.9	0.8	0.6	0.5	0.4	0.8	0.9	0.9	0.6
$AvgAvgT_{0,-1,-2,-3}$	0.0	0.6	0.5	0.2	0.8	0.8	0.9	0.6	0.5	0.3	0.7	0.8	0.9	0.6
$DDMaxT_0$	0.0	1.0	0.2	0.0	0.7	0.7	0.6	0.9	0.1	0.0	0.7	0.6	0.6	0.9
$DDMaxT_{0,-1}$	0.0	0.7	0.6	0.0	0.9	0.9	0.8	0.7	0.6	0.0	0.9	0.8	0.8	0.7
$DDMaxT_{0,-1,-2}$	0.0	0.7	0.6	0.3	0.9	0.9	0.8	0.7	0.5	0.2	0.8	0.9	0.8	0.7
$DDMaxT_{0,-1,-2,-3}$	0.0	0.6	0.5	0.2	0.8	0.9	0.9	0.6	0.5	0.1	0.8	0.8	0.9	0.6
$DDAvgT_0$	0.1	0.9	0.2	0.0	0.7	0.6	0.6	0.9	0.3	0.0	0.8	0.7	0.6	1.0
$DDAvgT_{0,-1}$	0.1	0.6	0.5	0.0	0.7	0.7	0.6	0.5	0.7	0.1	0.9	0.8	0.7	0.8
$DDAvgT_{0,-1,-2}$	0.0	0.6	0.5	0.3	0.7	0.8	0.7	0.6	0.6	0.4	0.8	0.9	0.8	0.7
$DDAvgT_{0,-1,-2,-3}$	0.0	0.6	0.5	0.2	0.7	0.8	0.8	0.5	0.6	0.4	0.8	0.9	0.9	0.6
HS_0-HS_{-1}	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
HS_0-HS_{-2}	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
HS_0-HS_{-3}	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
$Stl_{0,-1}$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
$Stl_{0,-1,-2}$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
$Stl_{0,-1,-2,-3}$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Cell Contents: Pearson's Correlation Coefficient (r)
Shaded cells contain r values between –1.0 to –0.5 and 0.5 to 1.0

Table 9. Continued

	$AvgT_{-1}$	$AvgT_{-2}$	$AvgAvgT_{0,-1}$	$AvgAvgT_{0,-1,-2}$	$AvgAvgT_{0,-1,-2,-3}$	$DDMaxT_{0}$	$DDMaxT_{0,-1}$	$DDMaxT_{0,-1,-2}$	$DDMaxT_{0,-1,-2,-3}$	$DDAvgT_{0}$	$DDAvgT_{0,-1}$	$DDAvgT_{0,-1,-2}$	$DDAvgT_{0,-1,-2,-3}$	HS_{0}-HS_{-1}
$AvgT_{-2}$	0.0													
$AvgAvgT_{0,-1}$	0.7	0.0												
$AvgAvgT_{0,-1,-2}$	0.6	0.4	0.8											
$AvgAvgT_{0,-1,-2,-3}$	0.5	0.4	0.8	0.9										
$DDMaxT_{0}$	0.2	0.0	0.7	0.7	0.6									
$DDMaxT_{0,-1}$	0.6	0.0	0.9	0.8	0.8	0.7								
$DDMaxT_{0,-1,-2}$	0.6	0.2	0.9	0.9	0.8	0.7	0.9							
$DDMaxT_{0,-1,-2,-3}$	0.5	0.2	0.8	0.8	0.9	0.6	0.8	0.9						
$DDAvgT_{0}$	0.2	0.0	0.8	0.6	0.6	0.9	0.7	0.7	0.6					
$DDAvgT_{0,-1}$	0.6	0.1	0.9	0.7	0.6	0.6	0.8	0.7	0.6	0.8				
$DDAvgT_{0,-1,-2}$	0.6	0.4	0.8	0.9	0.8	0.6	0.8	0.8	0.7	0.7	0.9			
$DDAvgT_{0,-1,-2,-3}$	0.5	0.4	0.8	0.8	0.9	0.6	0.8	0.8	0.9	0.6	0.7	0.9		
HS_{0}-HS_{-1}	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9
HS_{0}-HS_{-2}	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9
HS_{0}-HS_{-3}	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
$Stl_{0,-1}$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9
$Stl_{0,-1,-2}$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9
$Stl_{0,-1,-2,-3}$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9

	HS_{0}-HS_{-2}	HS_{0}-HS_{-3}	$Stl_{0,-1}$	$Stl_{0,-1,-2}$	$Stl_{0,-1,-2,-3}$
HS_{0}-HS_{-3}	0.9				
$Stl_{0,-1}$	0.9	0.9			
$Stl_{0,-1,-2}$	0.9	0.9	0.9		
$Stl_{0,-1,-2,-3}$	0.9	0.9	0.9	0.9	0.9

Cell Contents: Pearson's Correlation Coefficient (r)
Shaded cells contain r values between –1.0 to –0.5 and 0.5 to 1.0

Table 10. New Snow Dataset - Correlation Test Results

	$MinT_0$	**$AvgMinT_{0,-1}$**	**$AvgT_0$**	**$DDAvgT_0$**	**$MaxT_0$-$MaxT_{-2}$**	**$MinT_0$-$MinT_{-1}$**	**$MinT_0$-$MinT_{-2}$**	**$MinT_0$-$MinT_{-3}$**	**$AvgT_0$-$AvgT_{-1}$**	**$AvgT_0$-$AvgT_{-2}$**	**$AvgT_0$-$AvgT_{-3}$**
$AvgMinT_{0,-1}$	0.8										
$AvgT_0$	0.8	0.8									
$DDAvgT_0$	0.8	0.8	1.0								
$MaxT_0$-$MaxT_{-2}$	0.2	0.1	0.4	0.4							
$MinT_0$-$MinT_{-1}$	0.4	0.0	0.3	0.3	0.3						
$MinT_0$-$MinT_{-2}$	0.5	0.2	0.4	0.6	0.6	0.6					
$MinT_0$-$MinT_{-3}$	0.5	0.4	0.5	0.5	0.5	0.3	0.7				
$AvgT_0$-$AvgT_{-1}$	0.3	0.0	0.3	0.3	0.5	0.8	0.6	0.3			
$AvgT_0$-$AvgT_{-2}$	0.4	0.2	0.5	0.5	0.9	0.5	0.8	0.6	0.6		
$AvgT_0$-$AvgT_{-3}$	0.5	0.3	0.5	0.5	0.6	0.3	0.6	0.9	0.4	0.7	
$MaxT_{-1}$-$MinT_0$	-0.4	-0.1	-0.2	-0.2	-0.3	-0.6	-0.6	-0.4	-0.7	-0.5	-0.3
$HN_{0,-1,-2}$	-0.2	-0.2	-0.3	-0.3	-0.1	0.0	-0.1	-0.1	0.0	-0.1	-0.2
$HN_{0,-1,-2,-3}$	-0.2	-0.2	-0.3	-0.3	0.0	0.0	0.0	-0.1	0.0	0.0	-0.1
$Stl_{0,-1}$	0.0	0.1	0.1	0.1	0.0	-0.1	0.0	0.0	-0.1	0.0	0.0
$Stl_{0,-1,-2}$	0.0	0.1	0.1	0.1	-0.1	-0.1	-0.1	0.0	-0.1	-0.1	0.0
$Stl_{0,-1,-2,-3}$	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1
$HNW_{0,-1}$	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	0.0	-0.2	-0.1	-0.1
$HNW_{0,-1-2}$	0.0	0.0	-0.1	-0.1	-0.1	0.0	-0.1	-0.1	0.0	-0.1	-0.2
$HNW_{0,-1,-2,-3}$	0.0	-0.1	-0.1	-0.1	0.0	0.0	0.0	-0.1	0.0	0.0	-0.1
$HND_{0,-1}$	0.3	0.3	0.3	0.3	0.0	0.0	0.0	0.1	0.0	0.0	0.1
$HND_{0,-1,-2,-3}$	0.3	0.3	0.3	0.3	0.0	0.0	0.0	0.0	-0.1	0.0	0.0

	$MaxT_{-1}$-$MinT_0$	**$HN_{0,-1,-2}$**	**$HN_{0,-1,-2,-3}$**	**$Stl_{0,-1}$**	**$Stl_{0,-1,-2}$**	**$Stl_{0,-1,-2,-3}$**	**$HNW_{0,-1}$**	**$HNW_{0,-1-2}$**	**$HNW_{0,-1,-2,-3}$**	**$HND_{0,-1}$**	**$HND_{0,-1,-2,-3}$**
$Stl_{0,-1,-2,-3}$	0.1	-0.4	-0.5	0.6	0.8						
$HNW_{0,-1}$	0.1	0.6	0.5	-0.2	-0.2	-0.1					
$HNW_{0,-1-2}$	0.0	0.8	0.6	-0.3	-0.3	-0.2	0.8				
$HNW_{0,-1,-2,-3}$	-0.1	0.7	0.8	-0.3	-0.4	-0.3	0.7	0.8			
$HND_{0,-1}$	0.0	-0.1	-0.1	0.1	0.1	0.1	0.3	0.2	0.1		
$HND_{0,-1,-2,-3}$	0.0	-0.1	-0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.8	

Cell Contents: Pearson's Correlation Coefficient (r)
Shaded cells contain r values between –1.0 to –0.5 and 0.5 to 1.0

Variable Selection Criteria and Process

The hypothesis testing results provide a list of old snow and new snow predictor variables (Table 6 and 7) that are potential candidates for the binomial logistic regression prediction models. The correlation tests have established which variables are strongly correlated and should therefore be kept separate from one another in the final model building process. At this time, the significant old snow and new snow variables are tested for their predictive capabilities using binomial logistic regression.

Variable Selection Process – Part 1 Each variable in the old snow and new snow datasets were entered into a binomial logistic regression model individually to test their predictive significance at the $\alpha = 0.05$ significance level. Next, all possible variable pairs were entered into a binomial logistic regression model to determine which variables became significant when coupled with another variable and which variables lost their significance when coupled with another variable. Many variables were dropped because of correlation issues. A process of 'within group' correlation comparisons and 'between group' correlation comparisons was used to determine which variables had the greatest predictive capabilities. For example, a 'within group' correlation comparison was made with the old snow one day, two day and three day averaged average temperature variables ($AvgAvgT_{0,-1}$, $AvgAvgT_{0,-1,-2}$, $AvgAvgT_{0,-1,-2,-3}$). All three variables are correlated with one another ($r>0.05$) (Table 9), but because $AvgAvgT_{0,-1}$ has greater predictive success than the other two variables, it was retained for a 'between group' correlation comparison and the other averaged average temperature variables were dropped from the analysis. The old snow $AvgAvgT_{0,-1}$ was then compared to the old snow prediction day average temperature variable ($AvgT_0$). This is considered a 'between group' correlation comparison. In this case, the prediction day average temperature variable was selected over the one day averaged average temperature variables because it had a slightly higher percent concordant pairs value. See Appendix B for results ("Old Snow Binomial Logistic Regression Results" and "New Snow Binomial Logistic Regression Results").

The variables that were found to have the best predictive capabilities for old snow and new snow wet avalanche conditions are listed in Table 11. Variables from each of the variable categories (temperature, snowpack settlement, and precipitation) were selected for further analysis as long as they fulfilled the criteria described above. These variables (Table 11) had the highest percent concordant pairs (approximately 60-70% or greater) when tested individually and in combination with other variables. When tested with another variable in a binomial logistic regression model, these variables maintained a significant p-value (≤ 0.05) in the majority of the tests. In most cases, only the best predictor from a group of correlated variables was retained, however some correlated variables were retained such as new snow cumulative snowfall ($HN_{0,-1,-2}$, $HN_{0,-1,-2,-3}$), snow water equivalent ($HNW_{0,-1}$, $HNW_{0,-1,-2}$, $HNW_{0,-1,-2,-3}$), and density variables ($HND_{0,-1}$, $HND_{0,-1,-2,-3}$). These correlated variables had nearly identical predictive success or their success would depend on which temperature or snowpack settlement variables it was tested with. The second and third phase of the variable selection process will determine which variable arrangement will produce the final old snow and new snow wet avalanche prediction models.

Table 11. Old Snow Model and New Snow Model Design Variables

Old Snow Variables – Model Design Phase	**New Snow Variables – Model Design Phase**
Day	$MinT_0$
$MaxT_0$	$MaxT_{-1}$-$MinT_0$
$MinT_0$	$Stl_{0,-1,-2}$
$AvgT_0$	$HN_{0,-1,-2}$
HS_0-HS_{-2}	$HN_{0,-1,-2,-3}$
	$HNW_{0,-1}$
	$HNW_{0,-1,-2}$
	$HNW_{0,-1,-2,-3}$
	$HND_{0,-1}$
	$HND_{0,-1,-2,-3}$

Variable Selection Process – Part 2 At this point, the old snow and new snow training and testing datasets were created following the steps described in the methods section. Refer to Table 2 for their descriptive statistics. All possible combinations of the old snow and new snow variables listed in Table 11 were entered into a binomial logistic regression model using the appropriate 'training' datasets and then tested on the appropriate old snow and new snow 'testing' datasets (Table 3). Model performance was ranked primarily on p-values; percent concordant, discordant and tied pairs; how consistent the models are when comparing 'training' dataset model results with 'testing' dataset model results; and whether the user will need to use forecasted information to calculate the model variables or if that information is readily available. The last 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. As before, p-values less than or equal to 0.05 indicate that there is sufficient evidence that the variable's coefficient is significantly different than zero at the $\alpha = 0.05$ significance level, and greater percent concordant pairs and fewer discordant and tied pairs reflect the model's increased predictive accuracy. The top three old snow and new snow models were retained for further analysis, all other models were discarded. See Appendix B for discarded old snow and new snow model selection results ("Old Snow Model Selection Results" and "New Snow Model Selection Results").

Variable Selection Process – Part 3 To further test the predictive capabilities of the top three old snow and new snow models, each model was converted into the binomial logistic regression equation in Figure 12.

General Form: $$P_n(i) = \frac{e^{\beta X_{in} + \varepsilon}}{1 + e^{\beta X_{in} + \varepsilon}}$$

Where

$P_n(i)$ represents the probability of a specific outcome (1 = wet avalanche day)

β is the regression coefficient estimated by maximum likelihood methods

X is the independent explanatory variables (e.g., prediction day minimum temperature)

ε is a random error or disturbance term that accounts for unobserved effects.

1- $P_n(i)$ represents the probability of the alternate outcome (0 = no-wet-avalanche day)

Figure 12. Binomial Logistic Regression Equation

Old snow models 'A', 'B', and 'C' (in unranked order) and new snow models 'D', 'E', and 'F' (also in unranked order), in the form described in Figure 12, were run once more using the appropriate training and testing datasets. The best old snow and new snow model showed the most consistency between training and testing dataset results and had fewer problems with over or underestimating the predicted wet avalanche probabilities.

Top Three Old Snow Model Results

The top three old snow model results are shown in Table 12 and Figures 13 though 18. Test results were very similar for Model A (Table 12, Figures 13 and 14), Model B (Table 12, Figures 15 and 16), and Model C (Table 12, Figures 17 and 18). Old snow Model B was selected as the best old snow model for spring-time wet avalanche prediction because it has fewer problems with overestimating wet avalanche probabilities. Model B predictor variable p-values for the training and testing dataset results were similar to those of Model A and C. Odds ratios were slightly higher and more consistent for Model B variables. Model B's percent concordant pairs were slightly lower, and discordant and tied pairs were slightly higher but still very comparable to Model A and C.

Table 12. Top Three Old Snow Model Results

	Old Snow Training Dataset Results			Old Snow Testing Dataset Results		
Model A: $P_n(i) = \dfrac{e^{\beta MaxT_{0\,in} + \beta HS_{0} - HS_{-2\,in} + \varepsilon}}{1 + e^{\beta MaxT_{0\,in} + \beta HS_{0} - HS_{-2\,in} + \varepsilon}}$						
Predictor Variables	$MaxT_0$	HS_0-HS_{-2}		$MaxT_0$	HS_0-HS_{-2}	
Coefficients (β)	0.06315	-0.10157		0.05432	-0.07757	
P-Values	0.001	0.005		0.107	0.207	
Odds Ratios	1.07	0.90		1.06	0.93	
% Concordant, Discordant & Tied Pairs	Concordant 77.3%	Discordant 21.8%	Tied 0.8%	Concordant 73.8%	Discordant 25.4%	Tied 0.8%
Model B: $P_n(i) = \dfrac{e^{\beta MinT_{0\,in} + \beta HS_{0} - HS_{-2\,in} + \varepsilon}}{1 + e^{\beta MinT_{0\,in} + \beta HS_{0} - HS_{-2\,in} + \varepsilon}}$						
Predictor Variables	$MinT_0$	HS_0-HS_{-2}		$MinT_0$	HS_0-HS_{-2}	
Coefficients (β)	0.14511	-0.10199		0.15582	-0.06423	
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%
Model C: $P_n(i) = \dfrac{e^{\beta MinT_{0\,in} + Day_{in} + \beta HS_{0} - HS_{-2\,in} + \varepsilon}}{1 + e^{\beta MinT_{0\,in} + Day_{in} + \beta HS_{0} - HS_{-2\,in} + \varepsilon}}$						
Predictor Variables	$MinT_0$	Day of Year	HS_0-HS_{-2}	$MinT_0$	Day of Year	HS_0-HS_{-2}
Coefficients (β)	0.12767	0.04441	-0.10015	0.14226	0.02408	-0.05704
P-Values	0.031	0.067	0.007	0.115	0.623	0.374
Odds Ratios	1.14	1.05	0.90	1.15	1.02	0.94
% Concordant, Discordant & Tied Pairs	Concordant 75.0%	Discordant 24.2%	Tied 0.8%	Concordant 74.6%	Discordant 24.6%	Tied 0.8%

Model B's performance is best illustrated by comparing Figures 13 through 18. The gray bars represent the proportion of observed days with no wet avalanches (given as a percentage on the Y-axis) in the old snow dataset that were given the corresponding wet avalanche probability (as a percentage on the X-axis) by the models. The black bars represent the proportion of observed wet avalanche days (given as a percentage on the

Y-axis) in the old snow dataset that were given the corresponding wet avalanche probability (as a percentage on the X-axis) by the models. For example, in Figure 13 approximately 85% of all observed days with no wet avalanches in the old snow training dataset were given a wet avalanche probability of 91-100% by Model A. Approximately 95% of all observed wet avalanche days in the old snow dataset were also given a wet avalanche probability of 91-100% by Model A. Ideally, all of the days with no wet avalanches (gray bars) would be clustered around low wet avalanche probabilities and all of the wet avalanche days (black bars) would be clustered around high wet avalanche probabilities. Compared to Model A and C, Model B gives a much more reasonable predicted wet avalanche day and no-wet-avalanche day distribution. Although very consistent between training and testing dataset results, Models A and C both severely overestimate wet avalanche probabilities and the distributions are extremely skewed. In other words, models A and C tend to give many 'false alarms' by predicting very high wet avalanche probabilities for both wet avalanche days *and* days with no wet avalanches. Model B is also consistent between training and testing dataset results and more accurately predicts lower probabilities on observed no-wet-avalanche days and higher probabilities on observed wet avalanche days.

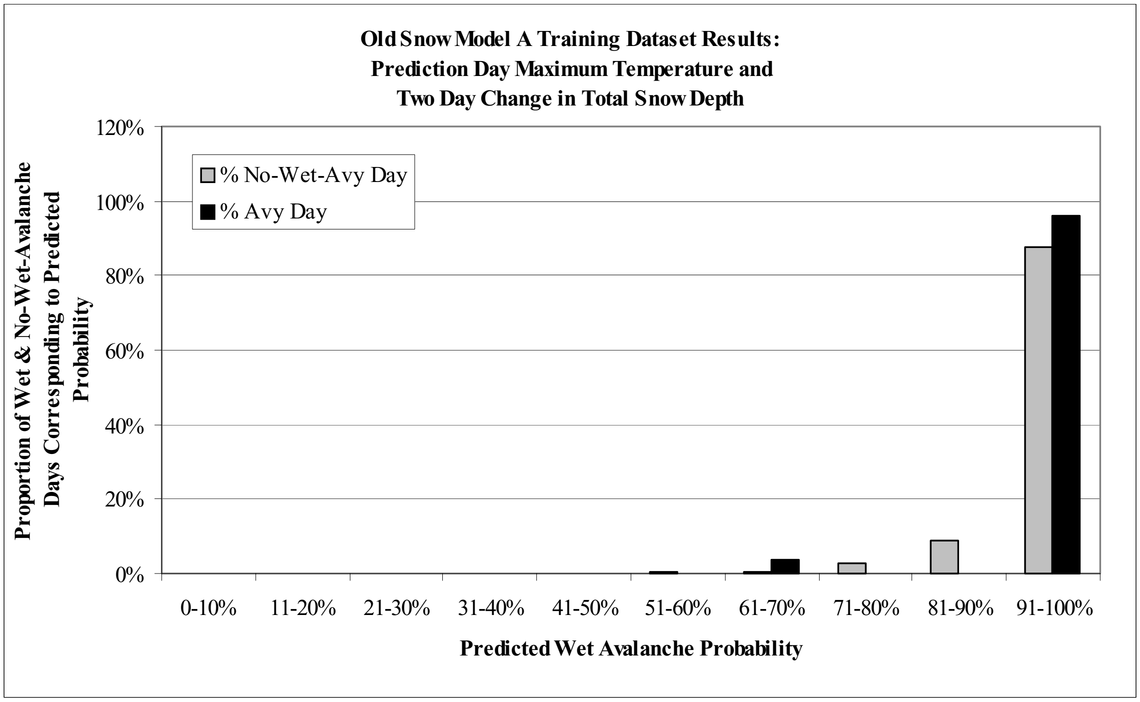

Figure 13. Old Snow Training Dataset Model A Results (predictors = $MaxT_0$, HS_0-HS_{-2})

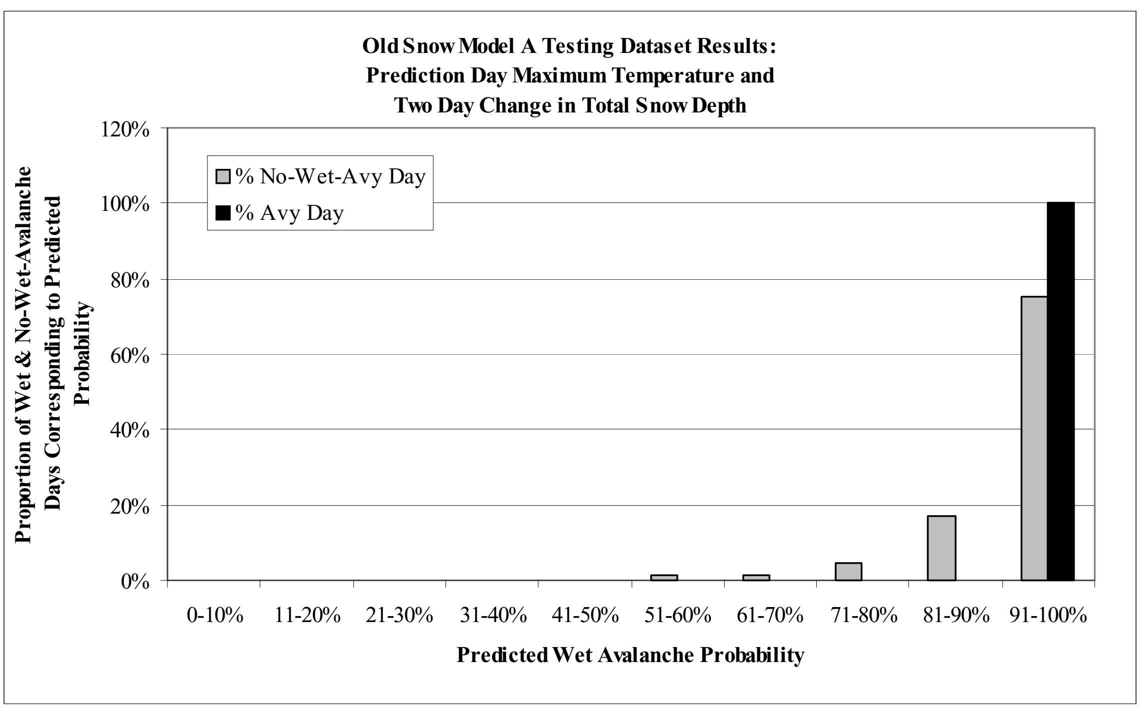

Figure 14. Old Snow Testing Dataset Model A Results (predictors = $MaxT_0$, HS_0-HS_{-2})

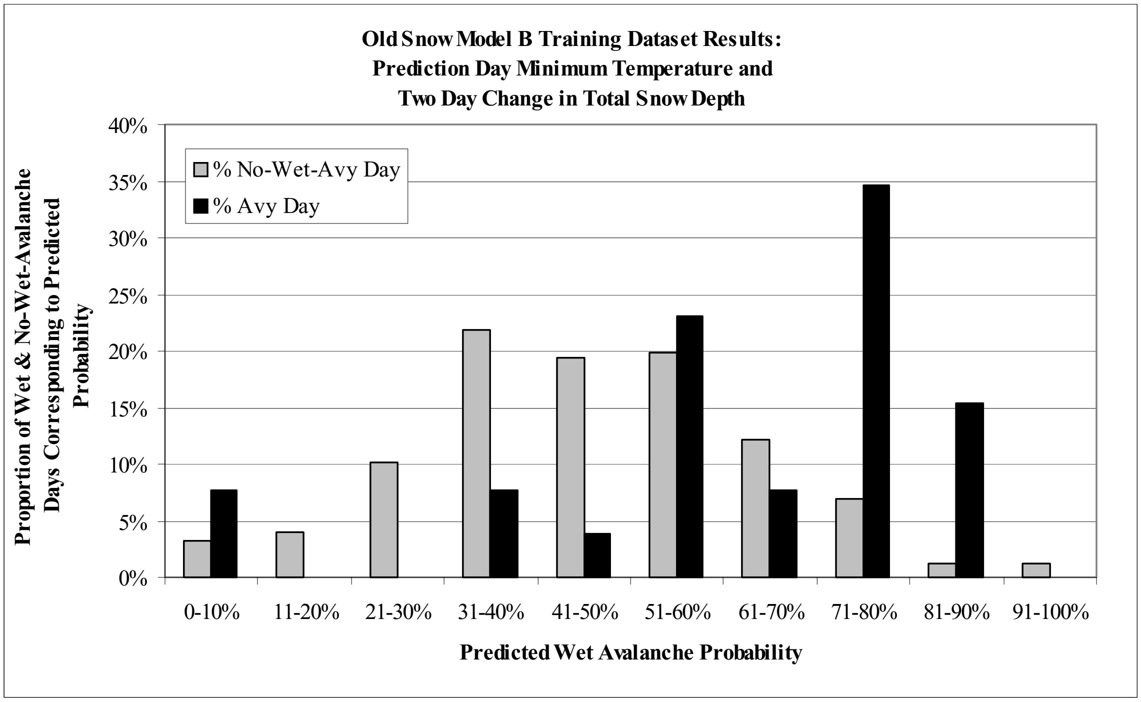

Figure 15. Old Snow Training Dataset Model B Results (predictors = $MinT_0$, HS_0-HS_{-2})

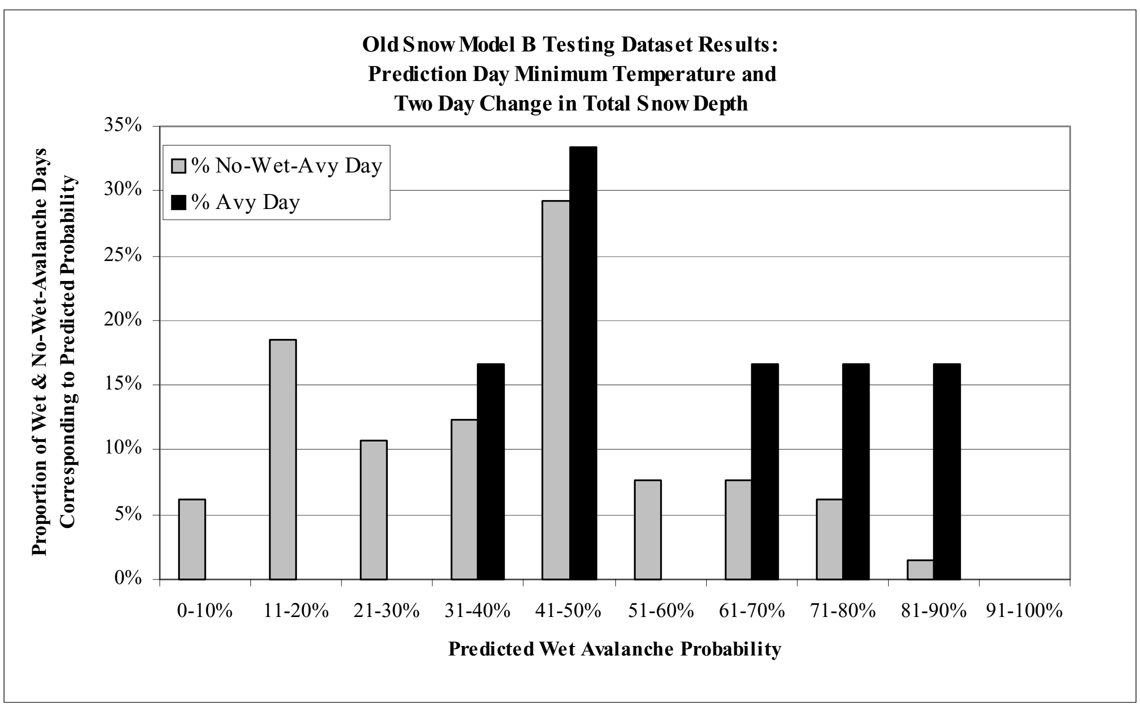

Figure 16. Old Snow Testing Dataset Model B Results (predictors = $MinT_0$, HS_0-HS_{-2})

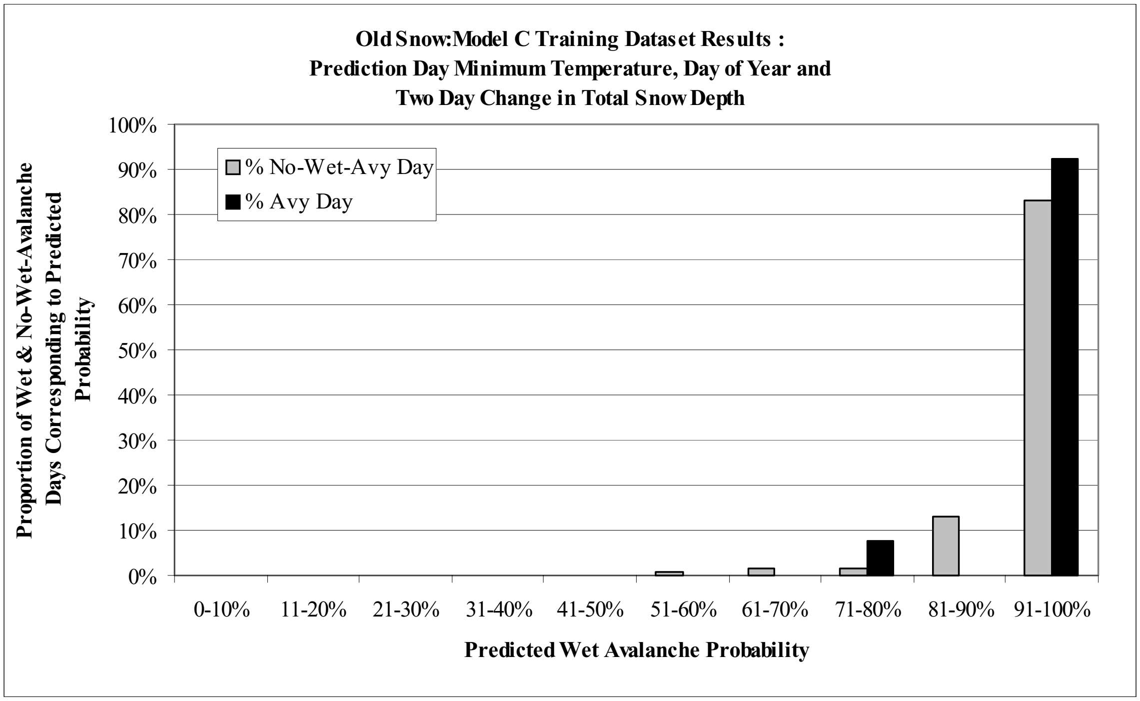

Figure 17. Old Snow Training Dataset Model C Results (predictors = $MinT_0$, Day, HS_0-HS_{-2})

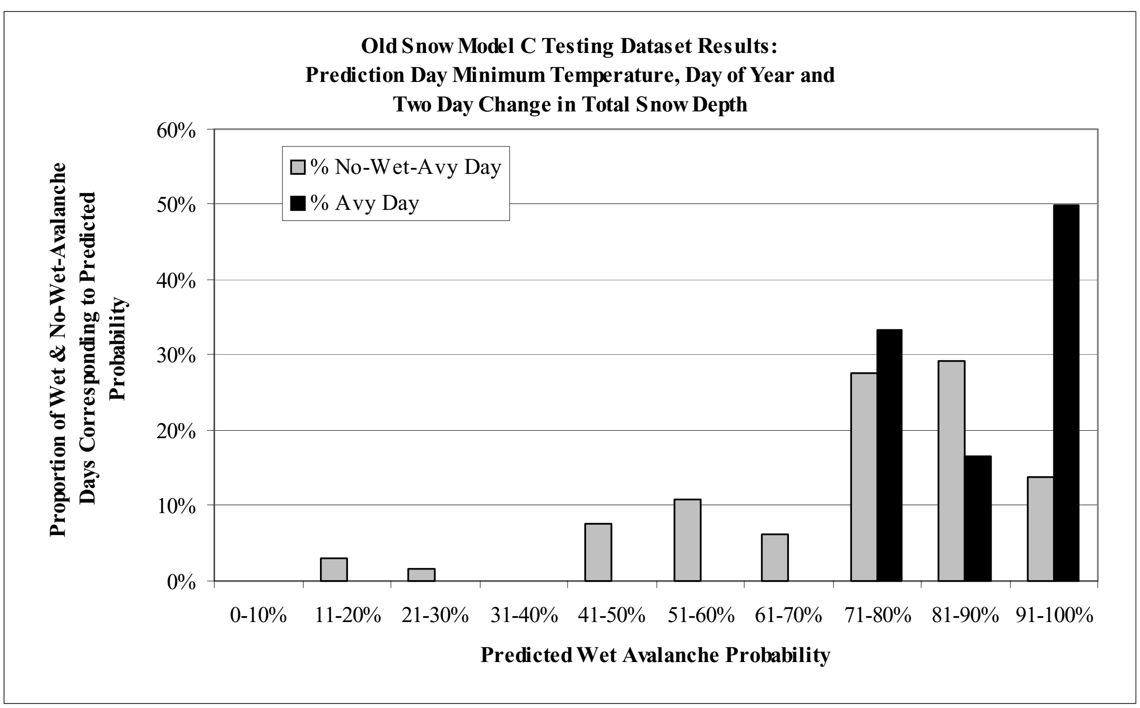

Figure 18. Old Snow Testing Dataset Model C Results (predictors = $MinT_0$, Day, $HS_0 - HS_{-2}$)

The testing and training datasets were combined, and Model B was run on the entire old snow dataset (Fig. 19). This creates slightly different coefficients in the model as well as slightly different results. The model will never provide the user with a definitive 'yes/no' answer, however, the results in Figure 19 demonstrate that all but one recorded wet avalanche in the past 32 years have occurred when the model predicts a 31-80% probability for wet avalanche conditions.

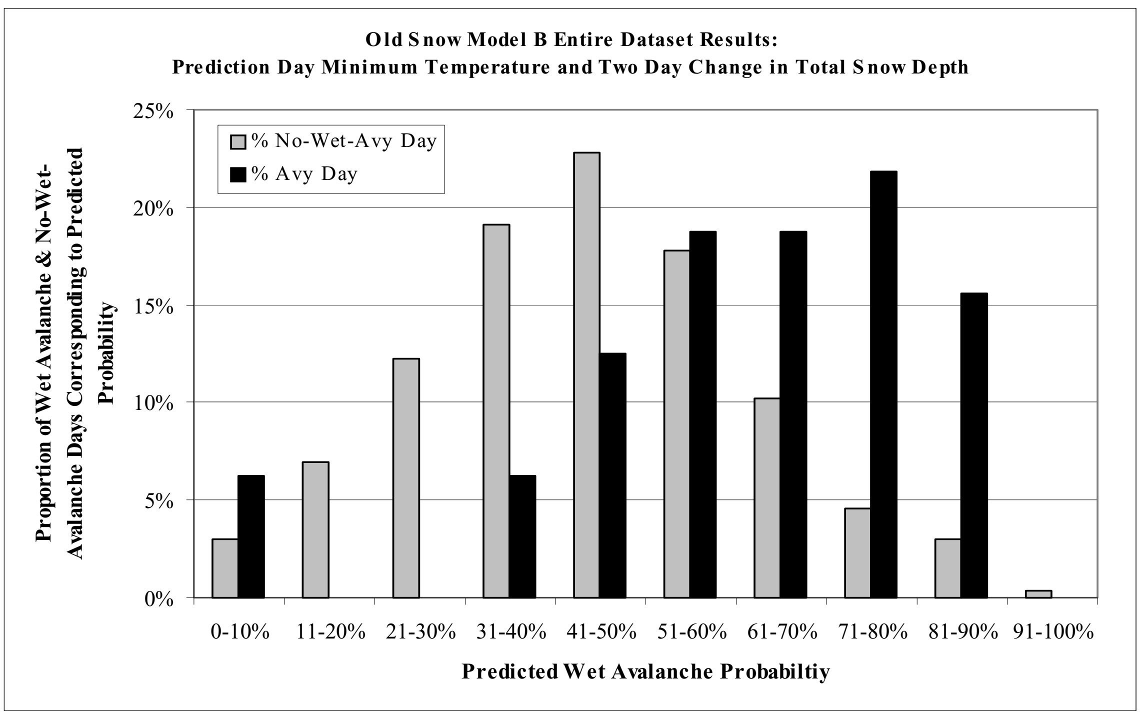

Figure 19. Combined Training and Testing Dataset Old Snow Model B Results (predictors = $MinT_0$, HS_0-HS_{-2})

The old snow model has a 75% overall success rate, that is, 75% of all the days in the old snow dataset were given accurate probabilities based on the model's decision rule. The old snow models decision rule is positioned at 57%, the point that best divides the distributions of the observed wet avalanche days and no-wet-avalanche days (Fig 19). According to this decision rule, any day given a predicted wet avalanche probability of 57% or greater *should* be a wet avalanche day and any day given a predicted wet avalanche probability less than 57% *should* be a day without wet avalanches.

In order to correctly interpret a probability calculated by the old snow model, the following must be considered: how often does the model give observed wet avalanche days a probability of 57% or greater, and how often does the model give observed no-wet-avalanche days a probability less than 57%? There were 90 old snow days that were given a wet avalanche probability of 57% or greater (Table 13). According to the model's decision rule, all 90 days should be wet avalanche days. Only 18 of the 90 days (20%) were observed wet avalanche days. The remaining 72 days (80%) were actually observed days with no wet avalanches that were given an inaccurate probability by the model. There were 245 old snow days that were given a probability less than 57% by the model (Table 13). According to the model's decision rule, all 245 days should be no-wet-avalanche days. Out of the 245 days, 231 days (94%) were observed days with no wet avalanches days. The remaining 14 days (6%) were inaccurately predicted observed wet avalanche days.

Table 13. Old Snow Model Accuracy

	Observed Old Snow Wet Avalanche Days	Observed Old Snow No-Wet-Avalanche Days	
Old Snow Model Predicted Wet Avalanche Day (Probability $\geq$ 57%)	18 days (correctly predicted)	72 days (incorrectly predicted)	Total: 90 days
Old Snow Model Predicted No-Wet-Avalanche Day (Probabiltiy < 57%)	14 days (incorrectly predicted)	231 days (correctly predicted)	Total: 245 days
	Total: 32* days	Total: 303* days	

*One wet avalanche day and six no-wet-avalanches days had missing data.

The model user should keep two types of uncertainty in mind when assessing any given probability calculated by the old snow model. First the user needs to consider the fundamental uncertainty associated with a probabilistic outcome. As the predicted probability increases, the odds for a wet avalanche day increase and the odds for a day without wet avalanches decrease. Even if the old snow model was 100% accurate, always calculating a probability of 57% or greater for wet avalanche days and always calculating a probability less than 57% for days with no wet avalanches, there would still be uncertainty in the predicted probability. The only time this uncertainty would not exist would be if a model with 100% accuracy calculated a 0% or 100% probability for wet avalanches. The second type of uncertainty relates to the old snow model's success rates for wet avalanche days and days with no wet avalanches. The old snow model has a 20% success rate for accurately calculating probabilities for wet avalanche days ($\geq$ 57%) and a 94% success rate for accurately calculating probabilities for days with no wet avalanches (<57%) based on its decision rule. For example, suppose the old snow model calculates a wet avalanche probability of 30%. The odds for a wet avalanche day (30%) are lower than the odds for a day with no wet avalanches (70%). Next the user needs to consider the model's accuracy given this predicted probability. Based on the success rate described above, when the old snow model predicts a wet avalanche probability between 0-56%, 9 out of 10 days will not have wet avalanches. Therefore the user can be fairly confident that the prediction day will not be a wet avalanche day, but there is a small possibility for wet avalanche occurrence. Suppose the old snow model calculates a wet avalanche probability of 70%. The odds for a wet avalanche day (70%) are now greater than the odds for a day with no wet avalanches (30%). When the old snow model calculates a wet avalanche probability between 57-100%, only 2 out of 10 days will have wet avalanche conditions. Given this relatively low success rate, the user cannot be as confident in the predicted probability. To gain more confidence in the model's predicted probability, the user can compare the prediction day's meteorological and snowpack conditions with the old snow wet avalanche indicator variables described below to determine whether current conditions are similar to wet avalanche conditions in the past.

Old Snow Wet Avalanche Indicator Variables

Histograms were created to determine whether there are wet avalanche threshold values for the old snow variables that were used in models A, B, and C (Fig. 11 and Figs. 20-22). If thresholds are evident, the variables can be used independently from the model as wet avalanche indicators and at the very least, provide a graphical summary of 32 years of wet avalanche data. The figures are simple frequency plots of each variable against old snow wet avalanche days.

'Day' of year (Fig. 11) does not appear to have clear upper and lower wet avalanche thresholds as wet avalanches have been recorded on old snow every day in March. Wet avalanche activity appears to be at its minimum during the first five days of March (day 60-64). Wet avalanche activity generally increases from day 65 through 84 and begins to taper off during the last six days of March.

The prediction day maximum temperature ($MaxT_0$) wet avalanche day distribution (Fig. 20) shows that all recorded wet avalanches have occurred between –10°C and 16°C. A wet avalanche releasing on a day where the maximum temperature is below 0°C may seem unlikely, but recall that temperature is only one component (longwave component) of the total energy available to melt snow (Brandt and Warren, 1993). The wet avalanche that released when the maximum temperature was between 0°C and -10°C (actual temperature was –8.3°C) (Fig. 20) may be an outlier that should be ignored, however there is a possibility that the day was very sunny and no wind was present or that there may have been a strong air temperature inversion present that day. In such a case, the upper mountain could have been warm enough to produce a wet avalanche while the Alpine weather station, located at mid-mountain remained very cool. Wet avalanches that went unrecorded may have also released when temperatures were greater than 16°C. A reliable threshold with the prediction day maximum temperature distribution in Figure 20 is difficult to determine, but the data do illustrate that over 75%

of the recorded wet avalanches occurred between 4°C and 14°C, with 24% occurring when the maximum temperature is between 12°C and 14°C.

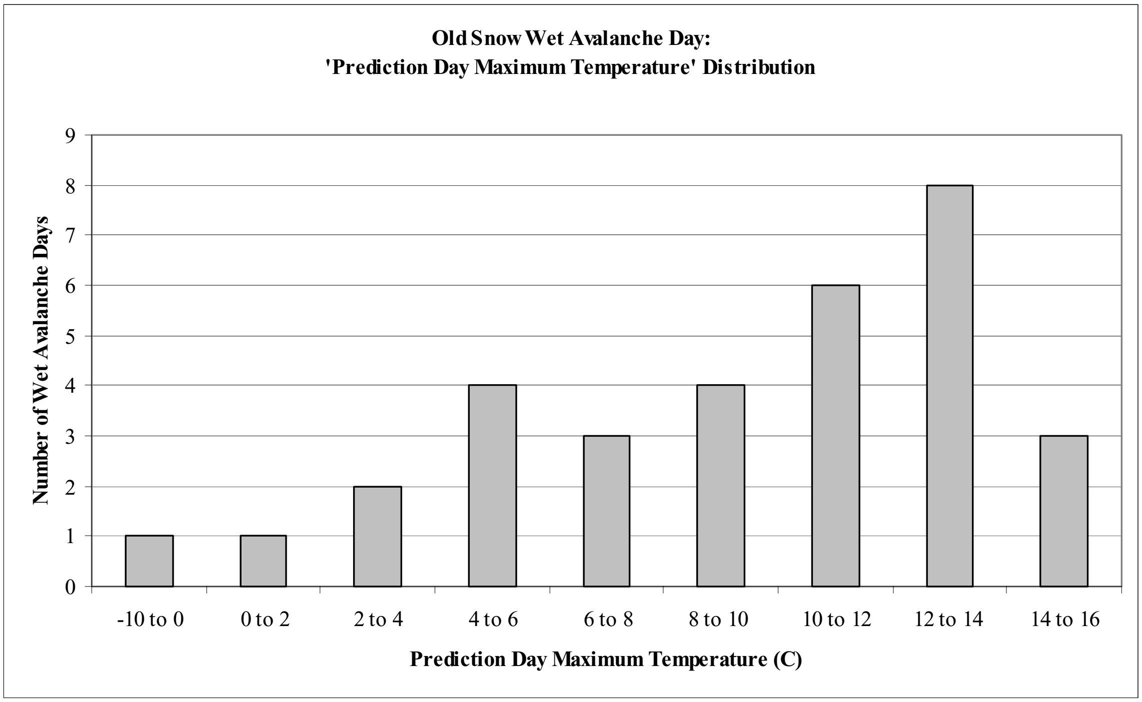

Figure 20. Old Snow Prediction Day Maximum Temperature Distribution on Wet Avalanche Days

The prediction day minimum temperature ($MinT_0$) wet avalanche day distribution (Fig. 21) appears to have a bimodal distribution with wet avalanches recorded when minimum temperatures ranged between –20°C and -5°C and -2°C and 3°C. Whether this bimodal distribution is a real pattern or simply the result of a few wet avalanches going unrecorded on days with minimum temperatures of –4°C and -3°C is uncertain. Perhaps the wet avalanches associated with the sub-zero temperatures occurred under clear sky conditions which would allow for very cool night-time temperatures followed by warm sunny days with increased incoming shortwave radiation. The wet avalanches associated with the positive minimum temperatures may have released under cloudy conditions, which would maintain mild minimum temperatures. Thresholds are difficult to determine, however it is apparent that nearly one-quarter of the observed wet avalanches released when the prediction day minimum temperature was -5°C.

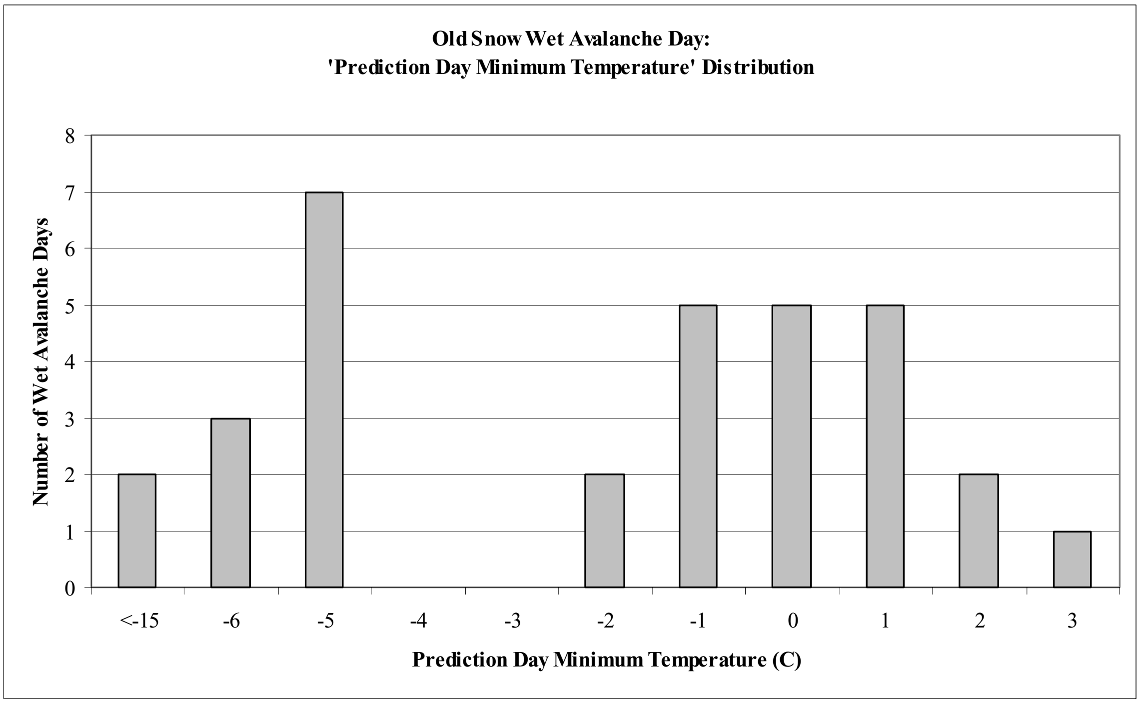

Figure 21. Old Snow Prediction Day Minimum Temperature Distribution on Wet Avalanche Days

The two–day change in total snowpack depth (HS_0-HS_{-2}) wet avalanche day distribution (Fig. 22) also has a split, or bimodal distribution. There is uncertainty about whether the lack of recorded wet avalanches in the 8cm to 10cm range is a real phenomenon or an artifact of this dataset. The HS_0-HS_{-2} distribution does clearly show that over one-third of the recorded wet avalanches released when the total snowpack depth decreased 10cm to 12cm between the prediction day and two days prior, and 75%

of the recorded wet avalanches released when the total snowpack depth decreased between 16cm and 6cm between the prediction day and two days prior.

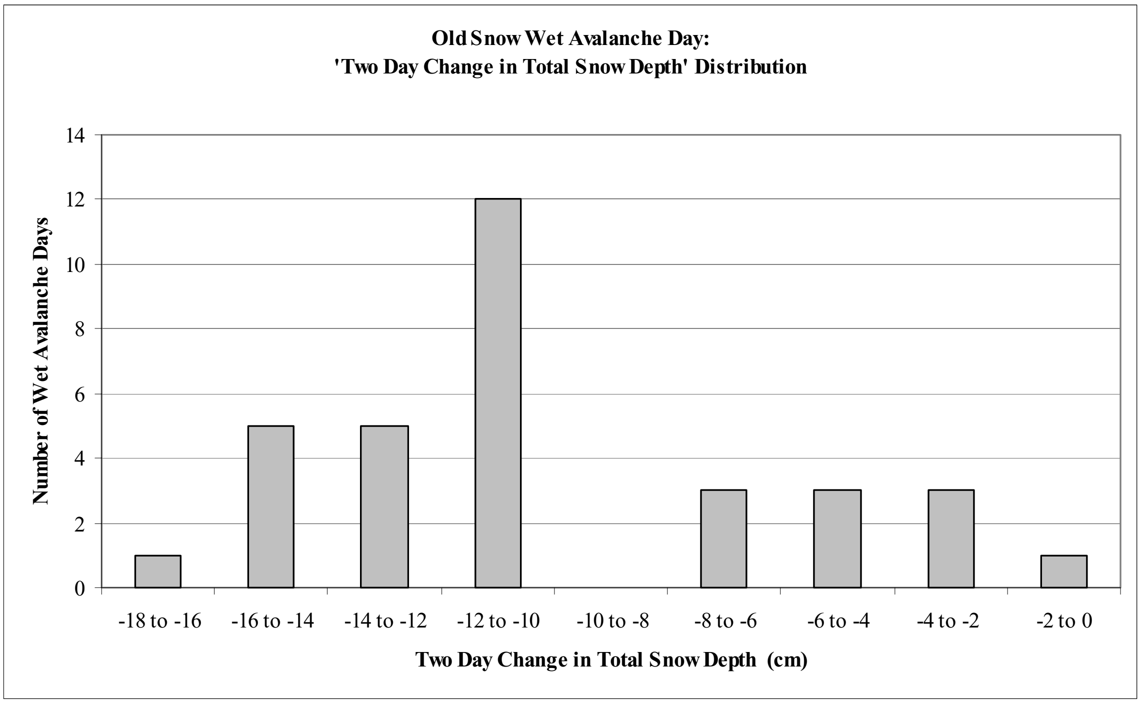

Figure 22. Old Snow Two Day Change in Total Snow Depth Distribution on Wet Avalanche Days

Top Three New Snow Model Results

The top three new snow model results are illustrated in Table 14 and Figures 23 through 28. New snow Model E was chosen as the best new snow wet avalanche prediction model (Table 14, Fig. 25 and Fig. 26) because it has fewer problems with underestimating wet avalanche probability. Model E's predictor variable p-values were similar to Model D's (Table 14, Fig. 23 and Fig. 24) and better than Model F's (Table 14, Fig. 27 and Fig. 28). Odds ratios were greater and more consistent for Model E variables than the other two models. Model E's percent concordant pairs were greater than Model

D's and equal to model F's, while the percent discordant and tied pairs were lower than Model D and nearly identical to Model F's.

Table 14. Top Three New Snow Model Results

	New Snow Training Dataset Results			**New Snow Testing Dataset Results**		
Model D: $P_n(i) = \frac{e^{\beta MinT_{0\,in} + \beta HN_{0,-1,-2\,in} + \varepsilon}}{1 + e^{\beta\beta Min_{0\,in} + \beta HN_{0,-1,-2\,in} + \varepsilon}}$						
Predictor Variables	$MinT_0$	$HN_{0,-1,-2}$		$MinT_0$	$HN_{0,-1,-2}$	
Coefficients (β)	0.12978	0.020115		0.23299	0.03315	
P-Values	0.009	0.022		0.010	0.109	
Odds Ratios	1.14	1.02		1.26	1.03	
% Concordant, Discordant & Tied Pairs	Concordant 67%	Discordant 30.8%	Tied 2.2%	Concordant 70.6%	Discordant 28.1%	Tied 1.2%
Model E: $P_n(i) = \frac{e^{\beta MinT_{0\,in} + \beta HNW_{0,-1,-2,-3\,in} + \varepsilon}}{1 + e^{\beta MinT_{0\,in} + \beta HNW_{0,-1,-2,-3\,in} + \varepsilon}}$						
Predictor Variables	$MinT_0$	$HNW_{0,-1,-2,-3}$		$MinT_0$	$HNW_{0,-1,-2,-3}$	
Coefficients (β)	0.12379	0.3362		0.21486	0.4153	
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%
Model F: $P_n(i) = \frac{e^{\beta MinT_{0\,in} + \beta HNW_{0,-1,-2,-3\,in} + \beta MaxT_{-1} - MinT_{0\,in} + \varepsilon}}{1 + e^{\beta MinT_{0\,in} + \beta HNW_{0,-1,-2,-3\,in} + \beta MaxT_{-1} - MinT_{0\,in} + \varepsilon}}$						
Predictor Variables	$MinT_0$	$HNW_{0,-1,-2,-3}$	$MaxT_{-1}$-$MinT_0$	$MinT_0$	$HNW_{0,-1,-2,-3}$	$MaxT_{-1}$-$MinT_0$
Coefficients (β)	0.11333	0.3275	-0.0857	0.1346	0.3222	-0.3428
P-Values	0.033	0.001	0.574	0.214	0.197	0.215
Odds Ratios	1.12	1.39	0.92	1.14	1.38	0.71
% Concordant, Discordant & Tied Pairs	Concordant 72.1%	Discordant 26.6%	Tied 1.4%	Concordant 74.4%	Discordant 24.8%	Tied 0.8%

One would likely choose Model F as the best predictive model based on the test scores alone. However, the distributions shown in Figures 23 through 28 show that Models D and F underestimate wet avalanche probabilities. Model D (Figs. 23 and 24) predicts almost as accurately as Model E, but Model D seems to slightly underestimate wet avalanche probability in general. The training dataset distribution for Model E (Fig. 25) shows two well-defined bell-shaped curves for the observed no-wet-avalanche day and wet avalanche day occurrence vs. the model's predicted probability. The observed days with no wet avalanches are centered about the 31-40% predicted probability range and the observed wet avalanche days are centered about the 51-60% predicted probability range. The testing dataset plot (Fig. 26) does not have as well-defined bell-shaped curves, but the results are fairly consistent with the model predicting higher wet avalanche probabilities for wet avalanche days and lower probabilities on days with no wet avalanches. Model F underestimates the wet avalanche probability to a greater degree than Model D, and its testing dataset results are not as consistent with its training dataset results (Figs. 27 and 28). Out of the three models, Model E most accurately assigns wet avalanche days higher wet avalanche probabilities and days with no wet avalanches lower wet avalanche probabilities.

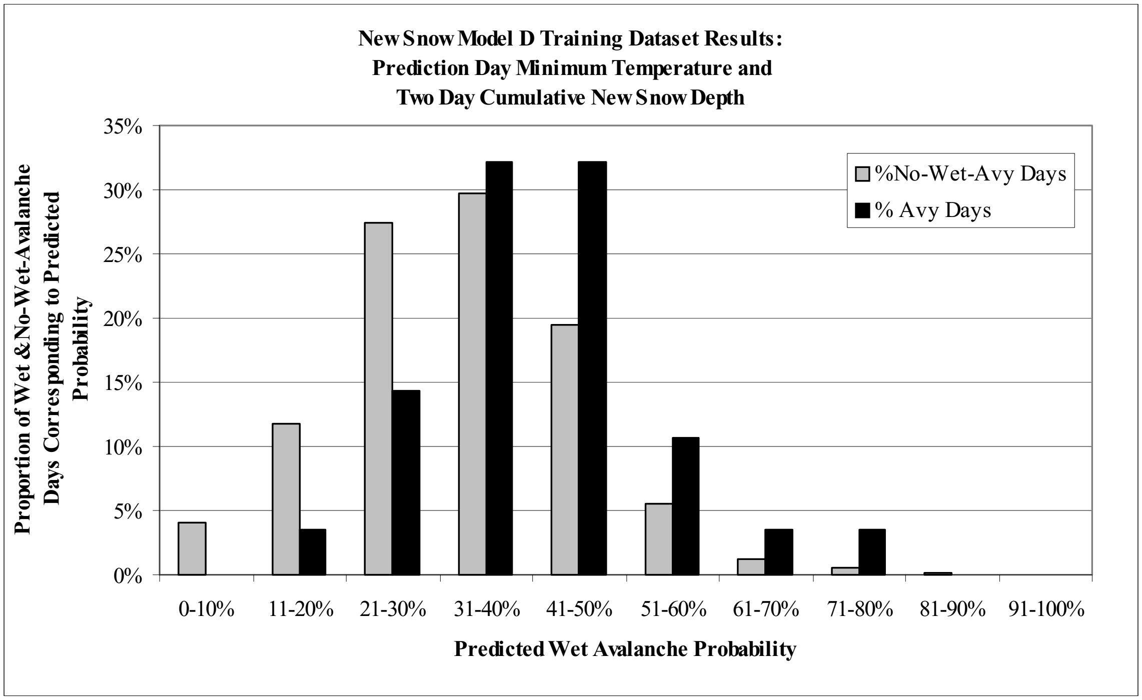

Figure 23. New Snow Training Dataset Model D Results (predictors = $MinT_0$, $HN_{0,-1,-2}$)

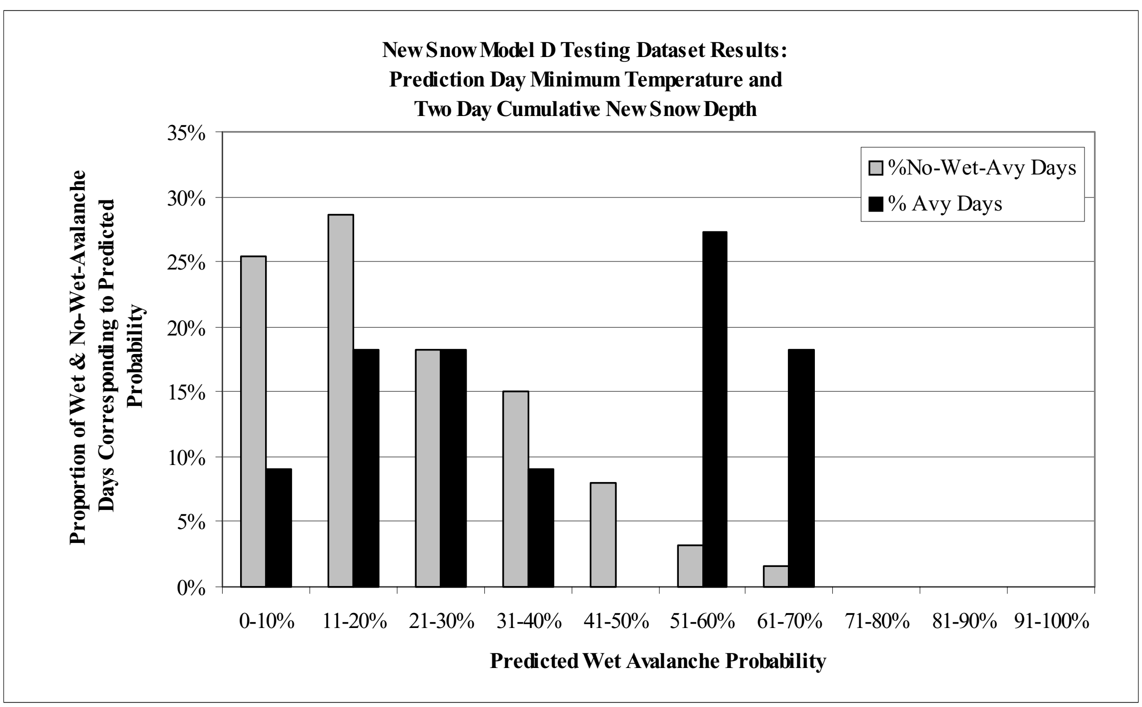

Figure 24. New Snow Testing Dataset Model D Results (predictors = $MinT_0$, $HN_{0,-1,-2}$)

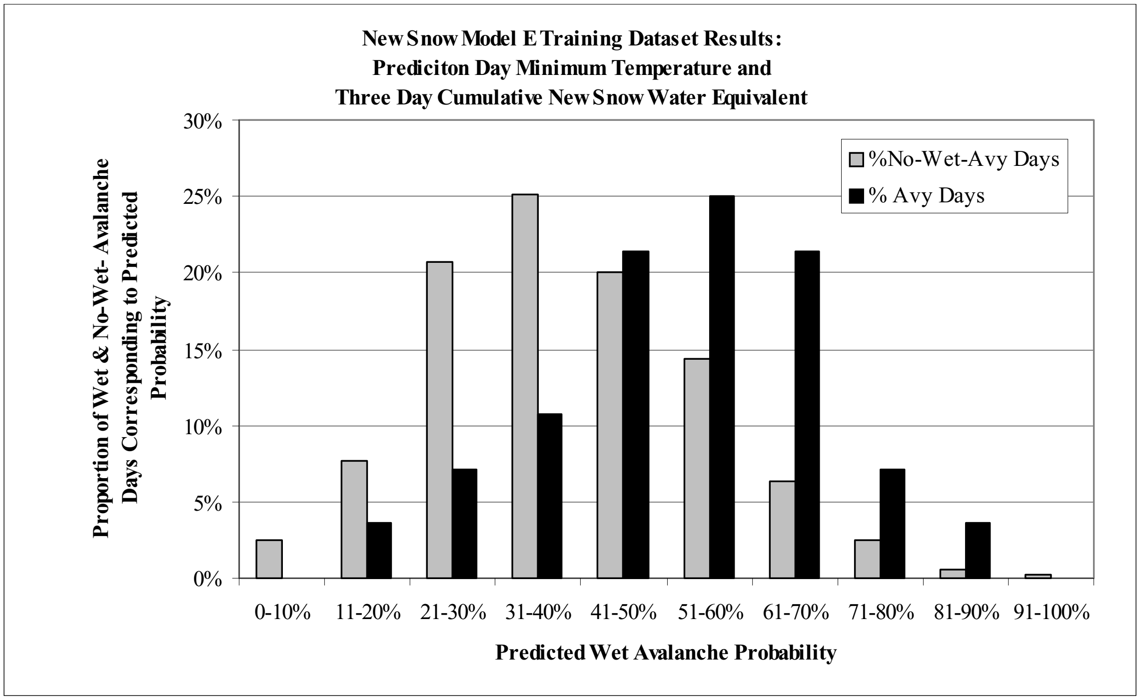

Figure 25. New Snow Training Dataset Model E Results
(predictors = $MinT_0$, $HNW_{0,-1,-2,-3}$)

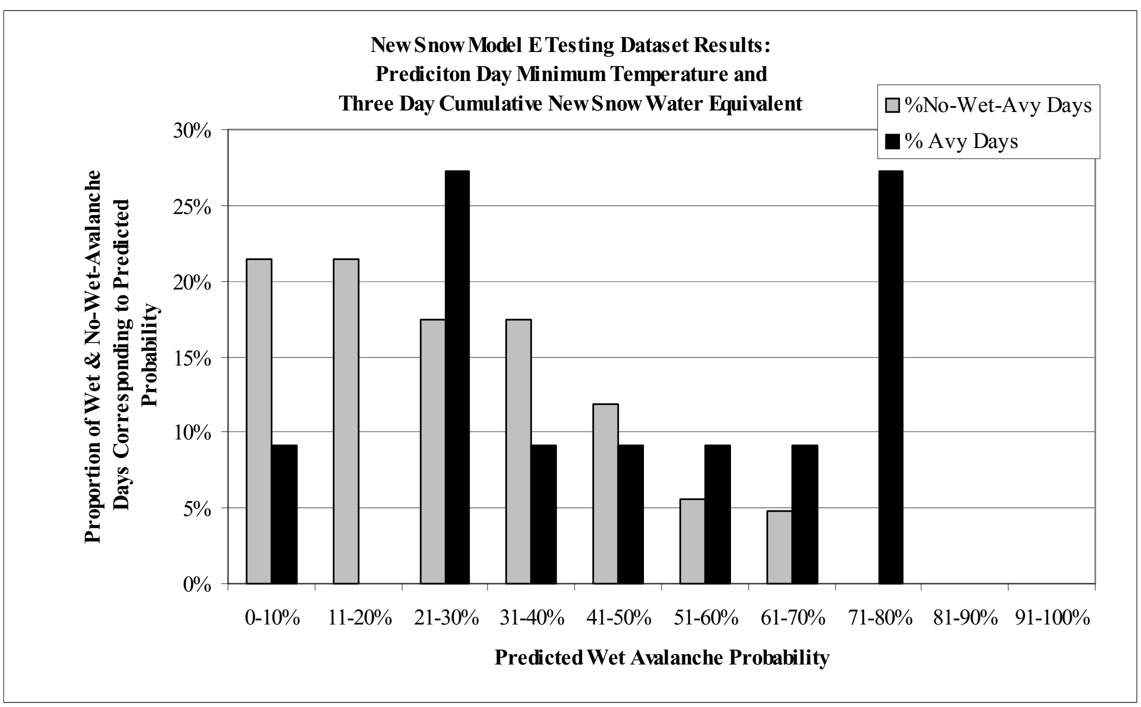

Figure 26. New Snow Testing Dataset Model E Results
(predictors = $MinT_0$, $HNW_{0,-1,-2,-3}$)

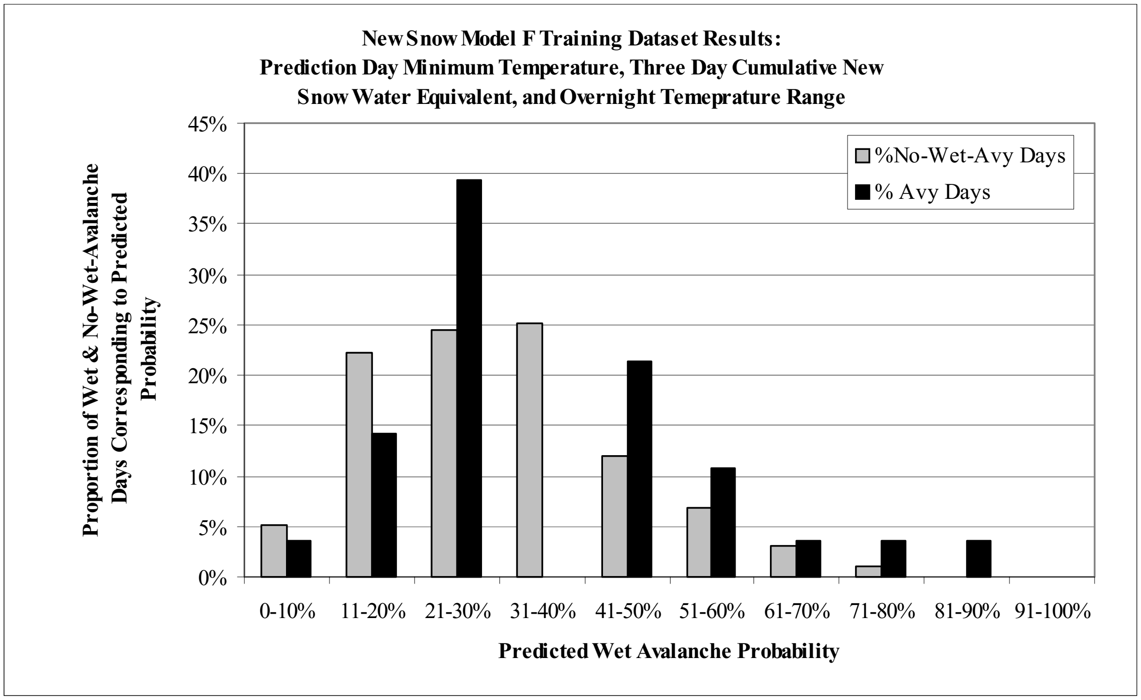

Figure 27. New Snow Training Dataset Model F Results
(predictors = $MinT_0$, $HNW_{0,-1,-2,-3}$, $MaxT_{-1}$-$MinT_0$)

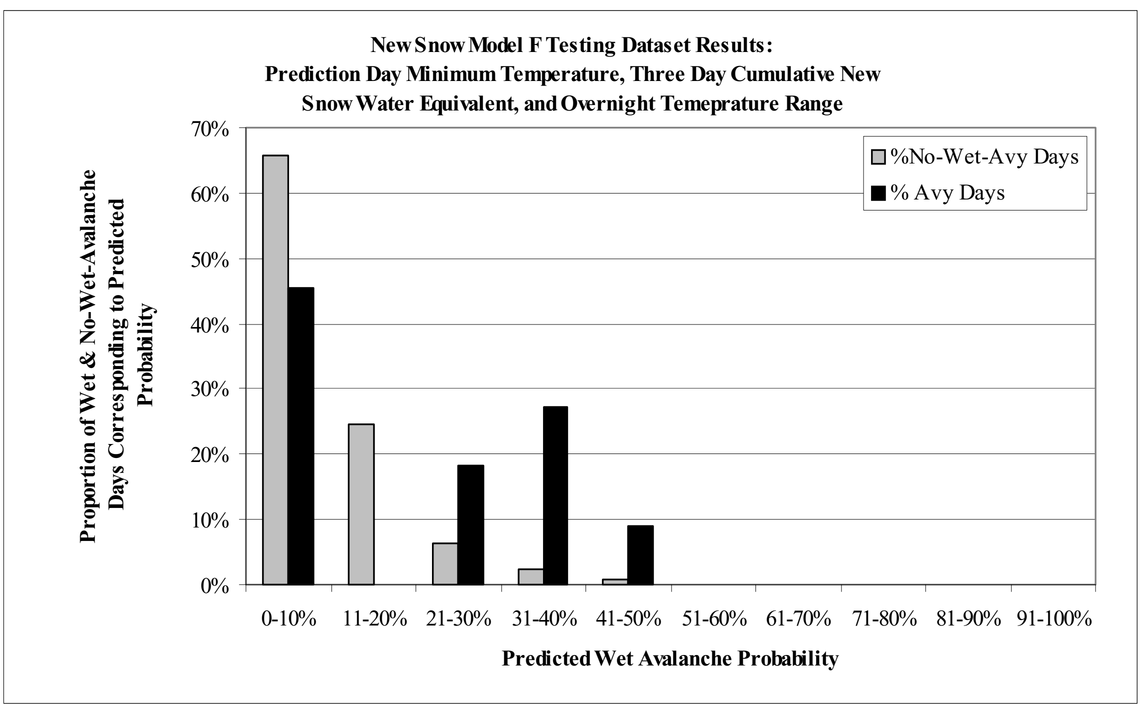

Figure 28. New Snow Testing Dataset Model F Results
(predictors = $MinT_0$, $HNW_{0,-1,-2,-3}$, $MaxT_{-1}$-$MinT_0$)

Figure 29 provides Model E results when the training and testing datasets are combined and the model is run on the entire new snow dataset. This creates slightly different coefficients in the model equation, and results vary somewhat from the training and testing dataset results described above. As with the old snow prediction model, this new snow prediction model will not provide the user with a definitive ‘yes/no’ answer. Results in Figure 29 demonstrate that all wet avalanches in the past 32 years have occurred when the model predicts an 11-80% probability for wet avalanche conditions.

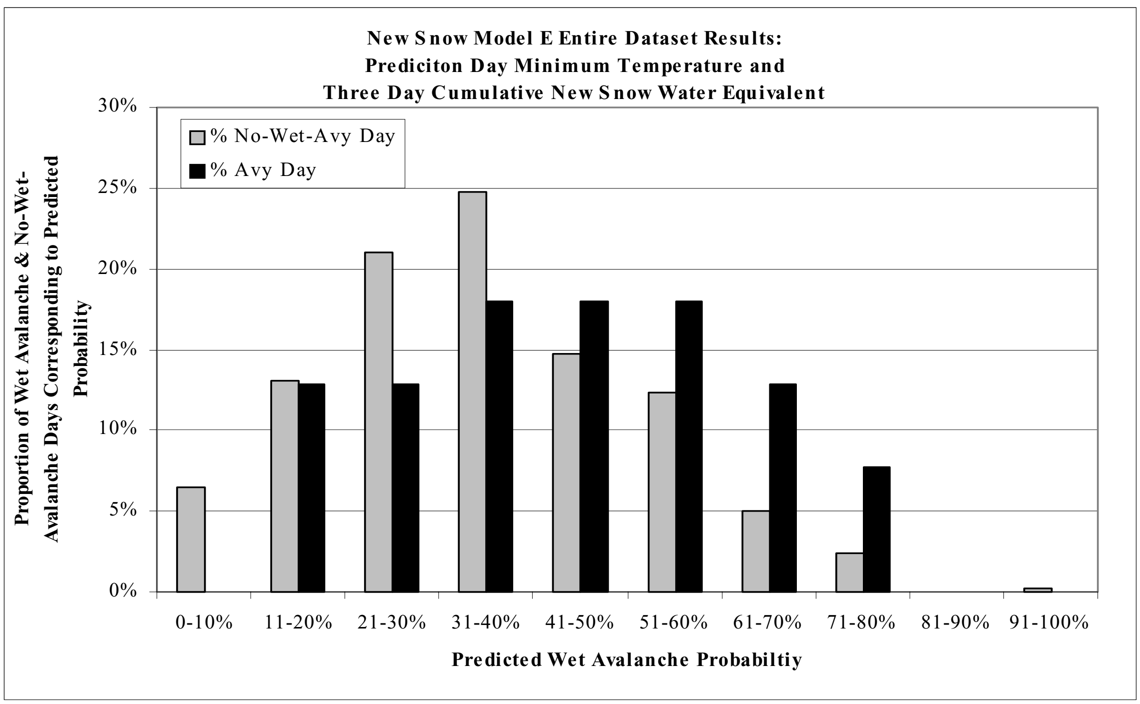

Figure 29. Combined Training and Testing Dataset New Snow Model E Results (predictors = $MinT_0$, $HNW_{0,-1,-2,-3}$)

The new snow model has a 72% overall success rate, in other words, 72% of all the days in the new snow dataset were given accurate probabilities based on the model's decision rule. The new snow model's decision rule is positioned at 45%, the point that best divides the distributions of the observed wet avalanche days and days with no wet avalanches (Fig. 29). According to the new snow model's decision rule, any day that is given a wet avalanche probability of 45% or greater *should* be a wet avalanche day and any day given a predicted wet avalanche probability less than 45% *should* be a day without wet avalanches.

The same questions asked of the old snow model must be taken into consideration with the new snow model in order to correctly interpret its predicted probabilities: how often does the model give observed wet avalanche days a probability of 45% or greater, and how often does the model give observed days with no wet avalanches a probability less than 45%? There were a total of 195 new snow days that were given a wet avalanche probability of 45% or greater (Table 15). According to the new snow model's decision rule, all 195 days should be wet avalanche days. Only 18 days (9%) were observed wet avalanche days. The remaining 177 days (91%) were observed days with no wet avalanches that were inaccurately given a probability greater than 45%. There were 477 days in the new snow dataset that were given a wet avalanche probability less than 45% (Table 15). According to the new snow model's decision rule, all 477 days should be days with no wet avalanches. Of the 477 days, 456 days (96%) were observed days with no wet avalanches. The remaining 21 days (4%) were observed wet avalanche days that were given inaccurate probabilities by the model.

Table 15. New Snow Model Accuracy

	Observed New Snow Wet Avalanche Days	Observed New Snow No-Wet-Avalanche Days	
Old Snow Model Predicted Wet Avalanche Day (Probability ≥ 57%)	18 days (correctly predicted)	177 days (incorrectly predicted)	Total: 195 days
Old Snow Model Predicted No-Wet-Avalanche Day (Probabiltiy < 57%)	21 days (incorrectly predicted)	456 days (correctly predicted)	Total: 477 days
	Total: 39 days	Total: 633* days	

*71 no-wet-avalanche days were missing data.

Interpretation of the new snow model's predicted wet avalanche probability is similar to the interpretation described for the old snow model. When assessing any given probability by the new snow model, the user needs to consider the fundamental uncertainty associated with a probabilistic outcome in addition to the uncertainties associated with the model's success rates for wet avalanche days and days with no wet avalanches. The new snow model has a 9% success rate for accurately calculating probabilities for wet avalanche days (≥ 45%) and a 96% success rate for accurately calculating probabilities for days with no wet avalanches (<45%). If the new snow model calculates a low wet avalanche probability, such as 25%, the odds for a wet avalanche day (25%) are lower than the odds for a day without wet avalanches (75%). Based on 32 years of wet avalanche data, when the new snow model calculates a wet avalanche probability between 0-44%, 9 out of 10 days will not have wet avalanches. Given the low predicted probability and the new snow model's high success rate for days with no wet avalanches, the user can be fairly confident that no wet avalanches will occur on the prediction day, however, the possibility of a wet avalanche occurrence, although small, cannot be ruled out. If the new snow model calculates a high wet avalanche probability, such as 75%, the odds for a wet avalanche day (75%) are greater than the odds for a day with no wet avalanches (25%). When the new snow model calculates a wet avalanche probability between 45-100%, only 1 out of 10 days will be a wet avalanche day. Given this low success rate, the user cannot be as confident in the predicted probability. As with the old snow model, the user can gain more confidence in the new snow model's predicted probability by comparing the prediction day's meteorological and snowpack conditions with the new snow wet avalanche indicator variables described below.

New Snow Wet Avalanche Indicator Variables

Frequency charts were created to determine whether there are wet avalanche threshold values for the new snow variables that were used in models D, E, and F (Figs. 30-33). If thresholds do exist, the variables can be used independently from the model as wet avalanche indicators and at the very least, provide a graphical summary of 32 years of wet avalanche data. The figures are simple histograms of each variable against new snow wet avalanche days.

New snow prediction day minimum temperature ($MinT_0$) (Fig. 30) may have minimum and maximum threshold values at -11°C and -1°C with outliers at -17°C, -14°C, -13°C and 2°C. Figure 30 shows that almost 85% of all recorded wet avalanches occurred when the minimum temperature ranged from -9°C to -1°C, with 23% occurring at -7°C and 18% occurring at -3°C.

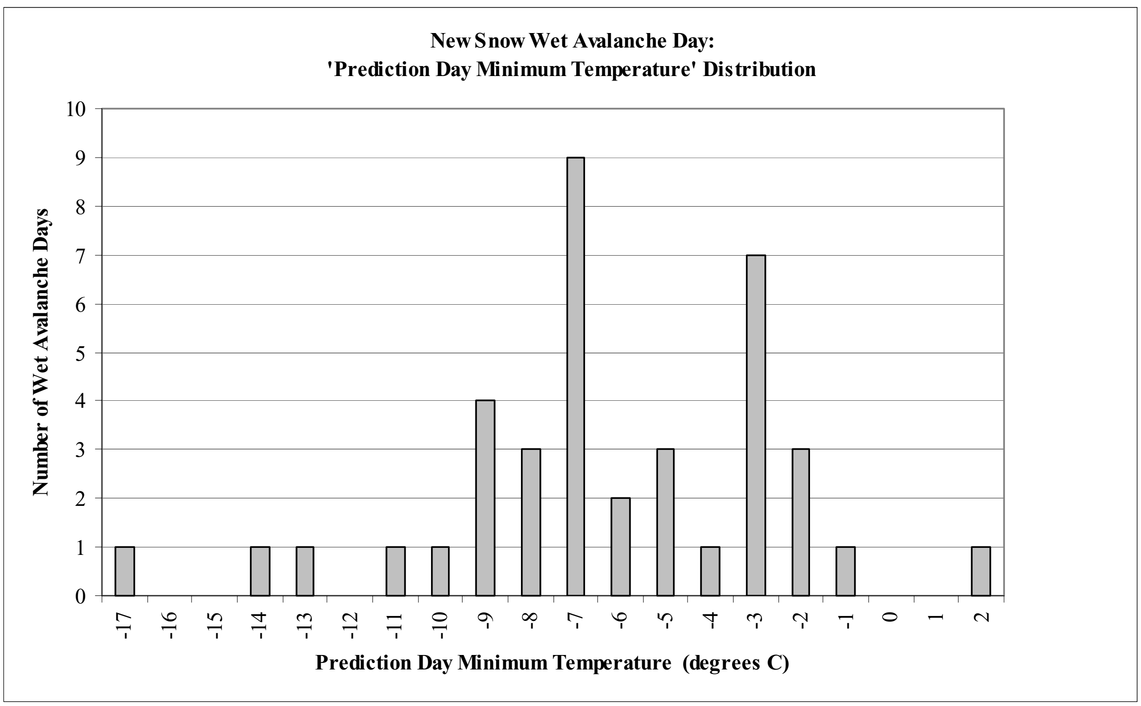

Figure 30. New Snow Prediction Day Minimum Temperature Distribution on Wet Avalanche Days.

The cumulative two day new snow depth ($HN_{0,-1,-2}$) (Fig. 31) has fairly clear minimum and maximum values for wet avalanche days (0cm to 50cm), particularly if one can determine if the observed avalanche that occurred when the cumulative two day new snow total at 90-100cm is an outlier. Almost all of the observed wet avalanches (95%) released on 2.5cm to 40cm of cumulated two day new snow totals. Approximately 28%

of all new snow wet avalanches released with 10cm to 20cm of new snow, 25% released on 20cm to 30cm of new snow, and approximately 31% occurred when cumulative two day new snow ranged from 30cm to 40cm.

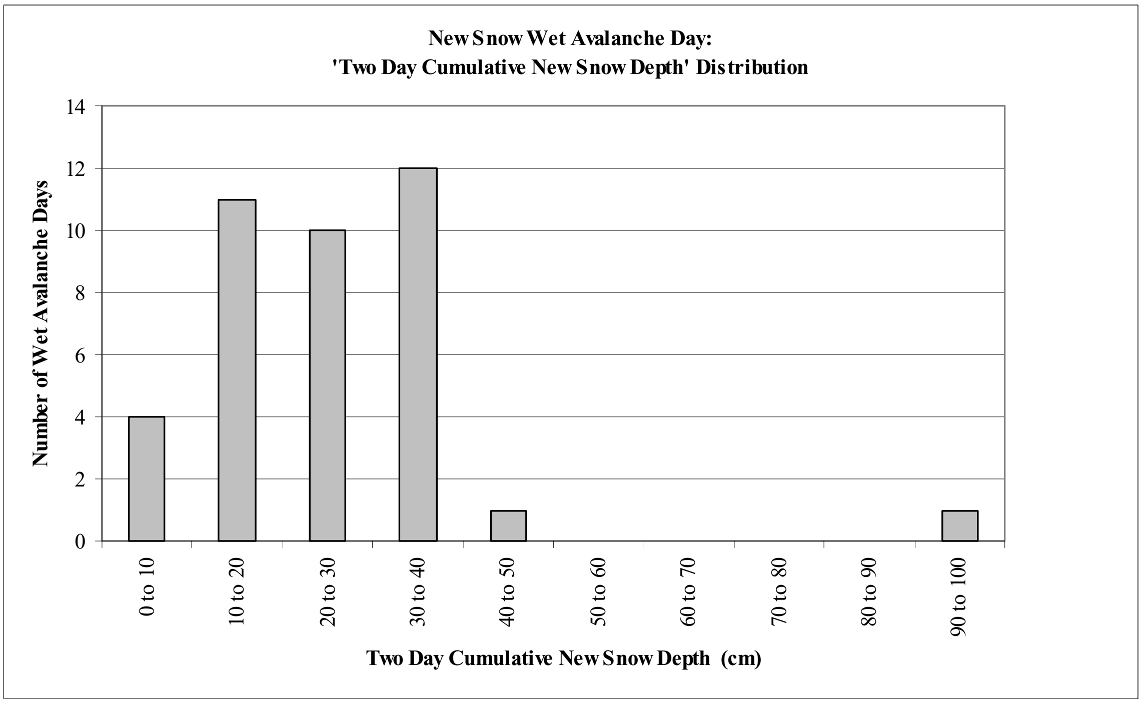

Figure 31. New Snow Two Day Cumulative New Snow Depth Distribution on Wet Avalanche Days

Approximately 62% of all recorded wet avalanches released on days with a three day cumulative new snow water equivalent of 1cm to 3cm and 77% of all recorded wet avalanches released when the three day new snow water equivalent totals ranged from 1cm to 4cm (Fig. 32). Frequency drops off quickly when accumulation exceeds 3cm of liquid water. The higher snow water equivalents may be the result of heavy, deep snowfalls which behaved more like an insulating blanket over the snowpack and prevented it from being heated at depth by incoming radiation (Brandt and Warren, 1993).

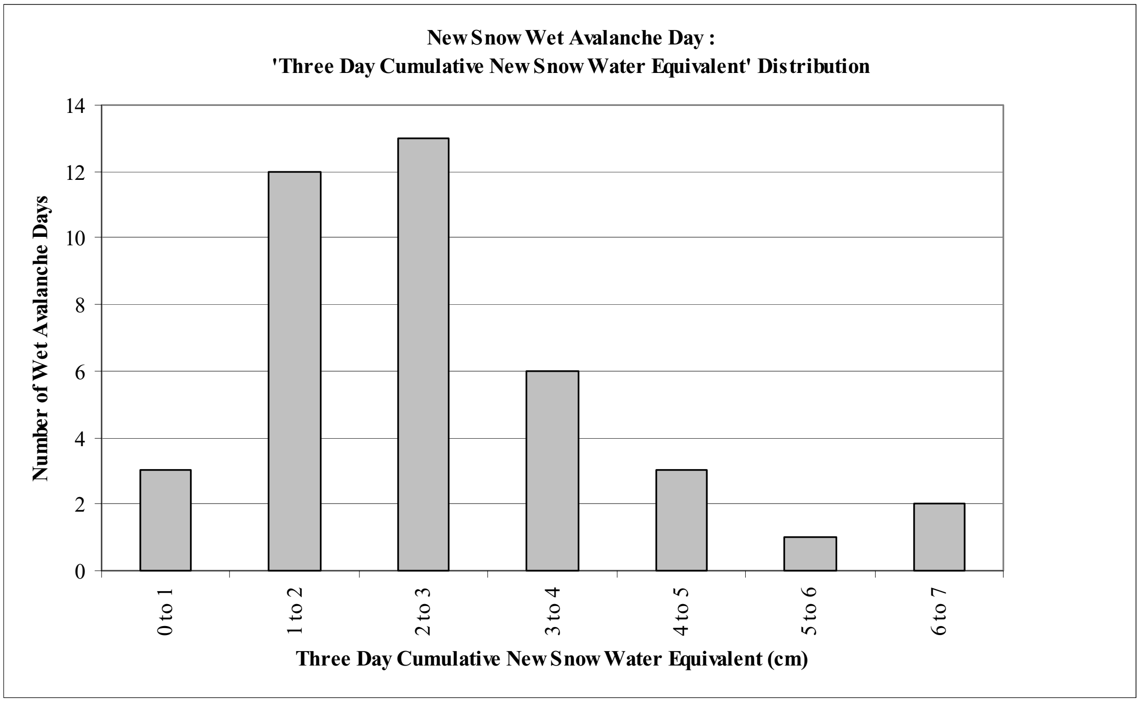

Figure 32. New Snow Wet Three Day Cumulative New Snow Water Equivalent Distribution on Wet Avalanche Days

There are no clear threshold values for the overnight temperature range preceding the prediction day ($MaxT_{-1}$-$MinT_0$) (Fig. 33). Approximately 67% of observed wet avalanches released when overnight temperature ranges were between 2°C and 12°C. In the past, the top three most likely overnight temperature ranges for wet avalanche conditions are 2°C to 4°C with 18% of the observed releases, 4°C to 6°C with 15% of the releases and 6°C to 8°C also with 15% of the recorded releases. The negative temperature values indicate that the prediction day minimum temperature is warmer than the previous day's maximum temperature. Wet avalanche releases are minimal in the

-6°C to 0°C overnight temperature range because the cooler maximum temperature from the previous day has caused the snowpack's 'heat deficit' to increase, which in turn increases the energy requirements for melt to take place the following day (Cline, 1997). Positive temperatures indicate that the air temperature cooled overnight. As expected, evenings with minimal cooling, particularly in the 2°C to 8°C temperature range, require less energy the following day to raise the snow temperature to 0°C prior to melt and are most likely to be followed by a wet avalanche day. Frequency drops off steadily as the overnight temperature cools more than 10°C and the next day's energy requirements for snowmelt increase.

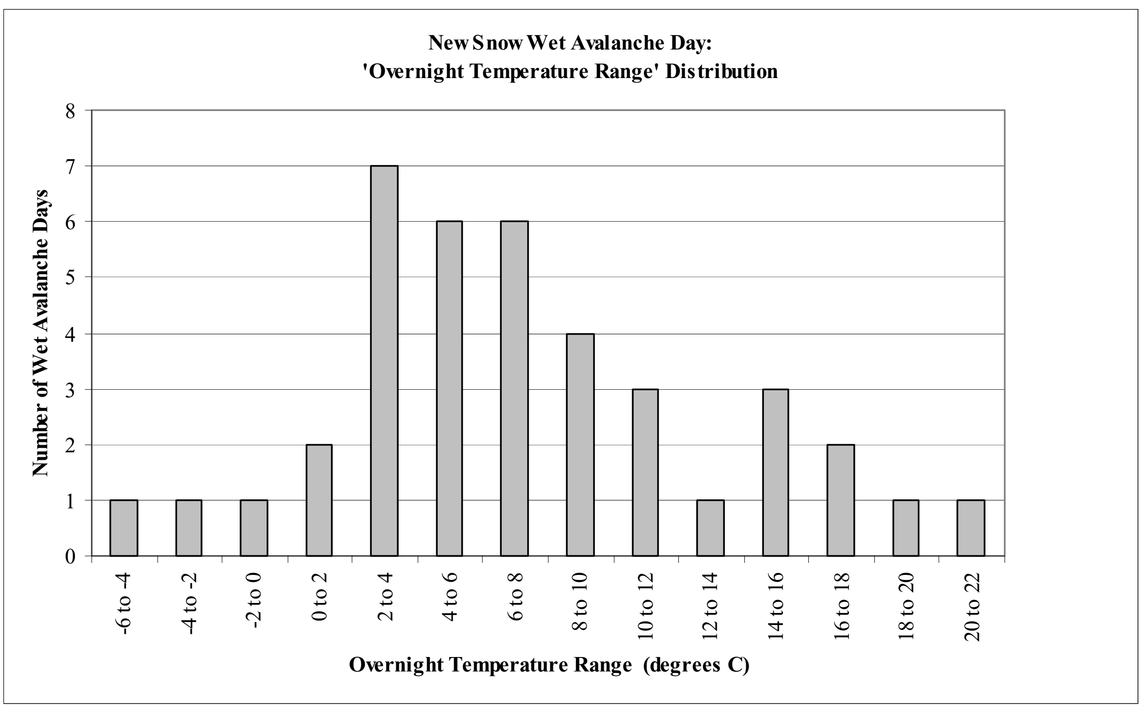

Figure 33. New Snow Prediction Day Overnight Temperature Range Distribution on Wet Avalanche Days

Data Analysis - Summary

Hypothesis Testing Summary

By dividing the original Bridger Bowl dataset into separate old snow and new snow datasets, patterns emerged that have gone overlooked in past wet avalanche studies. Old snow wet avalanche conditions tend to begin developing two to three days prior to the wet avalanche day (Table 6). In contrast, new snow wet avalanche conditions generally develop much more quickly with warning signs most evident just one day prior to the wet avalanche day (Table 7). Old snow wet avalanche conditions require more time and energy for development because the snow has had time to form stronger grain-to-grain bonds. Old snow may have gone through one or more cycles of melt-freeze before the avalanche day. This process can produce extremely well-bonded snow grains and snow layers that require a great deal of energy in order for those bonds to be destroyed (McClung and Schaerer, 1993). New snow requires less time and energy for wet avalanche development primarily because the new snow has finer-grained snow crystals that tend to retain liquid water more readily because of increased surface tension associated with the increased surface area within the new snow matrix. New snow has fewer, smaller and weaker grain-to-grain contacts, and can fail at a lower water content than snow with greater initial strength, such as old snow (McClung and Schaerer, 1993).

Predictor variable behavior for old snow and new snow wet avalanche day vs. no-wet-avalanche days was quite distinct as well. Temperature variables were particularly important for distinguishing between a day with no wet avalanches and a wet avalanche day for old snow conditions. Maximum, minimum and average temperatures generally increase rapidly and total snowpack depth decreases rapidly prior to an old snow wet avalanche day (Table 6, Table 8 and Figs. 20-22). These patterns suggest that old snow avalanches most often develop under warm spring-time conditions. New snow wet avalanches seem to develop with a less distinct pattern. Temperature variables are generally just 1°C to 2°C warmer on wet avalanche days than days with no wet avalanches (Table 7). Temperatures remain fairly stable and cool suggesting that new snow wet avalanche conditions may develop under very moist, cool and cloudy conditions or under sunny conditions that develop immediately after a new snowfall event (Fig. 30 and Fig. 33). New snowfall characteristics provide the best distinction between new snow wet avalanche days and no-wet-avalanche days. Two to three consecutive days of greater than average, wetter than average and more dense than average snowfalls with slightly warmer temperatures appear to be the driving factors for new snow wet avalanche formation (Table 7, Fig. 31 and Fig. 32).

Model Design and Application Summary

The old snow and new snow final models will provide the Bridger Bowl patrol with a new way to assess the probability of wet avalanche conditions based on 32 years of wet avalanche data. The experience of the Bridger patrol enables them to anticipate the onset of wet avalanche conditions when they present themselves with classic wet snow characteristics such as increased snowpack settlement rates after successive days of intense heating (McClung and Schaerer, 1993). When typical wet snow conditions are developing, ski patrollers are assigned a route on the mountain and continually ski this route to observe changes occurring in the snowpack. Running the appropriate model the morning of a possible wet avalanche day will give the patrollers the probability for wet avalanche danger. Comparing the model's probability as well as the prediction day's current meteorological and snowpack conditions with historical wet avalanche data will give patrollers supplementary information to help prepare them for any additional safety measures that need to take place later that day. The models will also serve as a useful learning tool for new patrollers who can quickly and easily check the accuracy of their own thoughts on wet avalanche probability with the model's calculations. They can also quickly access graphs of wet avalanche indicator variables (Figs. 11, 20-22 and Figs. 30-33) to gain a better understanding of historical wet avalanche activity given the present day meteorological and snowpack conditions. The old and new snow wet avalanche indicator graphs will be very helpful when used on days when wet avalanches are not expected. The wet avalanche indicator graphs (Figs. 11, 20-22 and Figs. 30-33) show that wet avalanches have occurred over a surprisingly broad range of temperatures, snowpack depth change, and precipitation totals.

The models are easy to use and provide reliable, practical results that do not require the user (a ski patroller) to have a strong statistical background or calculate complex variables. The user should adopt the old snow model when there has been no recorded new snowfall within the last 48 hours. Simply enter the present day minimum temperature, the present day total snowpack depth and the snowpack depth from two days prior into the Excel program. The model will automatically calculate a wet avalanche probability based on the present day minimum temperature and the total change in snowdepth that occurred over the last two days. The old snow model has an overall success rate of 75%, that is, 75% of all the old snow days were given accurate probabilities by the old snow model. In order to correctly interpret the wet avalanche probability predicted by the old snow model, the model's decision rule must be taken into consideration. The old snow models decision rule is positioned at 57%. According to this decision rule any day given a wet avalanche probability of 57% or greater *should* be a wet avalanche day and any day given a wet avalanche probability less than 57% *should* be a day without wet avalanches. When the old snow model's predicted probabilities are compared to 32 years of observed data, 9 out of 10 days with no wet avalanches are correctly given a predicted probability less than 57% and 2 out of 10 wet avalanche days are correctly given a predicted probability of 57% or greater. When assessing a probability calculated by the old snow model, the user must take into consideration the fundamental uncertainties associated with a probabilistic outcome in addition to the uncertainties associated with the model's success rates for wet avalanche days (20%) and days with no wet avalanches (94%).

If there has been measurable new snowfall within the last 48 hours, the new snow model should be used. This model uses the present day minimum temperature, and the cumulated snow water equivalent total over the last three days, including the present day to calculate the current wet avalanche probability (the SWE for the present day may need to be estimated by the user). This model has given accurate wet avalanche probabilities for 72% of the new snow dataset. The decision rule for the new snow model is positioned at 45%. According to this rule, any day given a wet avalanche probability less than 45% *should* be a day with no wet avalanches, and any day given a wet avalanche probability of 45% or greater *should* be a wet avalanche day. When the new snow model's predicted probabilities are compared to 32 years of observed data, 9 out of 10 days with no wet avalanches are correctly given a probability less than 45% by the model and only 1 out of 10 wet avalanche days are correctly given predicted probabilities of 45% or greater. When the user is assessing a probability calculated by the new snow model, the fundamental uncertainties associated with a probabilistic outcome must be taken into consideration in addition to the uncertainties associated with the new snow model's success rates for wet avalanche days (9%) and days with no wet avalanches (96%).

The uncertainty associate with both models reinforces the importance of the historical wet avalanche data provided in the wet avalanche indicator graphs (Figs. 11, 20-22 and Figs. 30-33). When the models' predicted probabilities are compared to the observed wet avalanches vs. predicted probability charts (Fig. 19 and Fig. 29) and the wet avalanche indicator graphs (Figs. 11, 20-22 and Figs. 30-33), the user will be able to assess the current probability of wet avalanche conditions based on historical wet avalanche data.

The procedure for running the new snow and old snow models is outlined below (Fig. 34). The models were originally developed using Microsoft Excel software, but the algorithms can be computed on any spreadsheet software similar to Excel. Instructions for creating the models in Microsoft Excel and a detailed 'help' document are available in Appendix C. A copy of the models, as well as the observed wet avalanche vs. predicted probability charts, wet avalanche indicator charts, and the 'help' document are available on CD at the Montana State University Earth Science Department.

Bridger Bowl Wet Avalanche Probability Models

Was there measurable new snow today, or do you expect a measurable amount to fall today?
If YES, go to "New Snow Model"
IF NO, go to the next question….

Was there measurable new snow yesterday?
If YES, go to "New Snow Model"
If NO, go to "Old Snow Model"

New Snow Model
Use the "Prediction Day Minimum Temperature" and "Cumulative Three Day Snow Water Equivalent (SWE)" measurements recorded at the Alpine weather station to calculate the probability of wet avalanche conditions today

		DO NOT TYPE IN THIS COLUMN
Enter today's recorded, or expected minimum temperature (degrees Fahrenheit):	32	**0.0**
Enter today's recorded, or expected snow water equivalent (inches):	0	0.0
Enter yesterday's recorded snow water equivalent (inches):	0.5	1.3
Enter the day before yesterday's snow water equivalent (inches):	0.1	0.3
Enter the snow water equivalent from two days before yesterday (inches):	0.3	0.8
		2.3
Predicted New Snow Wet Avalanche Probability →		**68%**

Old Snow Model
Uses the "Prediction Day Minimum Temperature" and the "Two Day Total Change in Snow Depth" measurements recorded at the Alpine weather station to calculate the probability of wet avalanche conditions today

		DO NOT TYPE IN THIS COLUMN
Enter today's recorded, or expected minimum temperature (degrees Fahrenheit):	27	**-2.8**
Enter today's recorded total snow depth (inches):	59	149.9
Enter the day before yesterday's total snow depth (inches):	61	154.9
		-5.1
Predicted Old Snow Wet Avalanche Probability →		**51%**

Figure 34. Old Snow and New Snow Model Example in Excel Worksheet

Although the models were developed using March data, it seems reasonable to extend their use to late February and early April. As mentioned in the introduction, Bridger Bowl is just one of several ski areas in the intermountain snow climate that has long term meteorological, snowpack and avalanche database on the WWAN (Mock and Birkeland, 2000). The same statistical approach might be applied to another intermountain ski area such as Alta or Jackson Hole to compare the results with the Bridger Bowl results. The 75% and 72% overall success rates for the old and new snow models compare well with previous statistical studies, especially considering that the Bridger Bowl dataset lack several important data types such as wind speed, sunshine hours, cloudiness, precipitation intensity, hourly temperature intervals and net radiation data. A direct comparison of this study's model results to other studies' model results is somewhat difficult because most of the models are tailored for dry snow avalanche conditions and were developed using discriminant-based analysis rather than a probabilistic model approach. A handful of studies referenced in the introduction included wet snow avalanche prediction in their models. Bovis (1977) developed eleven wet avalanche forecasting models for the San Juan Mountains in Colorado (continental climate (Mock and Birkeland, 2000)) that had an 85% success rate for correctly classifying wet avalanche days and an 80% success rate for correctly classifying days with no wet avalanches (Table 16).

Table 16. Wet Avalanche Predictor Variables (Bovis, 1977, p.94)

Author	**Bovis (1977)**										
Model Name	1	2	3	4	5	6	7	8	9	10	11
Variable											
Total precip over an N*-day period prior to prediction day	X	X	X	X	X		X	X		X	
Total SWE in the period from 12.00h on the day prior to the prediction day and 12.00h on the prediciton day							X				
Max 6h precip intensity in the period from 12.00h on the day prior to the prediction day and 12.00h on the prediction day									X		
Mean 2h air temp over an N*-day period prior to the prediction day					X					X	X
Mean 2h air temp in the period from 12.00h on the day prior to the prediction day and 12.00h on the prediction day					X	X	X	X			X
Max 2h air temp in the period from 12.00h on the day prior to the prediction day and 12.00h on the prediciton day	X	X	X	X						X	X
Mean 6h wind speed over N*-day period prior to the prediction day			X								
Mean 6h wind speed in the period from 12.00h on the day prior to the prediction day and 12.00h on the prediction day		X		X	X	X		X	X		
Max 6h wind speed in the period from 12.00h on the day prior to the prediction day and 12.00h on the prediction day		X				X					
Overall Prediction Model Success Rate	80%	80%	78%	86%	83%	85%	86%	100%	81%	64%	84%

Fohn et al., (1977) discussed four prediction models developed on data from Weissfluhjoch/Davos, Switzerland (intermountain climate (personal communication M. Schneebeli, 2004)), two of which (Model #1 and Model #4) incorporated wet avalanches into the model prediction process. The prediction success rate for these models ranged from 70% to 80% (Table 17). Judson and King (1985) developed a model designed to predict 'early season' and 'late season' avalanches for the Colorado Front Range (continental climate (Mock and Birkeland, 2000)). This model was unusual in that it did not use typical weather and precipitation data for development, instead, it was based on daily avalanche control data collected by the Colorado highway department, a mining operation and a ski area. Rather than predicting the probability for a wet avalanche occurrence, this model calculates predictions in terms of a low, moderate, or high stability index. The model was 90% successful in correctly predicting a low, moderate or high snowpack stability (Table 17).

Table 17. Wet Avalanche Predictor Variables (Fohn et al., 1977, p. 377; Judson and King)

Author	**Fohn et al., (1977)**		**Judson and King (1985)**	**This Study**	
Model Name	Model 1	Model 4	Stability Index	Old Snow	New Snow
Variable					
Total precipitation (last 24h)		X			
New fallen snow (last 24h)	X	X			
Water equivalent of new snow (last 24h)		X			
Maximum 3h precipitation intensity (last 24h)		X			
Maximum wind-speed for day j (j = 0 to 5 days)	X	X			
Global radiation for day j		X			
Sunshine hour for day j	X	X			
Cloudiness for day j	X	X			
Maximum air temperature for day j	X	X			
Minimum air temperature for day j	X	X			
Total snow depth for day j	X	X			
Penetration depth of cone penetrometer		X			
Temperature of snow cover (10cm below surface)		X			
Number of avalanches on previous day					
Snow-drift conditions for day j		X			
Avalanche control data			X		
Prediction day minimum air temperature				X	X
The difference in total snowpack depth between the prediction day and two days prior				X	
New snow water equivalent accumulation over three days prior, two days prior, one day prior and the prediction day					X
Overall Prediction Model Success Rate	80%	70-80%	90%	75%	72%

The higher success rates of the previous models may be attributable to the snow climate for which the models were designed. Perhaps wet avalanches in continental climates have more robust trends prior to wet avalanche days than intermountain snow climates, making them easier to predict. Success rates may also be better because the data quality may have been slightly higher for some studies, a number of outliers may have been removed from the datasets, or the inclusion of dry snow avalanche data may have increased the success rate. There are three points to consider when comparing the greater success rates of the Bovis (1977) models (Table 16) to the success rates of this study's models. First, the models developed by Bovis were based on just two seasons of data. The small sample sizes used to create the models may skew the results, making them appear more successful than they may otherwise be if a longer data record was used. Second, the models were designed with a dataset that has a relatively small number of observations and the models use more than two predictor variables resulting in fewer degrees of freedom. Third, the data were obtained from a snow avalanche research site where additional instrumentation was available. The models with the greatest success use wind speed and temperature interval data that are not available at Bridger Bowl.

The two models by Fohn et al. (1977) described in Table 17 also have slightly higher, but comparable success rates to the old snow and new snow wet avalanche prediction models presented in this study. The increased success rate is likely due to the additional data types that are not available at Bridger Bowl such as precipitation intensity, wind speed, global radiation, sunshine hours, cloudiness, cone penetrometer depth, and snow temperature. The stability index model presented in Judson and King (1985) is difficult to compare to this study's models because the predictions are given in terms of low, moderate or high snowpack stability rather than the probability of a wet avalanche day. As mentioned, the data used to create this model are very different from typical meteorological, snowpack and avalanche data used in most models. The 90% success of the 'late season' predictions may be influenced by dry avalanches that likely make up a larger proportion of the total number of avalanches in the dataset.

This study takes a unique approach to wet avalanche prediction by considering wet avalanches that develop directly after a new snowfall separately from wet avalanches that occur after several days of warm spring-like weather. The results compare well with and support observations made by Bridger Bowl ski patrollers who know that wet avalanche conditions vary depending on whether it has recently snowed or not.

There will always be some element of human error that will lower the success rate of the old snow and new snow models because the determination of what is and is not a wet avalanche is so subjective and each person has their own slightly different definition. However, there are several ways in which this model could be improved. Both models may be enhanced by adding net radiation data and wind speed data in order to calculate an overall daily energy budget variable into the model. Whether snow is going to melt or not hinges upon how much excess energy is available for snow melt. The variables used to develop the old and new snow models represent a portion of the excess energy that relates to temperature (longwave), but as the results indicate, they only provide approximately 75% accuracy in the model prediction. If acquiring the instrumentation for net radiation data is not feasible, an alternative would be to observe and record daily cloudiness and sunshine hours. Another important variable that is missing from the models is representative snow surface wind speeds. Turbulent heat exchange at the snow surface can have significant effects on snow surface temperature. Warm Chinook winds can cause rapid snowmelt. Cool winds, even very slight breezes, can cause enough evaporative cooling at the snow surface to keep the snow from avalanching (Obled and Harder, 1978). A snow temperature variable may improve the model accuracy, without increasing the complexity. Bridger Bowl has been recording the snowpack temperature at 20cm below the snow surface and has been using this temperature as one indicator of developing wet avalanche conditions. Unfortunately, the data have not been consistently recorded and could not be used in this study, but this type of information could add insight as to how effective this predictor is. Finally, hourly air temperature data may prove to be extremely helpful. The daily maximum and minimum temperatures only provide information about a single point in time each day. Hourly temperature readings recorded by a data logger would show how many hours throughout the day and night were above and below freezing.

CONCLUSION

The objective of this study was to develop a practical and useful means of predicting springtime wet avalanche conditions for the Bridger Bowl Ski Area in the intermountain snow climate of southwest Montana. The inspiration for this study came from discussions with Bridger Bowl ski patrollers who expressed their concern about the uncertainties they face during the spring when wet avalanche conditions can develop quickly. Patrollers face the difficult task of deciding when ski area snow conditions are becoming too wet and dangerous for skiers. Wet avalanche conditions are particularly problematic because they are difficult to control artificially and the shift from safe wet conditions to dangerous wet conditions can happen very quickly. The West Wide Avalanche Network (WWAN) database provides a useful tool for the assessment of wet avalanche risk. This study used Bridger Bowl, Montana weather, snowpack and avalanche WWAN records, which date from 1968 to 1995, and Bridger's archived data from 1997-2001. Bridger Bowl was selected based on its long and thorough records, the proximity to its records, terrain and ski safety personnel, and because very few avalanche prediction studies have been done in the intermountain snow climate.

The focus of this study was on springtime wet avalanche conditions. The Bridger Bowl data from 1968-2001 were restricted to all days in March. Fifteen meteorological, snowpack and precipitation related predictor variables were initially developed based on the factors that the past 30 years of research have found to drive the formation of wet snow. Wet avalanches can occur directly after a new snowfall or on old snow that has been on the ground for several days. Different significant predictor variables were expected for ‘new snow’ wet avalanche conditions and ‘old snow’ wet avalanche conditions. ‘New snow’ wet avalanche conditions develop when there has been new snowfall within 48 hours or a wet avalanche event. ‘Old snow’ wet avalanche conditions occur when there has not been any new snow for more than 48 hours prior to the prediction day. Since older snow is generally better-bonded than new snow, it was anticipated that old snow wet avalanche conditions would require more time and energy for development. To test this idea, ‘one day prior’, ‘two days prior’ and ‘three days prior’ variables were incorporated into the predictor variables which increased the total number of variables to 68.

The study was divided into two phases; a hypothesis testing phase and a model selection phase. The hypothesis testing phase tested old snow and new snow variables to determine which are significant predictors of wet avalanche conditions at Bridger Bowl. This phase of the study also determined if and how the significant old snow and new snow predictor variables differed from one another. The hypothesis tests reduced the number of old snow predictor variables from 68 to 33 and new snow variables from 68 to 22.

Twenty-seven of the 33 significant old snow variables are temperature related, and the remaining six variables describe changes in total snow depth and settlement. Only twelve of the 22 significant new snow variables are temperature related, three variables describe snowpack settlement, and the remaining seven are precipitation related variables that described new snowfall totals, snow water equivalent, and density.

Old snow wet avalanche conditions tend to begin developing two to three days prior to the wet avalanche day (Table 6). In contrast, new snow wet avalanche conditions generally develop much more quickly with warning signs most evident just one day prior to a wet avalanche day (Table 7). The difference in predictor variable behavior between wet avalanche days and days with no wet avalanches is quite distinct for old snow especially for the temperature variables. Temperatures generally increase rapidly and snowpack depths decrease rapidly prior to an old snow wet avalanche occurrence (Table 6, Table 8 and Figs. 20-22). This suggests that most old snow wet avalanche conditions develop under warm springtime conditions. Differences in variable trends for new snow wet avalanche days and days with no wet avalanches are much less distinct. Temperature variables are only 1°C to 2°C warmer on wet avalanche days compared to days with no wet avalanches (Table 7). The main distinction between new snow wet avalanche days and days with no wet avalanches lies in the new snowfall characteristics where leading day accumulations are greater, wetter and more dense than average for wet avalanche conditions (Table 7, Fig. 31and Fig.32). Mean new snow cumulative two day snowfall is about 25cm (8.4cm/day) and cumulative three day snowfall totals are 33cm (8.3cm/day) on average. Old snow cumulative two and three day snowfalls are just 2.3cm (0.8cm/day) and 6.9cm (1.7cm/day) respectively (Table 8). Temperatures remain fairly cool suggesting that new snow wet avalanche conditions either develop under very mild, moist and cloudy conditions or under sunny conditions that develop soon after the precipitation event (Fig. 30 and Fig. 33).

All of the significant old snow variables (33 total) and the significant new snow variables (22 total) were further tested in the model selection phase. Before the model selection process could begin, correlation tests were performed on all old snow and new snow significant variables (Table 9 and Table 10). The purpose of the correlation testing was to identify those variables that are too correlated with one another to be included in the same model. All of the significant old snow and new snow variables were then tested with binomial logistic regression for their predictive capabilities individually and in combination with other variables. The selection criterion for further testing was based on p-values, odds ratios, percent concordant pairs, and the degree of correlation. Five old snow variables and ten new snow variables had the best predictive success and were retained for the final model building process (Table 11). All possible combinations of the old snow and new snow variables in Table 11 were tested to determine which arrangement resulted in the best binomial logistic regression model. Model performance was ranked primarily on p-values, odds ratios, percent concordant, discordant and tied pairs, how consistent the models are when comparing 'training' dataset model results with 'testing' dataset model results, and whether the user will need to use forecasted information to calculate the model variables or if that information is readily available. The last 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 final old snow and new snow models contain only two predictor variables. Data for each variable are readily available each day and the models will give a daily probability for old snow or new snow wet avalanche conditions. The two models are easy-to-use, and provide dependable and practical results that can be readily understood by users who may not have a strong statistical background.

The final old snow model uses the present (prediction day) minimum temperature and total snowpack depth change between the prediction day and two days prior to calculate a wet avalanche probability. This model has a 75% overall success rate. According to the old snow model's decision rule (positioned at 57%), any day given a predicted probability less than 57% *should* be a day with no wet avalanches and any day given a predicted probability of 57% or greater *should* be a wet avalanche day. Based on this decision rule, the model's success rates for wet avalanche days and days with no wet avalanches were determined. The old snow model has a 94% success rate for predicting accurate probabilities for days with no wet avalanches and a 20% success rate for predicting accurate probabilities for days with wet avalanches. When assessing a probability calculated by the old snow model, the user must take into consideration the fundamental uncertainties associated with a probabilistic outcome in addition to the uncertainties associated with the model's success rates for wet avalanche days (20%) and days with no wet avalanches (94%). The uncertainties related to the old snow model reinforces the importance of comparing the current meteorological and snowpack data with historical wet avalanche data. Wet avalanche indicator graphs were created for easy access to historical old snow wet avalanche data. These graphs show wet avalanche day frequency vs. the day of year (Fig. 11), the prediction day maximum temperature (Fig. 20), the prediction day minimum temperature (Fig. 21) and the two day change in total snow depth (Fig. 22). Model users can find additional information about potential old snow wet avalanche occurrence when current meteorological and snowpack conditions are compared with the historical wet avalanche data provided in these graphs.

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 its calculations. This model has an overall success rate of 72%. According to the new snow model's decision rule (positioned at 45%), any day given a predicted probability less than 45% *should* be a day without wet avalanches and any day given a predicted probability of 45% or greater *should* be a wet avalanche day. The new snow model's success rates for wet avalanche days and days with no wet avalanches were based on the decision rule described above. The new snow model has a 96% success rate for predicting accurate probabilities for days with no wet avalanches and a 9% success rate for predicting accurate probabilities for days with wet avalanches. When interpreting a probability calculated by the new snow model, the model user must take into consideration the fundamental uncertainties associated with a probabilistic outcome in addition to the uncertainties associated the model's success rate for wet avalanche days (9%) and days with no wet avalanches (96%). These uncertainties reinforce the need for additional information about wet avalanche occurrence. Wet avalanche indicator graphs were created for easy access to historical new snow wet avalanche data. These graphs show wet avalanche frequency vs. the prediction day minimum temperature (Fig. 30), the two day cumulative new snow depth (Fig. 31), the three day cumulative new snow water equivalent (Fig. 32), and the overnight temperature range prior to the prediction day (Fig. 33). Model users can utilize the additional information about potential new snow wet avalanche occurrence when current meteorological and snowpack conditions are compared with the historical wet avalanche data provided in these graphs.

The overall predictive success rates of the old and new snow models are comparable to average success rates for past and current prediction models. Most of the predictive models that have been developed in the past are deterministic in nature and have excluded wet avalanche prediction from their models, focusing entirely on dry snow wet avalanche prediction. Comparing the success rate of this study's models to dry snow prediction models may be misleading, but there are several studies that incorporated wet avalanche prediction into their models. Bovis (1977) developed eleven wet avalanche forecasting models for the San Juan Mountains in Colorado (continental climate (Mock and Birkeland, 2000)) that had a 85% success rate for correctly classifying wet avalanche days and a 80% success rate for correctly classifying days with no wet avalanches. Table 14 describes the variables used in each model. Fohn et al. (1977) discussed four prediction models developed on data from Weissfluhjoch/Davos, Switzerland (intermountain climate (personal communications M. Schneebeli, 2004)), two of which incorporated wet avalanches into the model prediction process. The prediction success rate for these models ranged from 70% to 80% (Table 15). Although the old snow and new snow models developed in this study do not have the highest success rates, they do compare well with the average success rate attained by most other prediction models. Lower success rates may be attributed to the unavailability of certain data types used by Bovis (1977) and Fohn et al. (1977).

Neither model will ever give the user a 'yes/no' answer as to whether wet avalanche conditions are going to develop. This leaves the final decision making about closures and safety in the hands of the patrollers, where it should be. The models will serve as a useful tool for patrollers to assess the probability of wet avalanche conditions at Bridger Bowl based on 32 years of wet avalanche data. Patrollers can evaluate the present day's wet avalanche danger by considering the model's predicted probability and how the current meteorological and snowpack observations compare with past observations made on wet avalanche days. Experienced patrollers can use the model to compare their forecast with its predicted wet avalanche probability. New patrollers can use the model as a learning tool to quickly and easily check the accuracy of their own forecast with the model's predicted probability. Patrollers can also access other historical wet avalanche data related to the wet avalanche indicator variables discussed above to gain a better understanding of historical wet avalanche activity given the current meteorological and snowpack conditions. The wet avalanche indicator graphs will be very helpful when used on days when wet avalanche activity is unexpected. These graphs show that wet avalanches at Bridger Bowl have occurred over a broad range of temperatures, snowpack depth change, and precipitation totals (Figs. 11, 20-22 and Figs. 30-33). The unexpected wet avalanche is one of the greatest threats to ski area safety, especially at Bridger Bowl where wet avalanches often start in expert ski areas and can run out onto heavily used intermediate and beginner level ski runs below.

The old snow model should be used when there has been no measurable new snowfall amounts within the past 48 hours. The new snow model is appropriate when there has been measurable new snowfall amounts within the previous 48 hours. The models were originally developed using Microsoft Excel software, however, the algorithms can be computed on any software similar to Excel. Model procedures are outline in Figure 34 and included in Appendix C of this document. Copies of the original dataset spreadsheet used for this study, as well as working versions of the old and new snow Excel spreadsheet models and the associated documents are available on a CD from the Montana State University Earth Science Department, in Bozeman, Montana.

Although this model was developed on Bridger Bowl's March data, its use may have value into late February and early April when springtime conditions are most common. Because this model was developed on ski area data where natural and artificially released wet avalanches were used to train the models, the use of the models should be constrained to Bridger Bowl's in-bounds ski area. The models could also be tested on other intermountain ski area datasets. The WWAN has approximately 14 readily available datasets from ski areas considered to be in the intermountain climate regime, six of which have over fifteen years of archived data (Mock and Birkeland, 2000).

This study approaches wet avalanche prediction in a new way by focusing on wet avalanche prediction for ski area purposes in the intermountain snow climate. The 32-

year Bridger Bowl dataset is an unusually long dataset that provides a large amount of information on which sound statistical analysis can be performed. The statistical methods are rigorous and use a probabilistic approach to wet avalanche prediction rather than a deterministic, or 'yes/no' approach. Unlike previous wet avalanche prediction studies, this study does not lump wet avalanche occurrence into one category, but investigates wet avalanches that develop under 'old snow' conditions and wet avalanches that develop under 'new snow' conditions as two separate processes. The results show that old snow and new snow wet avalanche condition are indeed very different from one another. This is supported by ski patrol experience at Bridger Bowl Ski Area.

REFERENCES CITED

Ambach, W., and Howorka F., 1966, Avalanche activity and free water content of snow at Obergurgl: International Association of Scientific Hydrology, Publication 69, p.65-72.

Armstrong, R.L. and Fues, J.D., 1976, Avalanche release and snow characteristics: Institute of Arctic and Alpine Research, Report to the Bureau of Reclamation, Occasional Paper 19, p.67-81.

Armstrong, R.L., and Armstrong, B.R.,1987, Snow and avalanche climates of the western United States: A comparison of maritime, intermountain and continental climates: International Association of Hydrological Sciences, Publication 162, 14p.

Bovis, M.J., 1977, Statistical forecasting of snow avalanches, San Juan Mountains, Southern Colorado, U.S.A: Journal of Glaciology, v.18, p.87-99.

Brandt, R.E., and Warren, S.G, 1993, Solar-heating rates and temperature profiles in Antarctic snow and ice: Journal of Glaciology, v.39, p.99-110.

Cline, D.W., 1997, Effect of seasonality of snow accumulation on melt on snow surface energy exchanges at a continental alpine site: Journal of Applied Meteorology, v.36, p.32-51.

Colbeck, S.C., 1979, Grain clusters in wet snow: Journal of Colloid and Interface Sciences, v., 72, p.371-84.

Colbeck, S.C., 1982, An overview of seasonal snow metamorphism: Review of Geophysics and Space Physics, v.20, p.45-61.

Colbeck, S., Akitaya, E., Armstrong, R., Gubler, H., Lafeuille, J., Lied, K., McClung, D., and Morris, E., 1990, The international classification for seasonal snow on the ground: International Commission on Snow and Ice of the International Association of Scientific Hydrology, available from World Data Center A for Glaciology, Boulder, Colorado, 23 pp.

Davis, D.E., Elder, K., Howlett, D., and Bouzaglou, E., 1999, Relating storm and weather factors to dry slab avalanche activity at Alta, Utah, and Mammoth Mountain, California, using classification and regression trees: Cold Regions Science and Technology, v.30, p.79-89.

Fohn, P., Good, W., Bois, P., and Obled C., 1977, Evaluation and comparison of statistical and conventional methods of forecasting avalanche hazard: Journal of Glaciology, v.19, p.375-387.

Gassner, H., Etter, J., Birkeland, K., Leonard, T., 2000, NXD2000: An improved avalanche forecasting program based on the nearest neighbor method: Proceedings of the International Snow Science Workshop, Big Sky, Montana, October 2000, p. 52-59.

Judson, A. and Erickson,B.J., 1973, Predicting avalanche intensity from weather data: A statistical analysis: USDA Forest Service Research Paper, Rocky Mountain Forest and Range Experiment Station, Fort Collins, Colorado, Research Paper RM-112, 12p.

Judson, A., and King, R.M., 1985, An index of regional snow-pack stability based on natural slab avalanches: Journal of Glaciology, v.31, p.67-73.

Kattelmann, R., 1984, Wet slab instability: Proceedings of the International Snow Science Workshop, Aspen, Colorado, October 1984, p.102-108.

Kattelmann, R., Cooley, K., and Palmer, P., 1998, Maximum snowmelt rates: some observations: Proceedings of the 66th Western Snow Conference, p.112-115.

LaChapelle, E., 1966, Avalanche forecasting – a modern synthesis: International Association of Scientific Hydrology, Publication 69, p.350-356.

Linsley, R.K. Jr., Kohler, M.A., and Paulhus, L.H., 1958, Hydrology for Engineers: New York, McGraw-Hill, 340p.

McClung, D.M. and Schaerer, P., 1993, The Avalanche Handbook: Seattle, The Mountaineers, 272p.

McCollister, C., Birkeland, K., Hansen, K., Aspinall, R., and Comey, R., 2002, A probabilistic technique for exploring multi-scale spatial patterns in historical avalanche data by combining GIS and meteorological nearest-neighbors with an example from Jackson Hole Ski Area, Wyoming: Proceedings of the International Snow Science Workshop, Penticton, B.C., October 2002, [electronic resource], 8p.

Merindol, L., Guyomarc'h, G., and Giraud, G., 2002, A French tool for avalanche hazard forecasting: "Astral". Current state and new developments: Proceedings of the International Snow Science Workshop, Penticton, B.C., [electronic resource], 4p.

Minitab Inc., 2000, MINITAB User's Guide 2: Data Analysis and Quality Tools: Release 13 for Windows.

Mock, C.J. and Kay, P.A., 1992, Avalanche climatology of the western United States, with an emphasis on Alta, Utah: Professional Geographer, v.44, p.307-318.

Mock, C.J. and Birkeland, K.W., 2000, Snow avalanche climatology of the western United States mountain ranges: Bulletin of the American Meteorological Society, v.81, p.2367-2392.

NCEP/NCAR, 2004, NCEP/NCAR Reanalysis Project Webpage: http://wesley.wwb.noaa.gov/reanalysis.html, accessed 03/24/04.

Neter, J., Kutner, M.H., Nachtsheim, C.J., and Wasserman, W., 1996, Applied Linear Statistical Models, Fourth Edition: Boston, WCB McGraw-Hill, 1,048p.

Obled, C. and Harder, H., 1978, A review of snow melt in the mountain environment: Proceedings Modeling of Snow Cover Runoff, U.S. Army Cold Regions Research and Engineering Laboratory, Hanover, New Hampshire, 26-28 September 1978, 26p.

Perla, R.I., 1970, On contributory factors in avalanche hazard evaluation: Canadian Geotechnical Journal, v.7, p.414-419.

Perla, R.I. and Martinelli, M., 1978, Avalanche Handbook: Agricultural Handbook, 489, US Department of Agriculture Forest Service, 254p.

Rango, A. and Martinec, J., 1995, Revisiting the degree day method for snowmelt computations: Water Resources Bulletin, v.31, p.657-669.

Roch, A., 1949, Report on snow and avalanches conditions in the U.S.A. western ski resorts. From the 26th of January to the 24th of April 1949: Federal Institute For Research On Snow And Avalanches, Weissfluhjoch-Davos, Report No. 174, 39p.

WWAN, 2002, 1968-1995 Avalanche Notes: U.S. Forest Service, Fort Collins: http://www.avalanche.org, accessed March, 2002.

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APPENDICES

APPENDIX A:

DEFINITIONS AND DESCRIPTIVE STATISTICS

"DEFINITIONS"

The following provide definitions for the datasets, response variables, and predictor variables described in this study. The equation used to calculate each variable is included as well.

THE DATASETS

Original Dataset
Includes all days in March from 1968-2001. This dataset includes both old and new snow avalanche days. March, 1996 data were missing from the Bridger Bowl archives and is not included in this analysis.

New Snow Dataset
Includes all days in March from 1968-2001when there was new snow recorded the prediction day and/or one day prior to the prediction day. In other words, the age of the new snow in this dataset is less than 48 hours. This dataset was created to determine if there are different significant meteorological, snowpack and precipitation predictor variables for wet avalanches that occur directly after a new snowfall. These avalanches will be referred to as 'new snow wet avalanches'.

Old Snow Dataset
Includes all days in March from 1968-2001 when there was no new snow recorded on the prediction day or one day prior to the prediction day. The most recent snowfall in this dataset would have occurred two days prior to the prediction day. The age of the new snow in this dataset is greater than 48 hours. This dataset was created to determine if there are different significant meteorological, snowpack and precipitation predictor variables for wet avalanches that occur on old snow. These avalanches will be referred to as 'old snow wet avalanches'.

THE DATA

All avalanches in the datasets and variables refer to wet avalanches. All avalanche sizes (1-5) are ranked based on the U.S. avalanche recording scale.
"The sizes are based on an estimate of the volume of snow transported down the avalanche path:
1 = sluff or snowslide <50m of slow distance regardless of snow volume
2 = small, relative to path
3 = medium, relative to path
4 = large, relative to path
5 = major or maximum, relative to path"
(McClung and Schaerer, 1993).

All meteorological and snowpack data, except wind speed and direction, were recorded at the Bridger Bowl weather station, located near the top of the Alpine Lift. All temperatures are recorded in Fahrenheit and converted to Celsius. All depths are measured in inches and converted to centimeters. All directions are presented in compass degrees. All of the variables are recorded over a 24 hour observation period and are recorded daily by ski patrollers in the morning hours, generally between 6-9am.

The two datasets ("New Snow Dataset" and "Old Snow Dataset") and the variables within each dataset that are defined below are calculated in terms of "Prediction Day", "1 Day Prior", "2 Days Prior" and "3 Days Prior".

"Prediction Day" always refers to the day that the 1 Day Prior, 2 Days Prior and 3 Days Prior variables lead up to and is given the subscript "0". A prediction day may or may not have recorded wet avalanches.

"One Day Prior" always refers to the day that is one day prior to the prediction day and is given the subscript "-1".

"Two Days Prior" always refers to the day that is two days prior to the prediction day and is given the subscript "-2".

"Three Days Prior" always refers to the day that is three days prior to the prediction day and is given the subscript "-3".

The number of subscripts next to a variable name indicates what 'prior' days are included in the cumulative variable. Some variables are single-day measurements such as $MaxT_0$, $MaxT_{-1}$, $MaxT_{-2}$, and $MaxT_{-3}$. Others are cumulative measurements such as $AvgMaxT_{0,-1}$, $AvgMaxT_{0,-1,-2}$, and $AvgMaxT_{0,-1,-2,-3}$.

Refer to Figure 3 in the main text of this report for additional details.

THE RESPONSE VARIABLES

AvyDay
Wet Avalanche Day
0 = no wet avalanches were recorded on the prediction day
1 = one or more wet avalanches were recorded on the prediction day

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THE PREDICTOR VARIABLES

Day
Day of the year number. If January 1st is the day one of a calendar year, then March 1st is the day 60 of the year, or day 61 if it is a leap year.

$MaxT_0$
Prediction Day Maximum Temperature. The maximum temperature recorded on the prediction day.

$MaxT_{-1}$
One Day Prior Maximum Temperature. The maximum temperature recorded one day prior to the prediction day.

$MaxT_{-2}$
Two Days Prior Maximum Temperature. The maximum temperature recorded two days prior to the prediction day.

$MaxT_{-3}$
Three Days Prior Maximum Temperature. The maximum temperature recorded three days prior to the prediction day.

$AvgMaxT_{0,-1}$
One Day Averaged Maximum Temperature. The average maximum temperature for the prediction day and one day prior to the prediction day.
Calculation: $AvgMaxT_{0,-1} = (MaxT_0 + MaxT_{-1}) \div 2$

$AvgMaxT_{0,-1,-2}$
Two Day Averaged Maximum Temperature. The average maximum temperature for the prediction day, one day prior to the prediction day and two days prior to the prediction day.
Calculation: $AvgMaxT_{0,-1,-2} = (MaxT_0 + MaxT_{-1} + MaxT_{-2}) \div 3$

$AvgMaxT_{0,-1,-2,-3}$
Three Day Averaged Maximum Temperature. The average maximum temperature for the prediction day, one day prior to the prediction day, two days prior to the prediction day and three days prior to the prediction day.
Calculation: $AvgMaxT_{0,-1,-2,-3} = (MaxT_0 + MaxT_{-1} + MaxT_{-2} + MaxT_{-3}) \div 4$

$MinT_0$
Prediction Day Minimum Temperature. The minimum temperature recorded on the prediction day.

$MinT_{-1}$
One Day Prior Minimum Temperature. The minimum temperature recorded one day prior to the prediction day.

$MinT_{-2}$
Two Days Prior Minimum Temperature. The minimum temperature recorded two days prior to the prediction day.

$MinT_{-3}$
Three Days Prior Minimum Temperature. The minimum temperature recorded three days prior to the prediction day.

$AvgMinT_{0,-1}$
One Day Averaged Minimum Temperature. The average minimum temperature for the prediction day and one day prior to the prediction day.
Calculation: $AvgMinT_{0,-1} = (MinT_0 + MintT_{-1}) \div 2$

$AvgMinT_{0,-1,-2}$
Two Day Averaged Minimum Temperature. The average minimum temperature for the prediction day, one day prior to the prediction day and two days prior to the prediction day.
Calculation: $AvgMinT_{0,-1,-2} = (MinT_0 + MintT_{-1} + MinT_{-2}) \div 3$

$AvgMinT_{0,-1,-2,-3}$
Three Day Averaged Minimum Temperature. The average minimum temperature for the prediction day, one day prior to the prediction day, two days prior to the prediction day and three days prior to the prediction day.
Calculation: $AvgMinT_{0,-1,-2,-3} = (MinT_0 + MintT_{-1} + MinT_{-2} + MinT_{-3}) \div 4$

$AvgT_0$
Prediction Day Average Temperature. The average temperature recorded on the prediction day.
Calculation: $AvgT_0 = (MaxT_0 + MinT_0) \div 2$

$AvgT_{-1}$
One Day Prior Average Temperature. The average temperature recorded one day prior to the prediction day.
Calculation: $AvgT_{-1} = (MaxT_{-1} + MinT_{-1}) \div 2$

$AvgT_{-2}$
Two Days Prior Average Temperature. The average temperature recorded two days prior to the prediction day.
Calculation: $AvgT_{-2} = (MaxT_{-2} + MinT_{-2}) \div 2$

$AvgT_{-3}$
Three Days Prior Average Temperature. The average temperature recorded three days prior to the prediction day (not cumulative).
Calculation: $AvgT_{-3} = (MaxT_{-3} + MinT_{-3}) \div 2$

$AvgAvgT_{0,-1}$
One Day Averaged Average Temperature. The averaged average temperature for the prediction day and one day prior to the prediction day.
Calculation: $AvgAvgT_{0,-1} = (AvgT_0 + AvgT_{-1}) \div 2$

$AvgAvgT_{0,-1,-2}$
Two Day Averaged Average Temperature. The averaged average temperature for the prediction day, one day prior to the prediction day and two days prior to the prediction day.
Calculation: $AvgAvgT_{0,-1,-2} = (AvgT_0 + AvgT_{-1} + AvgT_{-2}) \div 3$

$AvgAvgT_{0,-1,-2,-3}$
Three Day Averaged Average Temperature. The averaged average temperature for the prediction day, one day prior to the prediction day, two days prior to the prediction day and three days prior to the prediction day.
Calculation: $AvgAvgT_{0,-1,-2,-3} = (AvgT_0 + AvgT_{-1} + AvgT_{-2} + AvgT_{-3}) \div 4$

$DDMaxT_0$
Prediction Day Degree Day Maximum Temperature. The calculated number of degree days using the prediction day maximum temperature where degree day is defined as a departure of one degree per day in the daily maximum temperature from an adopted reference temperature (0°C) (Rango and Martinec, 1995).
Calculation: $DDMaxT_0 = MaxT_0 - 0°C$

$DDMaxT_{0,-1}$
One Day Prior Degree Day Maximum Temperature. The cumulative number of degree days occurring one day prior to the prediction day and the prediction day using maximum temperature.
Calculation: $DDMaxT_{0,-1} = (MaxT_0 - 0°C) + (MaxT_{-1} - 0°C)$

$DDMaxT_{0,-1,-2}$
Two Days Prior Degree Day Maximum Temperature. The cumulative number of degree days occurring two days prior to the prediction day, one day prior to the prediction day and the prediction day using maximum temperature.
Calculation: $DDMaxT_{0,-1,-2} = (MaxT_0 - 0°C) + (MaxT_{-1} - 0°C) + (MaxT_{-2} -0°C)$

$DDMaxT_{0,-1,-2,-3}$
Three Days Prior Degree Day Maximum Temperature. The cumulative number of degree days occurring three days prior to the prediction day, two days prior to the prediction day, one day prior to the prediction day and the prediction day using maximum temperature.
Calculation:
$DDMaxT_{0,-1,-2,-3} = (MaxT_0 - 0°C)+(MaxT_{-1} - 0°C)+(MaxT_{-2} -0°C)+(MaxT_{-3} - 0°C)$

$DDAvgT_0$
Prediction Day Degree Day Average Temperature. The calculated number of degree days using the prediction day average temperature where degree day is defined as a departure of one degree per day in the daily mean temperature from an adopted reference temperature (0°C) (Rango and Martinec 1995).
Calculation: $DDAvgT_0 = AvgT_0 - 0°C$

$DDAvgT_{0,-1}$
One Day Prior Degree Day Average Temperature. The cumulative number of degree days occurring one day prior to the prediction day and the prediction day using average temperature.
Calculation: $DDAvgT_{0,-1} = (AvgT_0 - 0°C) + (AgT_{-1} - 0°C)$

$DDAvgT_{0,-1,-2}$
Two Days Prior Degree Day Average Temperature. The cumulative number of degree days occurring two days prior to the prediction day, one day prior to the prediction day and the prediction day using average temperature.
Calculation: $DDAvgT_{0,-1,-2} = (AvgT_0 - 0°C)+(AgT_{-1} - 0°C)+(AvgT_{-2} -0°C)$

$DDAvgT_{0,-1,-2,-3}$
Three Days Prior Degree Day Average Temperature. The cumulative number of degree days occurring three days prior to the prediction day, two days prior to the prediction day, one day prior to the prediction day and the prediction day using average temperature.
Calculation:
$DDAvgT_{0,-1,-2-3} = (AvgT_0 - 0°C)+(AvgT_{-1} - 0°C)+(AvgT_{-2} -0°C)+(AvgT_{-3} - 0°C)$

$MaxT_0 – MaxT_{-1}$
Maximum temperature difference between the prediction day and one day prior.
Calculation: $MaxT_0 – MaxT_{-1}$

$MaxT_0 – MaxT_{-2}$
Maximum temperature difference between the prediction day and two days prior.
Calculation: $MaxT_0 – MaxT_{-2}$

$MaxT_0 - MaxT_{-3}$
Maximum temperature difference between the prediction day and three days prior.
Calculation: $MaxT_0 - MaxT_{-3}$

$MinT_0 - MinT_{-1}$
Minimum temperature difference between the prediction day and one day prior.
Calculation: $MinT_0 - MinT_{-1}$

$MinT_0 - MinT_{-2}$
Minimum temperature difference between the prediction day and two days prior.
Calculation: $MinT_0 - MinT_{-2}$

$MinT_0 - MinT_{-3}$
Minimum temperature difference between the prediction day and three days prior.
Calculation: $MinT_0 - MinT_{-3}$

$AvgT_0 - AvgT_{-1}$
Average temperature difference between the prediction day and one day prior.
Calculation: $AvgT_0 - AvgT_{-1}$

$AvgT_0 - AvgT_{-2}$
Average temperature difference between the prediction day and two days prior.
Calculation: $AvgT_0 - AvgT_{-2}$

$AvgT_0 - AvgT_{-3}$
Average temperature difference between the prediction day and three days prior.
Calculation: $AvgT_0 - AvgT_{-3}$

$MaxT_0 - MinT_0$

Prediction day day-time (and occasionally night-time) temperature range.
Calculation: $MaxT_0 - MinT_0$

$MaxT_{-1} - MinT_{-1}$

One day prior day-time (and occasionally night-time) temperature range.
Calculation: $MaxT_{-1} - MinT_{-1}$

$MaxT_{-2} - MinT_{-2}$

Two days prior day-time (and occasionally night-time) temperature range.
Calculation: $MaxT_{-2} - MinT_{-2}$

$MaxT_{-3} - MinT_{-3}$

Three days prior day-time (and occasionally night-time) temperature range.
Calculation: $MaxT_{-3} - MinT_{-3}$

$MaxT_{-1} - MinT_0$
Prediction Day Overnight Temperature Range. The overnight (and occasionally day-time) temperature range occurring the night before the prediction day.
Calculation: $MaxT_{-1} - MinT_0$

$MaxT_{-2} - MinT_{-1}$
One Day Prior Overnight Temperature Range. The overnight (and occasionally day-time) temperature range occurring the night before the one day prior day.
Calculation: $MaxT_{-2} - MinT_{-1}$

$MaxT_{-3} - MinT_{-2}$
Two Days Prior Overnight Temperature Range. The overnight (and occasionally day-time) temperature range occurring the night before the two days prior day.
Calculation: $MaxT_{-3} - MinT_{-2}$

HS_0
Prediction Day Total Snow Depth. The total snow depth measured on the prediction day.

HS_{-1}
One Day Prior Total Snow Depth. The total snow depth measured one day prior to the prediction day.

HS_{-2}
Two Days Prior Total Snow Depth. The total snow depth measured two days prior to the prediction day.

HS_{-3}
Three Days Prior Total Snow Depth. The total snow depth measured three days prior to the prediction day.

$HS_0 - HS_{-1}$
One Day Total Change in Snow Depth. The change in total snow depth from one day prior, to the prediction day. Takes into account both the addition of new snow, the overall settlement of the snowpack and other factors such as ablation that might contribute to the overall change in total snow depth.
Calculation: $HS_0 - HS_{-1}$

$HS_0 - HS_{-2}$
Two Day Total Change in Snow Depth. The change in total snow depth from two days prior, to the prediction day. Takes into account both the addition of new snow, the overall settlement of the snowpack and other factors such as ablation that might contribute to the overall change in total snow depth.
Calculation: $HS_0 - HS_{-2}$

$HS_0 – HS_{-3}$
Three Day Change in Total Snow Depth. The change in total snow depth from three days prior, to the prediction day. Takes into account both the addition of new snow, the overall settlement of the snowpack and other factors such as ablation that might contribute to the overall change in total snow depth.
Calculation: $HS_0 – HS_{-3}$

HN_0
Prediction Day New Snow Depth. The amount of new snow that was measured on the prediction day.

$HN_{0,-1}$
One Day Cumulative New Snow Depth. The sum of the new snow that was measured on the prediction day and one day prior to the prediction day.
Calculation: $HN_{0,-1} = HN_0 + HN_{-1}$

$HN_{0,-1,-2}$
Two Day Cumulative New Snow Depth. The sum of the new snow that was measured on the prediction day, one day prior to the prediction day, and two days prior to the prediction day.
Calculation: $HN_{0,-1,-2} = HN_0 + HN_{-1} + HN_{-2}$

$HN_{0,-1,-2,-3}$
Three Day Cumulative New Snow Depth. The sum of the new snow that was measured on the prediction day, one day prior to the prediction day, two days prior to the prediction day, and three days prior to the prediction day.
Calculation: $HN_{0,-1,-2,-3} = HN_0 + HN_{-1} + HN_{-2} + HN_{-3}$

$Stl_{0,-1}$
One Day Settlement. This is a derived measurement of how much the total snowpack has settled between one day prior to the prediction day and the prediction day. It is the difference between the prediction day total snow depth, the one day prior total snow depth and the new snow measured on the prediction day. Settlement in this case represents the combined effect of all factors that lead to the decrease in total snow pack depth such as melt, densification and ablation.
Calculation: $Stl_{0,-1} = HS_0 – HS_{-1} – HN_0$

$Stl_{0,-1,-2}$
Two Day Settlement. This is a derived measurement of how much the total snowpack has settled between two days prior to the prediction day and the prediction day. It is the difference between the prediction day total snow depth, the two days prior total snow depth, the new snow measured on the prediction day, and the new snow measured one day prior to prediction day.
Calculation: $Stl_{0,-1,-2} = HS_0 – HS_{-2} – HN_0 – HN_{-1}$

$Stl_{0,-1,-2,-3}$
Three Day Settlement. This is a derived measurement of how much the total snowpack has settled between three days prior to the prediction day and the prediction day. It is the difference between the prediction day total snow depth, the three days prior total snow depth, the new snow measured on the prediction day, the new snow measured one day prior to prediction day and the new snow measured two days prior to the prediction day.
Calculation: $Stl_{0,-1,-2,-3} = HS_0 - HS_{-3} - HN_0 - HN_{-1} - HN_{-2}$

HNA_0
Age of Prediction Day New Snow. For the "New Snow Dataset" and the "Old Snow Dataset" the value of this variable reflects the number of days the new snow has been on the ground. For example, snow that fell on the prediction day is 0 days old and snow that fell one day prior to the prediction day is 1 day old.

For the "Original Dataset", this is a categorical variable where 0 = new snow and 1 = old snow. New snow is snow that is less than 48 hours in age. Old snow is snow that is more than 48 hours in age. For example, new snow measured on the prediction day or one day prior to the prediction day is considered 'new snow'. If there was no new snow recorded on the prediction day and no new snow recorded one day prior to the prediction day, the most recent new snowfall would have occurred two days prior to the prediction day. Any new snow measured two or more days prior to the prediction day is considered 'old snow'.

HNA_{-1}
Age of One Day Prior New Snow. For the "New Snow Dataset" and the "Old Snow Dataset" the value of this variable reflects the number of days the new snow has been on the ground. For example, snow that fell one day prior to the prediction day is 0 days old and snow that fell two days prior to the prediction day is 1 day old.

For the "Original Dataset", this is a categorical variable where 0 = new snow and 1 = old snow. New snow is snow that is less than 48 hours in age. Old snow is snow that is more than 48 hours in age. For example, new snow measured on the prediction day or one day prior to the prediction day is considered 'new snow'. If there was no new snow recorded on the prediction day and no new snow recorded one day prior to the prediction day, the most recent new snowfall would have occurred two days prior to the prediction day. Any new snow measured two or more days prior to the prediction day is considered 'old snow'.

HNA_{-2}
Age of Two Days Prior New Snow. For the "New Snow Dataset" and the "Old Snow Dataset" the value of this variable reflects the number of days the new snow has been on the ground. For example, snow that fell two days prior to the prediction day is 0 days old and snow that fell three days prior to the prediction day is 1 day old.

For the “Original Dataset”, this is a categorical variable where 0 = new snow and 1 = old snow. New snow is snow that is less than 48 hours in age. Old snow is snow that is more than 48 hours in age. For example, new snow measured on the prediction day or one day prior to the prediction day is considered ‘new snow’. If there was no new snow recorded on the prediction day and no new snow recorded one day prior to the prediction day, the most recent new snowfall would have occurred two days prior to the prediction day. Any new snow measured two or more days prior to the prediction day is considered ‘old snow’.

HNA_{-3}
Age of Three Days Prior New Snow. For the “New Snow Dataset” and the “Old Snow Dataset” the value of this variable reflects the number of days the new snow has been on the ground. For example, snow that fell three days prior to the prediction day is 0 days old and snow that fell four days prior to the prediction day is 1 day old.

For the “Original Dataset”, this is a categorical variable where 0 = new snow and 1 = old snow. New snow is snow that is less than 48 hours in age. Old snow is snow that is more than 48 hours in age. For example, new snow measured on the prediction day or one day prior to the prediction day is considered ‘new snow’. If there was no new snow recorded on the prediction day and no new snow recorded one day prior to the prediction day, the most recent new snowfall would have occurred two days prior to the prediction day. Any new snow measured two or more days prior to the prediction day is considered ‘old snow’.

HNW_0
Prediction Day New Snow Water Equivalent (SWE). The new snow SWE measured on the prediction day.

$HNW_{0,-1}$
One Day Cumulative New SWE. The sum of the new snow SWE measured on the prediction day and one day prior to the prediction day.
Calculation: $HNW_{0,-1} = HNW_0 + HNW_{-1}$

$HNW_{0,-1,-2}$
Two Day Cumulative New Snow SWE. The sum of the new snow SWE measured on the prediction day, one day prior to the prediction day and two days prior to the prediction day.
Calculation: $HNW_{0,-1-2} = HNW_0 + HNW_{-1} + HNW_{-2}$

$HNW_{0,-1,-2,-3}$
Three Day Cumulative New Snow SWE. The sum of the new snow SWE measured on the prediction day, one day prior to the prediction day, two days prior to the prediction day and three days prior to the prediction day.
Calculation: $HNW_{0,-1,-2,-3} = HNW_0 + HNW_{-1} + HNW_{-2} + HNW_{-3}$

HND_0
Prediction Day New Snow Density. The new snow density calculated from the new snow and SWE measured on the prediction day. $1000kg/m^3$ is the density of liquid water.
Calculation: $HND_0 = (HNW_0 * 1000kg/m^3) \div HN_0$

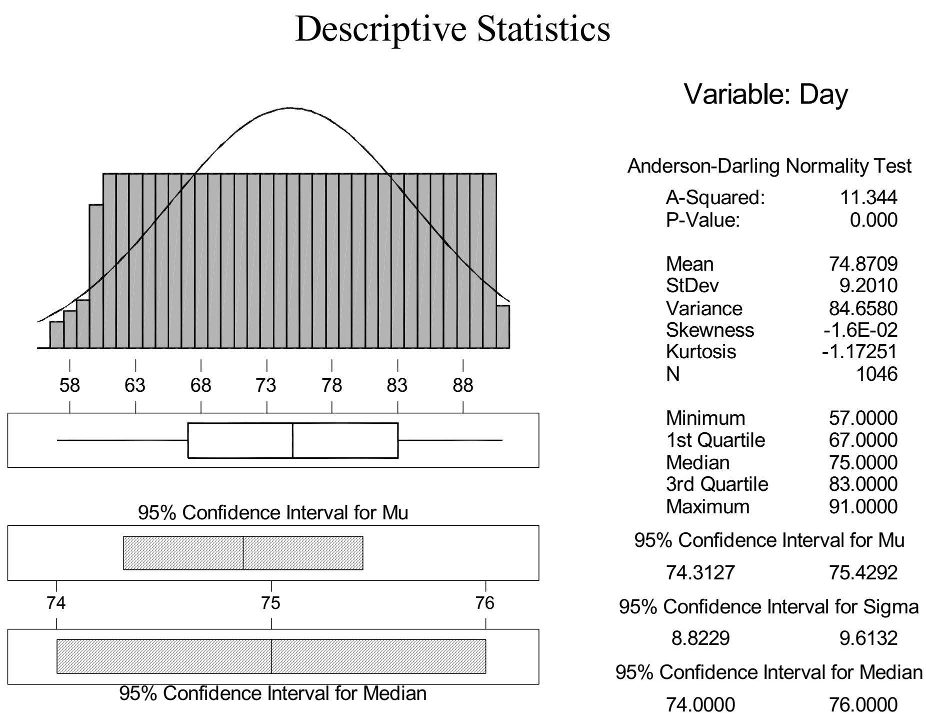
$HND_{0,-1}$
One Day Cumulative New Snow Density. The sum of the prediction day new snow density and one day prior new snow density calculated from the prediction day and one day prior SWE and new snow measurements. $1000kg/m^3$ is the density of liquid water.
Calculation: $HND_{0,-1} = HND_0 +(HNW_{-1} *1000kg/m^3) \div HN_{-1}$

$HND_{0,-1,-2}$
Two Day Cumulative New Snow Density. The sum of the prediction day, one day prior and two days prior new snow densities calculated from the prediction day, one day prior and two days prior SWE and new snow measurements. $1000kg/m^3$ is the density of liquid water.
Calculation: $HND_{0,-1,-2} = HND_0 + HND_{-1} + (HNW_{-2} * 1000kg/m^3) \div HN_{-2}$

$HND_{0,-1,-2,-3}$
Three Day Cumulative New Snow Density. The sum of the prediction day, one day prior, two days prior and three days prior new snow densities calculated from the prediction day, one day prior, two days prior and three days prior SWE and new snow measurements. $1000kg/m^3$ is the density of liquid water.
Calculation: $HND_{0,-1,-2,-3} = HND_0 + HND_{-1} + HND_{-2} + (HNW_{-3} * 1000kg/m^3) \div HN_{-3}$

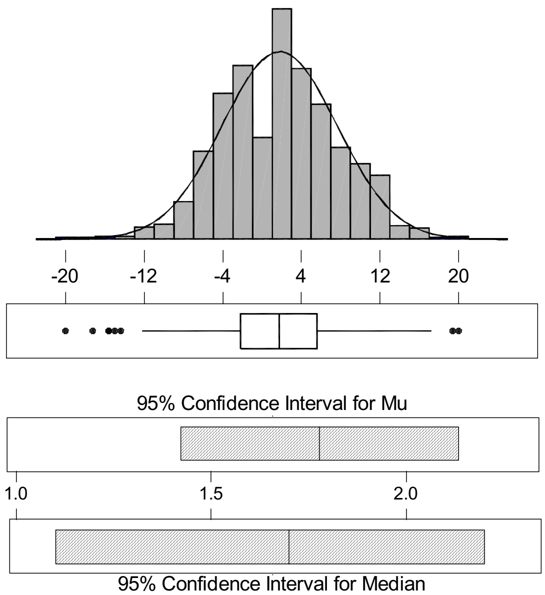
“DESCRIPTIVE STATISTICS”

The following plots provide basic descriptive statistics and charts for each predictor variable prior to any changes to the original Bridger Bowl dataset



Descriptive Statistics

Variable: MaxT(0)



Anderson-Darling Normality Test

A-Squared:	1.247
P-Value:	0.003
Mean	1.77775
StDev	5.84683
Variance	34.1855
Skewness	4.22E-03
Kurtosis	-4.1E-02
N	1038
Minimum	-20.0000
1st Quartile	-2.2000
Median	1.7000
3rd Quartile	5.6000
Maximum	20.0000

95% Confidence Interval for Mu

1.4216 2.1339

95% Confidence Interval for Sigma

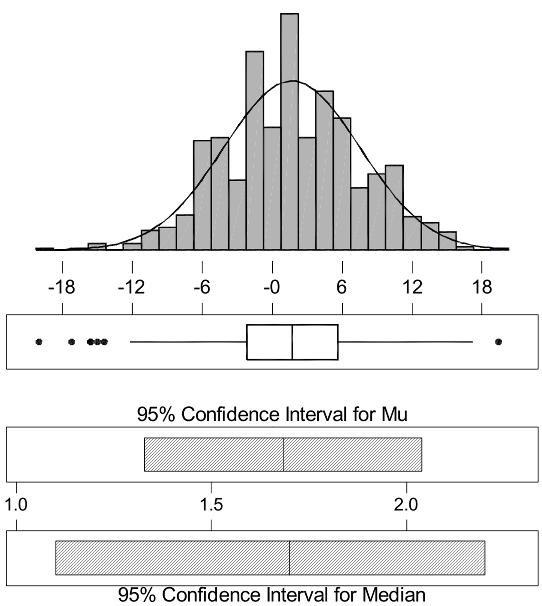
5.6057 6.1098

95% Confidence Interval for Median

1.1000 2.2000

Descriptive Statistics

Variable: MaxT(-1)



Anderson-Darling Normality Test

A-Squared:	1.152
P-Value:	0.005
Mean	1.68325
StDev	5.83720
Variance	34.0730
Skewness	-1.9E-02
Kurtosis	-9.9E-02
N	1039
Minimum	-20.0000
1st Quartile	-2.2000
Median	1.7000
3rd Quartile	5.6000
Maximum	19.4000

95% Confidence Interval for Mu

1.3279 2.0386

95% Confidence Interval for Sigma

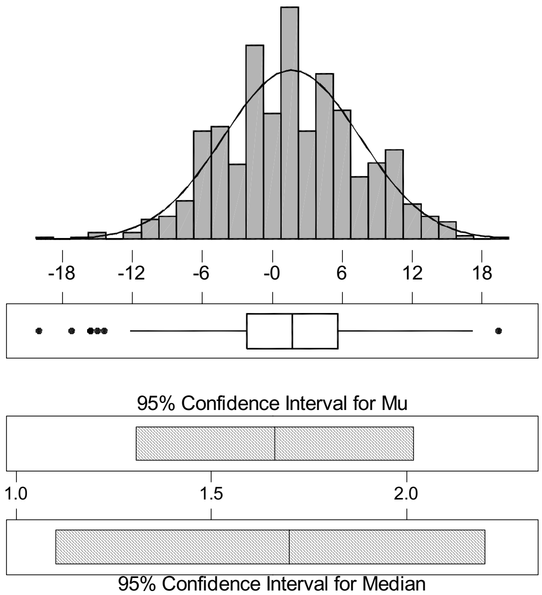
5.5966 6.0996

95% Confidence Interval for Median

1.1000 2.2000

Descriptive Statistics

Variable: MaxT(-2)



Anderson-Darling Normality Test

A-Squared:	1.204
P-Value:	0.004
Mean	1.66198
StDev	5.84155
Variance	34.1237
Skewness	-2.6E-02
Kurtosis	-1.2E-01
N	1039
Minimum	-20.0000
1st Quartile	-2.2000
Median	1.7000
3rd Quartile	5.6000
Maximum	19.4000

95% Confidence Interval for Mu

1.3064 2.0176

95% Confidence Interval for Sigma

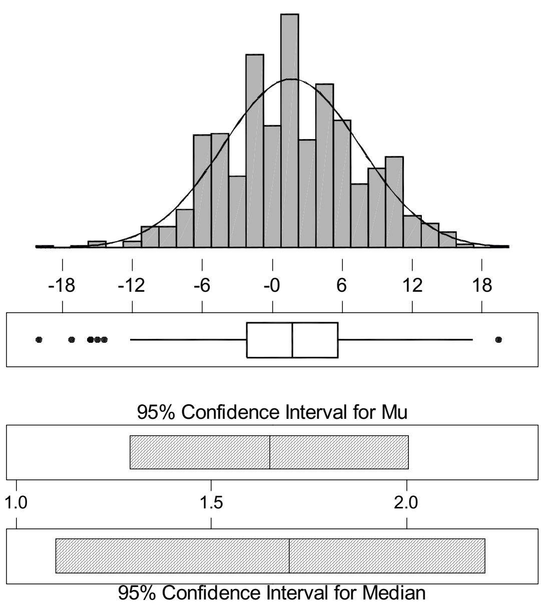
5.6007 6.1042

95% Confidence Interval for Median

1.1000 2.2000

Descriptive Statistics

Variable: MaxT(-3)



Anderson-Darling Normality Test

A-Squared:	1.281
P-Value:	0.002
Mean	1.64817
StDev	5.84843
Variance	34.2041
Skewness	-3.4E-02
Kurtosis	-1.5E-01
N	1040
Minimum	-20.0000
1st Quartile	-2.2000
Median	1.7000
3rd Quartile	5.6000
Maximum	19.4000

95% Confidence Interval for Mu

1.2923 2.0040

95% Confidence Interval for Sigma

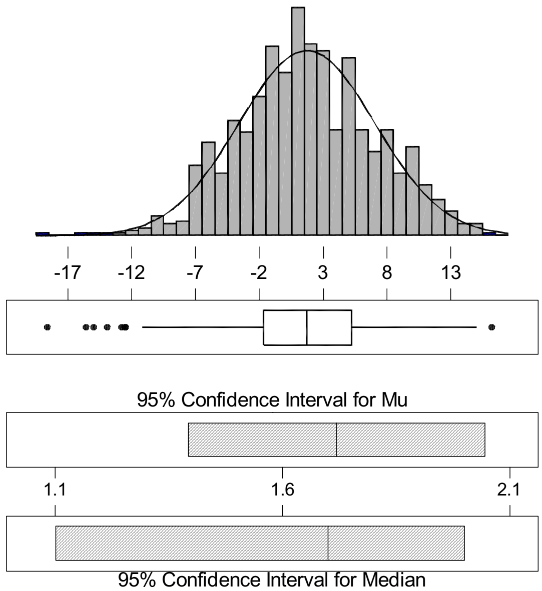
5.6074 6.1112

95% Confidence Interval for Median

1.1000 2.2000

Descriptive Statistics

Variable: AvgMaxT(0,-1)



Anderson-Darling Normality Test

A-Squared:	0.878
P-Value:	0.025
Mean	1.71870
StDev	5.33985
Variance	28.5140
Skewness	-2.0E-02
Kurtosis	-3.6E-02
N	1032
Minimum	-18.6000
1st Quartile	-1.7000
Median	1.7000
3rd Quartile	5.2250
Maximum	16.2000

95% Confidence Interval for Mu

1.3925	2.0449

95% Confidence Interval for Sigma

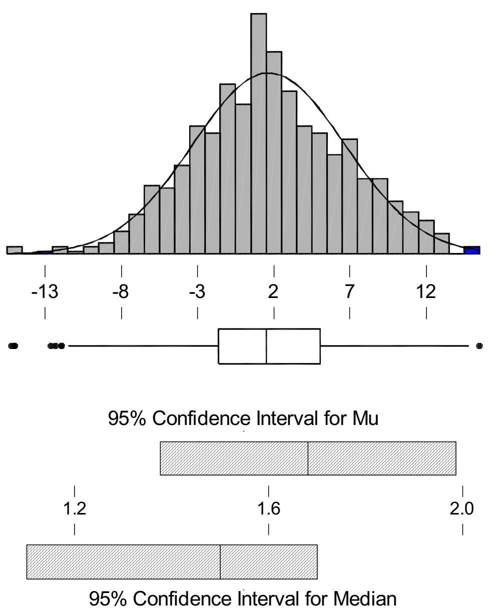
5.1190	5.5808

95% Confidence Interval for Median

1.1000	2.0000

Descriptive Statistics

Variable: AvgMaxT(0,-1,-2)



Anderson-Darling Normality Test

A-Squared:	0.979
P-Value:	0.014
Mean	1.68119
StDev	4.97922
Variance	24.7927
Skewness	-9.3E-03
Kurtosis	-3.9E-02
N	1026
Minimum	-15.2000
1st Quartile	-1.6250
Median	1.5000
3rd Quartile	5.0500
Maximum	15.5000

95% Confidence Interval for Mu

1.3762	1.9862

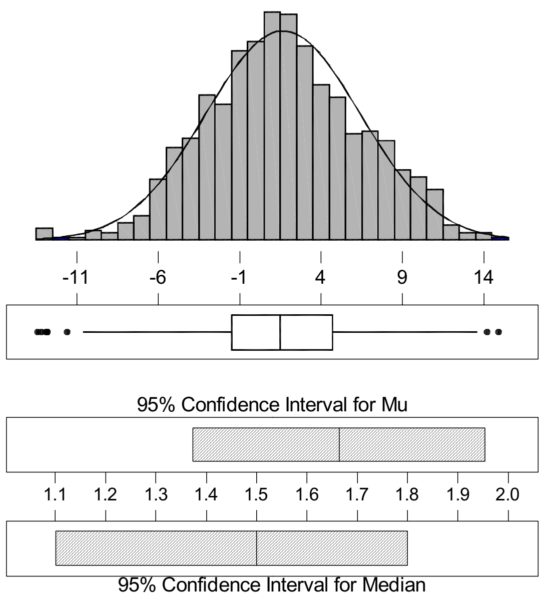
95% Confidence Interval for Sigma

4.7727	5.2046

95% Confidence Interval for Median

1.1000	1.7000

Descriptive Statistics



Variable: AvgMaxT(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	1.072
P-Value:	0.008
Mean	1.66376
StDev	4.72028
Variance	22.2810
Skewness	6.80E-04
Kurtosis	-1.1E-01
N	1021
Minimum	-13.4000
1st Quartile	-1.5000
Median	1.5000
3rd Quartile	4.7000
Maximum	14.9000

95% Confidence Interval for Mu

1.3739 1.9536

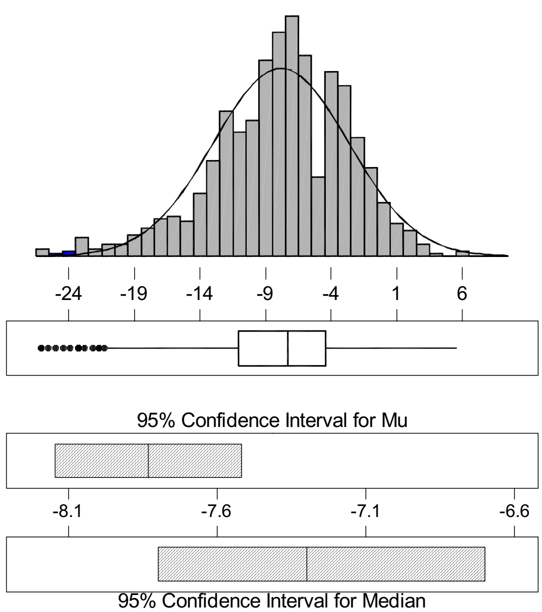
95% Confidence Interval for Sigma

4.5240 4.9344

95% Confidence Interval for Median

1.1000 1.8000

Descriptive Statistics



Variable: MinT(0)

Anderson-Darling Normality Test

A-Squared:	5.046
P-Value:	0.000
Mean	-7.83163
StDev	5.13315
Variance	26.3493
Skewness	-5.8E-01
Kurtosis	0.614920
N	1037
Minimum	-26.1000
1st Quartile	-11.1000
Median	-7.3000
3rd Quartile	-4.4000
Maximum	5.6000

95% Confidence Interval for Mu

-8.1444 -7.5188

95% Confidence Interval for Sigma

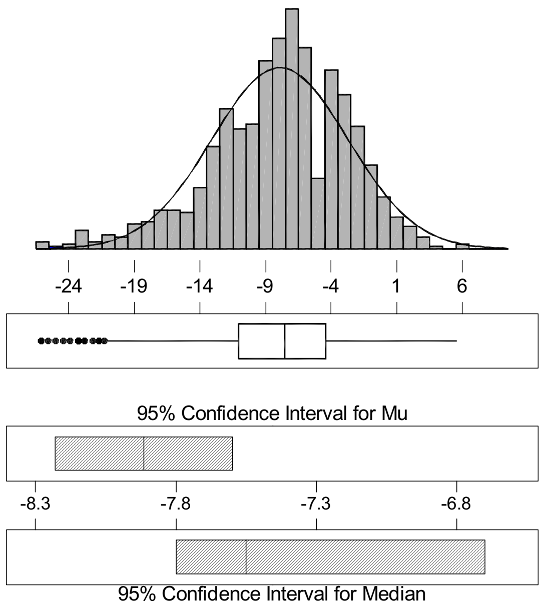
4.9213 5.3642

95% Confidence Interval for Median

-7.8000 -6.7000

Descriptive Statistics

Variable: MinT(-1)



Anderson-Darling Normality Test

A-Squared:	5.181
P-Value:	0.000
Mean	-7.91474
StDev	5.17296
Variance	26.7595
Skewness	-5.7E-01
Kurtosis	0.533425
N	1038
Minimum	-26.1000
1st Quartile	-11.1000
Median	-7.5500
3rd Quartile	-4.4000
Maximum	5.6000

95% Confidence Interval for Mu

-8.2298 -7.5997

95% Confidence Interval for Sigma

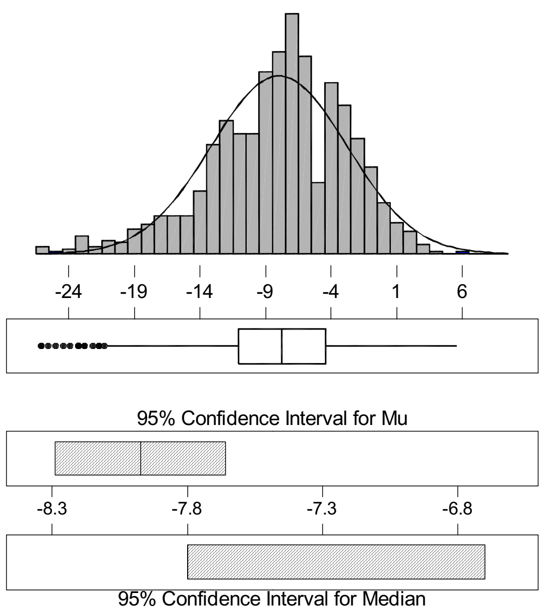
4.9596 5.4056

95% Confidence Interval for Median

-7.8000 -6.7000

Descriptive Statistics

Variable: MinT(-2)



Anderson-Darling Normality Test

A-Squared:	5.221
P-Value:	0.000
Mean	-7.97408
StDev	5.16745
Variance	26.7025
Skewness	-5.8E-01
Kurtosis	0.480964
N	1038
Minimum	-26.1000
1st Quartile	-11.1000
Median	-7.8000
3rd Quartile	-4.4000
Maximum	5.6000

95% Confidence Interval for Mu

-8.2888 -7.6594

95% Confidence Interval for Sigma

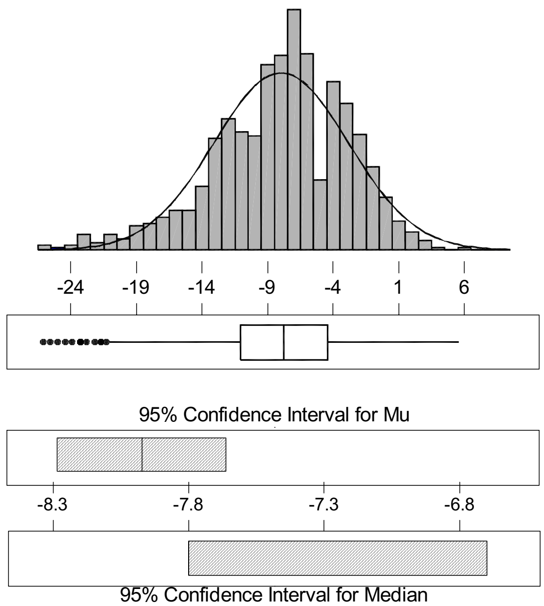
4.9543 5.3999

95% Confidence Interval for Median

-7.8000 -6.7000

Descriptive Statistics

Variable: MinT(-3)



Anderson-Darling Normality Test

A-Squared:	4.998
P-Value:	0.000
Mean	-7.97344
StDev	5.10388
Variance	26.0496
Skewness	-5.6E-01
Kurtosis	0.419797
N	1039
Minimum	-26.1000
1st Quartile	-11.1000
Median	-7.8000
3rd Quartile	-4.4000
Maximum	5.6000

95% Confidence Interval for Mu

-8.2841	-7.6627

95% Confidence Interval for Sigma

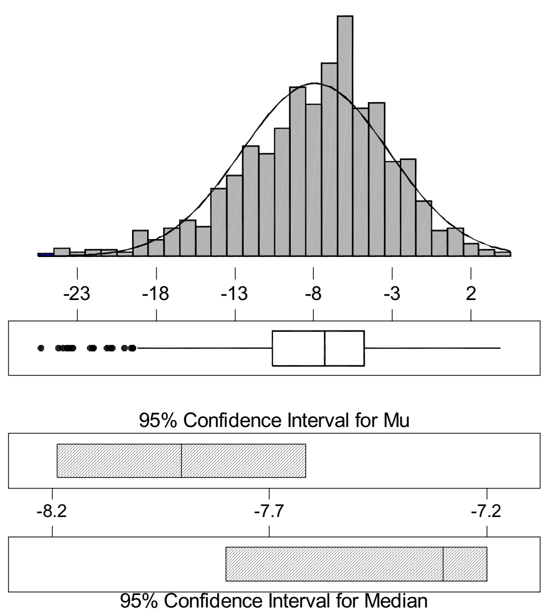
4.8935	5.3333

95% Confidence Interval for Median

-7.8000	-6.7000

Descriptive Statistics

Variable: AvgMinT(0,-1)



Anderson-Darling Normality Test

A-Squared:	4.603
P-Value:	0.000
Mean	-7.90233
StDev	4.67970
Variance	21.8996
Skewness	-5.6E-01
Kurtosis	0.578029
N	1030
Minimum	-25.3000
1st Quartile	-10.6000
Median	-7.3000
3rd Quartile	-4.8000
Maximum	3.9000

95% Confidence Interval for Mu

-8.1885	-7.6162

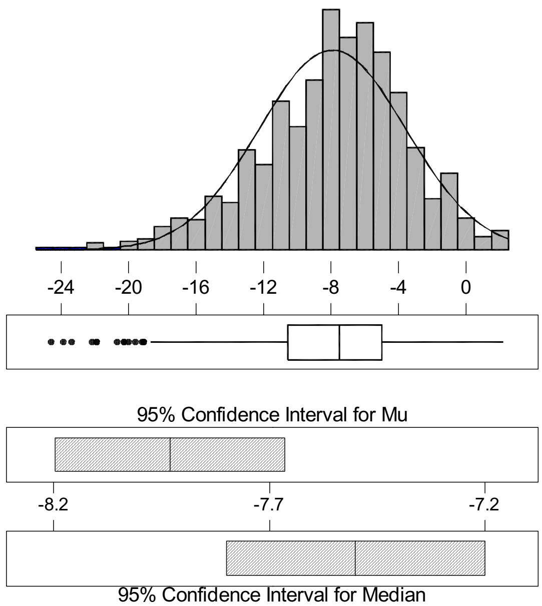
95% Confidence Interval for Sigma

4.4860	4.8910

95% Confidence Interval for Median

-7.8000	-7.2000

Descriptive Statistics



Variable: AvgMinT(0,-1,-2)

Anderson-Darling Normality Test

A-Squared:	4.351
P-Value:	0.000
Mean	-7.93001
StDev	4.34310
Variance	18.8625
Skewness	-5.2E-01
Kurtosis	0.499273
N	1023
Minimum	-24.6000
1st Quartile	-10.6000
Median	-7.5000
3rd Quartile	-5.0000
Maximum	2.2000

95% Confidence Interval for Mu

-8.1965 -7.6636

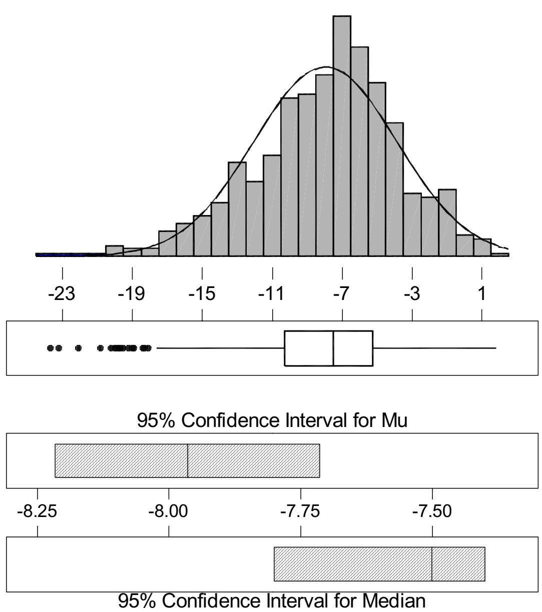
95% Confidence Interval for Sigma

4.1627 4.5399

95% Confidence Interval for Median

-7.8000 -7.2000

Descriptive Statistics



Variable: AvgMinT(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	3.782
P-Value:	0.000
Mean	-7.96480
StDev	4.08448
Variance	16.6830
Skewness	-4.7E-01
Kurtosis	0.402832
N	1017
Minimum	-23.7000
1st Quartile	-10.3000
Median	-7.5000
3rd Quartile	-5.2500
Maximum	1.8000

95% Confidence Interval for Mu

-8.2161 -7.7135

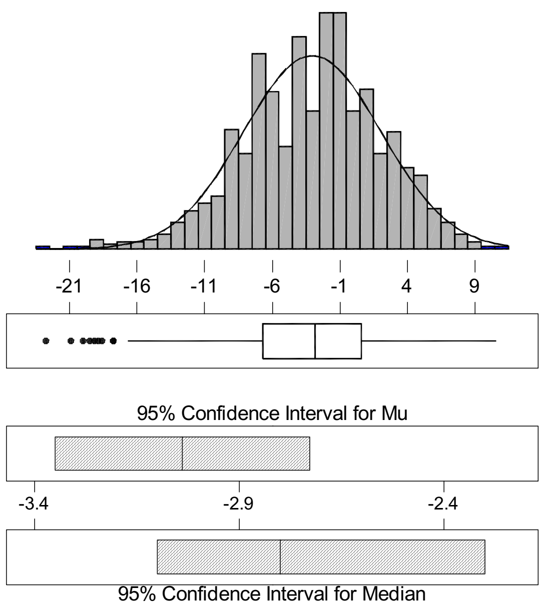
95% Confidence Interval for Sigma

3.9144 4.2702

95% Confidence Interval for Median

-7.8000 -7.4000

Descriptive Statistics



Variable: AvgT(0)

Anderson-Darling Normality Test

A-Squared:	1.140
P-Value:	0.006
Mean	-3.03770
StDev	5.09821
Variance	25.9918
Skewness	-3.2E-01
Kurtosis	0.266537
N	1037
Minimum	-22.8000
1st Quartile	-6.7000
Median	-2.8000
3rd Quartile	0.6000
Maximum	10.6000

95% Confidence Interval for Mu

-3.3484 -2.7270

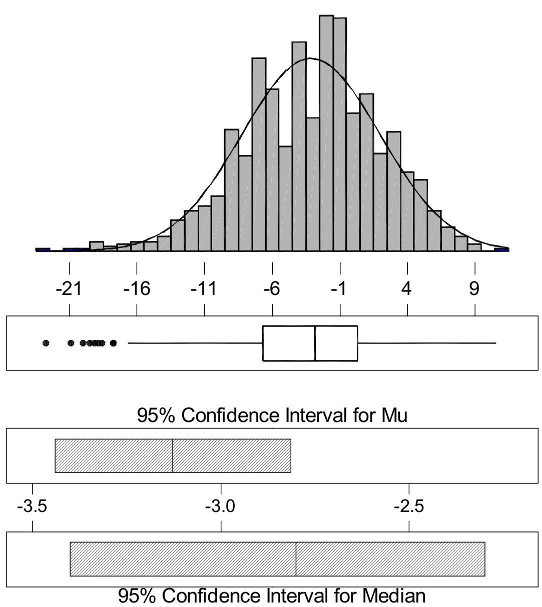
95% Confidence Interval for Sigma

4.8878 5.3276

95% Confidence Interval for Median

-3.1000 -2.3000

Descriptive Statistics



Variable: AvgT(-1)

Anderson-Darling Normality Test

A-Squared:	1.262
P-Value:	0.003
Mean	-3.12726
StDev	5.11882
Variance	26.2023
Skewness	-3.3E-01
Kurtosis	0.220065
N	1038
Minimum	-22.8000
1st Quartile	-6.7000
Median	-2.8000
3rd Quartile	0.3000
Maximum	10.6000

95% Confidence Interval for Mu

-3.4390 -2.8155

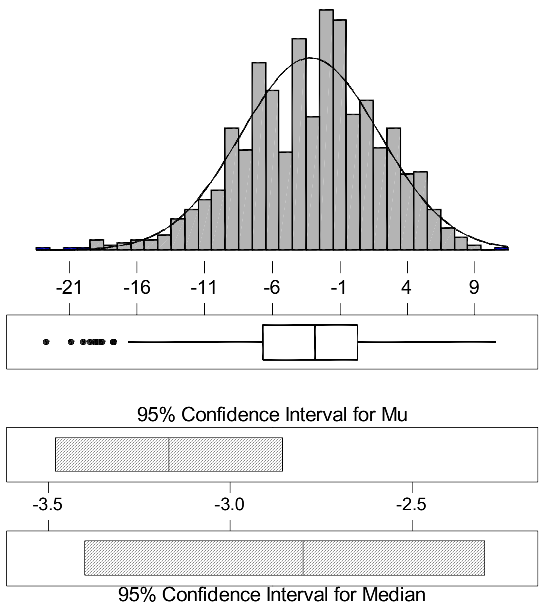
95% Confidence Interval for Sigma

4.9077 5.3491

95% Confidence Interval for Median

-3.4000 -2.3000

Descriptive Statistics



Variable: AvgT(-2)

Anderson-Darling Normality Test

A-Squared:	1.437
P-Value:	0.001
Mean	-3.16782
StDev	5.12039
Variance	26.2184
Skewness	-3.5E-01
Kurtosis	0.166333
N	1038
Minimum	-22.8000
1st Quartile	-6.7000
Median	-2.8000
3rd Quartile	0.3000
Maximum	10.6000

95% Confidence Interval for Mu

-3.4797 -2.8560

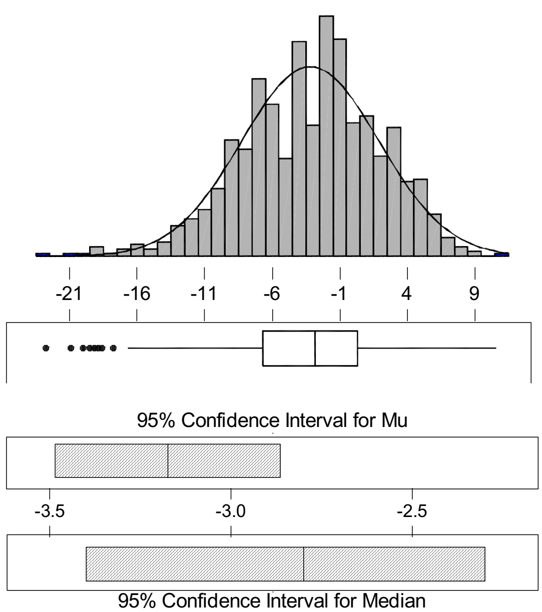
95% Confidence Interval for Sigma

4.9092 5.3507

95% Confidence Interval for Median

-3.4000 -2.3000

Descriptive Statistics



Variable: AvgT(-3)

Anderson-Darling Normality Test

A-Squared:	1.399
P-Value:	0.001
Mean	-3.17421
StDev	5.09858
Variance	25.9956
Skewness	-3.4E-01
Kurtosis	0.132413
N	1039
Minimum	-22.8000
1st Quartile	-6.7000
Median	-2.8000
3rd Quartile	0.3000
Maximum	10.6000

95% Confidence Interval for Mu

-3.4846 -2.8638

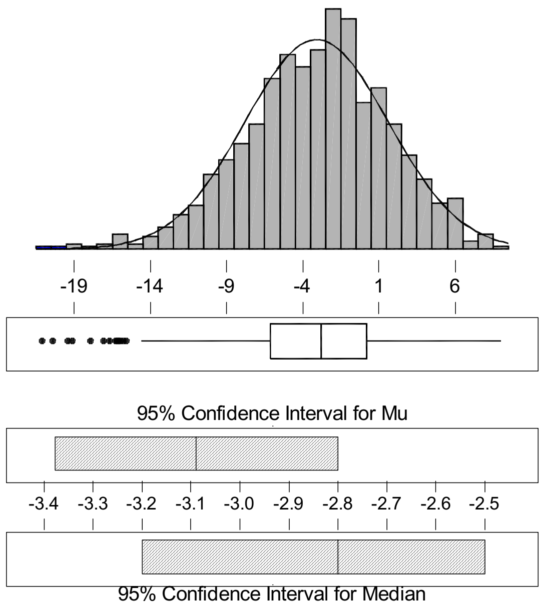
95% Confidence Interval for Sigma

4.8884 5.3278

95% Confidence Interval for Median

-3.4000 -2.3000

Descriptive Statistics



Variable: AvgAvgT(0,-1)

Anderson-Darling Normality Test

A-Squared:	0.993
P-Value:	0.013
Mean	-3.08893
StDev	4.71094
Variance	22.1929
Skewness	-3.4E-01
Kurtosis	0.287289
N	1030
Minimum	-21.1000
1st Quartile	-6.1000
Median	-2.8000
3rd Quartile	0.2000
Maximum	9.0000

95% Confidence Interval for Mu

-3.3770 -2.8009

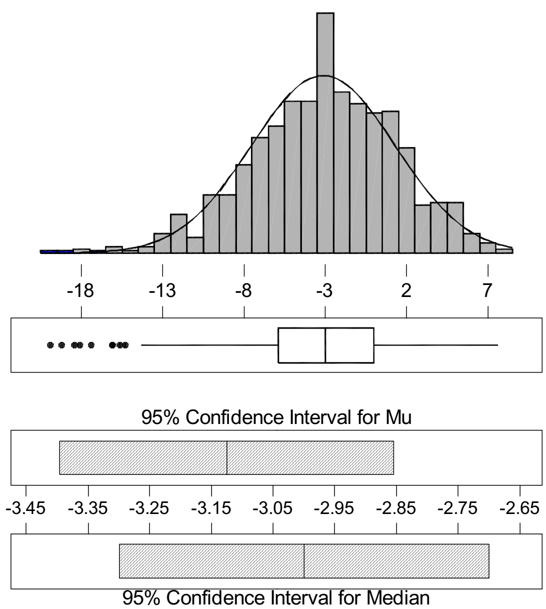
95% Confidence Interval for Sigma

4.5159 4.9237

95% Confidence Interval for Median

-3.2000 -2.5000

Descriptive Statistics



Variable: AvgAvgT(0,-1,-2)

Anderson-Darling Normality Test

A-Squared:	1.076
P-Value:	0.008
Mean	-3.12522
StDev	4.41171
Variance	19.4632
Skewness	-3.2E-01
Kurtosis	0.243517
N	1023
Minimum	-19.9000
1st Quartile	-5.9000
Median	-3.0000
3rd Quartile	0.0000
Maximum	7.6000

95% Confidence Interval for Mu

-3.3959 -2.8546

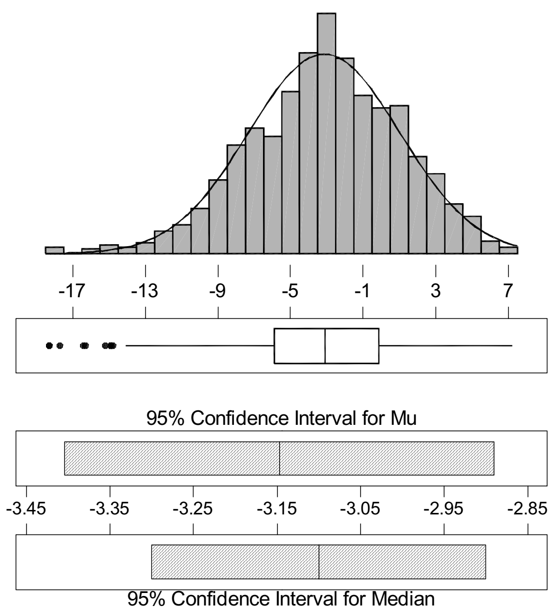
95% Confidence Interval for Sigma

4.2285 4.6117

95% Confidence Interval for Median

-3.3000 -2.7000

Descriptive Statistics



Variable: AvgAvgT(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	0.973
P-Value:	0.014
Mean	-3.14739
StDev	4.17225
Variance	17.4077
Skewness	-3.0E-01
Kurtosis	0.153065
N	1017
Minimum	-18.3000
1st Quartile	-5.9000
Median	-3.1000
3rd Quartile	-0.1500
Maximum	7.2000

95% Confidence Interval for Mu

-3.4041 -2.8907

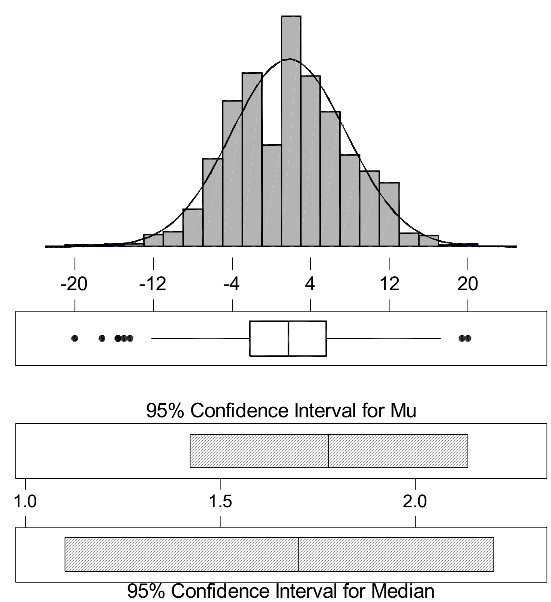
95% Confidence Interval for Sigma

3.9985 4.3619

95% Confidence Interval for Median

-3.3000 -2.9000

Descriptive Statistics



Variable: DDMaxT(0)

Anderson-Darling Normality Test

A-Squared:	1.247
P-Value:	0.003
Mean	1.77775
StDev	5.84683
Variance	34.1855
Skewness	4.22E-03
Kurtosis	-4.1E-02
N	1038
Minimum	-20.0000
1st Quartile	-2.2000
Median	1.7000
3rd Quartile	5.6000
Maximum	20.0000

95% Confidence Interval for Mu

1.4216 2.1339

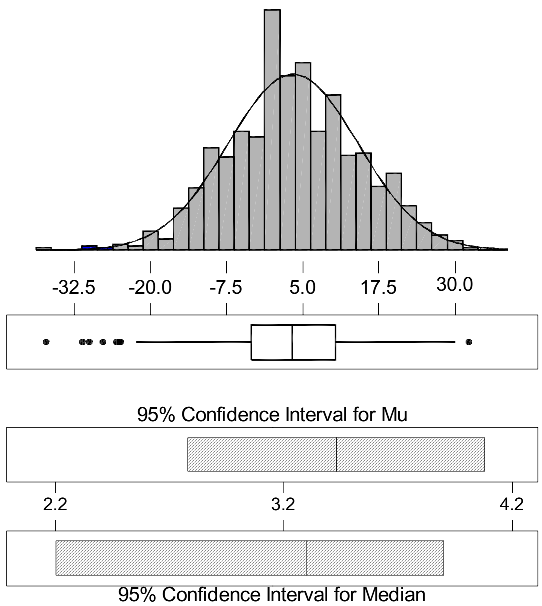
95% Confidence Interval for Sigma

5.6057 6.1098

95% Confidence Interval for Median

1.1000 2.2000

Descriptive Statistics



Variable: DDMaxT(0,-1)

Anderson-Darling Normality Test

A-Squared:	0.931
P-Value:	0.018
Mean	3.4281
StDev	10.6493
Variance	113.407
Skewness	-1.8E-02
Kurtosis	-2.4E-02
N	1032
Minimum	-37.2000
1st Quartile	-3.4000
Median	3.3000
3rd Quartile	10.4000
Maximum	32.3000

95% Confidence Interval for Mu

2.7776 4.0786

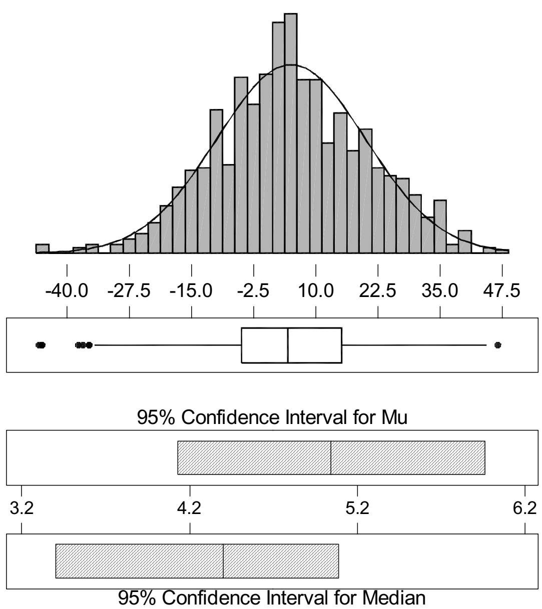
95% Confidence Interval for Sigma

10.2088 11.1297

95% Confidence Interval for Median

2.2000 3.9000

Descriptive Statistics



Variable: DDMaxT(0,-1,-2)

Anderson-Darling Normality Test

A-Squared:	0.965
P-Value:	0.015
Mean	5.0431
StDev	14.9379
Variance	223.140
Skewness	-8.8E-03
Kurtosis	-4.0E-02
N	1026
Minimum	-45.6000
1st Quartile	-4.9250
Median	4.4000
3rd Quartile	15.2000
Maximum	46.6000

95% Confidence Interval for Mu

4.1280 5.9582

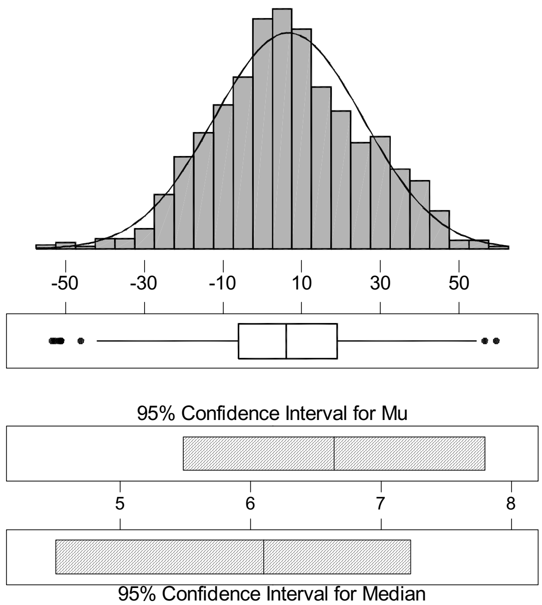
95% Confidence Interval for Sigma

14.3183 15.6139

95% Confidence Interval for Median

3.4000 5.0884

Descriptive Statistics



Variable: DDMaxT(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	1.072
P-Value:	0.008
Mean	6.6391
StDev	18.8507
Variance	355.349
Skewness	1.81E-03
Kurtosis	-1.0E-01
N	1021
Minimum	-53.4000
1st Quartile	-6.1000
Median	6.1000
3rd Quartile	18.9000
Maximum	59.4000

95% Confidence Interval for Mu

5.4814 7.7967

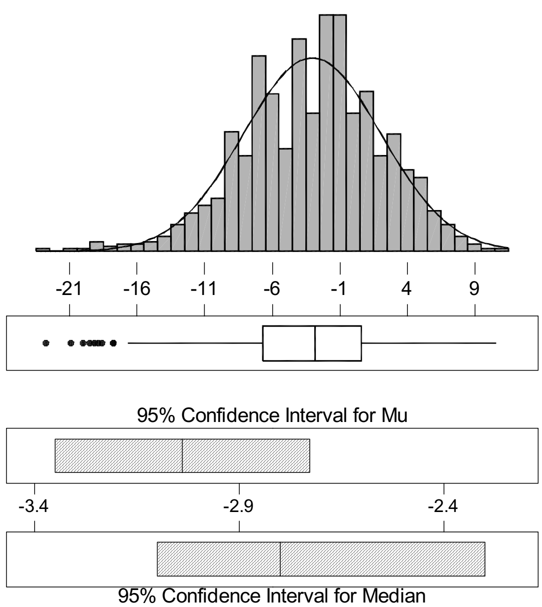
95% Confidence Interval for Sigma

18.0670 19.7060

95% Confidence Interval for Median

4.5000 7.2300

Descriptive Statistics



Variable: DDAvgT(0)

Anderson-Darling Normality Test

A-Squared:	1.140
P-Value:	0.006
Mean	-3.03770
StDev	5.09821
Variance	25.9918
Skewness	-3.2E-01
Kurtosis	0.266537
N	1037
Minimum	-22.8000
1st Quartile	-6.7000
Median	-2.8000
3rd Quartile	0.6000
Maximum	10.6000

95% Confidence Interval for Mu

-3.3484 -2.7270

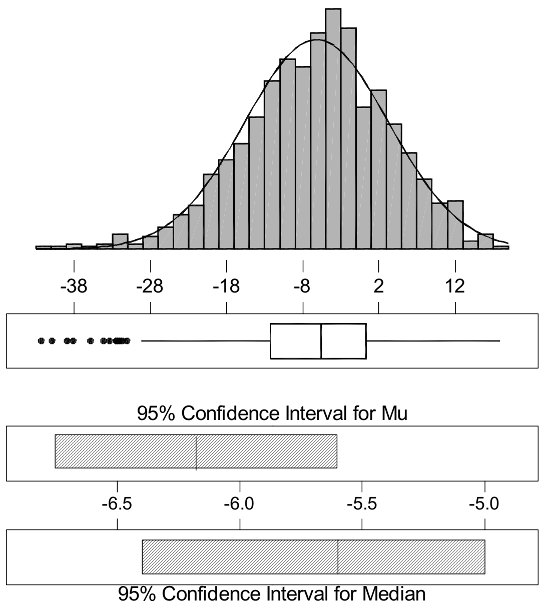
95% Confidence Interval for Sigma

4.8878 5.3276

95% Confidence Interval for Median

-3.1000 -2.3000

Descriptive Statistics



Variable: DDAvgT(0,-1)

Anderson-Darling Normality Test

A-Squared:	0.987
P-Value:	0.013
Mean	-6.17816
StDev	9.41981
Variance	88.7327
Skewness	-3.4E-01
Kurtosis	0.292612
N	1030
Minimum	-42.3000
1st Quartile	-12.2000
Median	-5.6000
3rd Quartile	0.3000
Maximum	17.9000

95% Confidence Interval for Mu

-6.7541 -5.6022

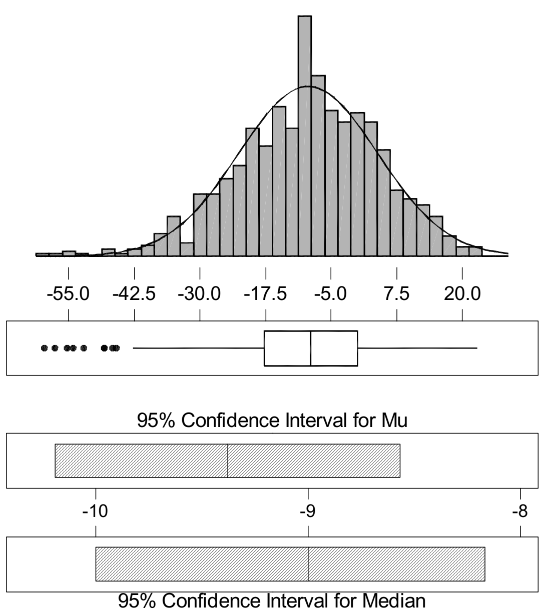
95% Confidence Interval for Sigma

9.0299 9.8452

95% Confidence Interval for Median

-6.4000 -5.0000

Descriptive Statistics



Variable:
DDAvgT(0,-1,-2)

Anderson-Darling Normality Test

A-Squared:	1.043
P-Value:	0.010
Mean	-9.3792
StDev	13.2339
Variance	175.137
Skewness	-3.2E-01
Kurtosis	0.242843
N	1023
Minimum	-59.7000
1st Quartile	-17.8000
Median	-9.0000
3rd Quartile	0.0000
Maximum	22.8000

95% Confidence Interval for Mu

-10.1911 -8.5673

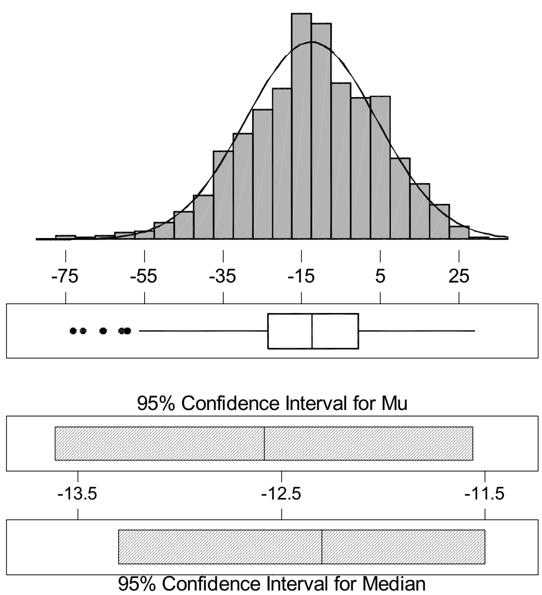
95% Confidence Interval for Sigma

12.6843 13.8337

95% Confidence Interval for Median

-10.0000 -8.1670

Descriptive Statistics



Variable:
DDAvgT(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	0.971
P-Value:	0.014
Mean	-12.5844
StDev	16.6815
Variance	278.271
Skewness	-3.0E-01
Kurtosis	0.151635
N	1017
Minimum	-73.1000
1st Quartile	-23.6000
Median	-12.3000
3rd Quartile	-0.7000
Maximum	29.0000

95% Confidence Interval for Mu

-13.6108 -11.5579

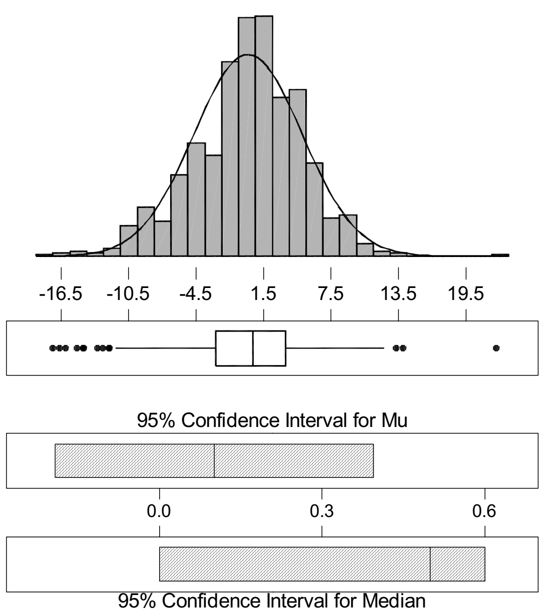
95% Confidence Interval for Sigma

15.9867 17.4398

95% Confidence Interval for Median

-13.3000 -11.5000

Descriptive Statistics



Variable:
MaxT(0)-MaxT(-1)

Anderson-Darling Normality Test

A-Squared:	3.553
P-Value:	0.000
Mean	0.10155
StDev	4.79975
Variance	23.0376
Skewness	-3.0E-01
Kurtosis	0.661595
N	1032
Minimum	-17.3000
1st Quartile	-2.8000
Median	0.5000
3rd Quartile	3.4000
Maximum	22.2000

95% Confidence Interval for Mu

-0.1916 0.3947

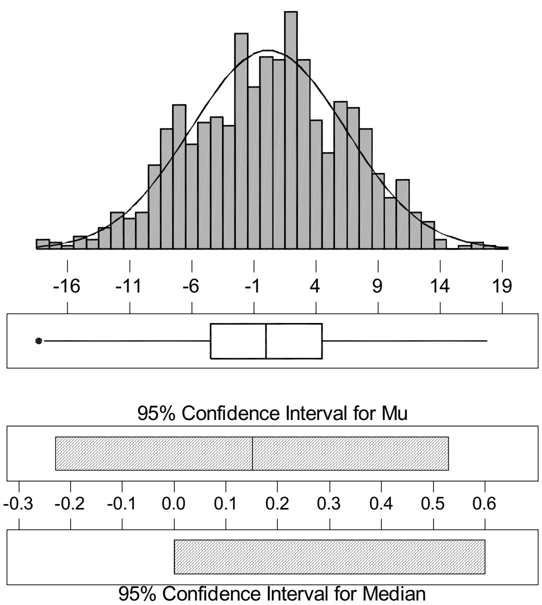
95% Confidence Interval for Sigma

4.6012 5.0163

95% Confidence Interval for Median

0.0000 0.6000

Descriptive Statistics



Variable:
MaxT(0)-MaxT(-2)

Anderson-Darling Normality Test

A-Squared:	1.066
P-Value:	0.008
Mean	0.15092
StDev	6.21063
Variance	38.5719
Skewness	-9.4E-02
Kurtosis	-3.1E-01
N	1031
Minimum	-18.3000
1st Quartile	-4.5000
Median	0.0000
3rd Quartile	4.5000
Maximum	17.8000

95% Confidence Interval for Mu

-0.2286 0.5305

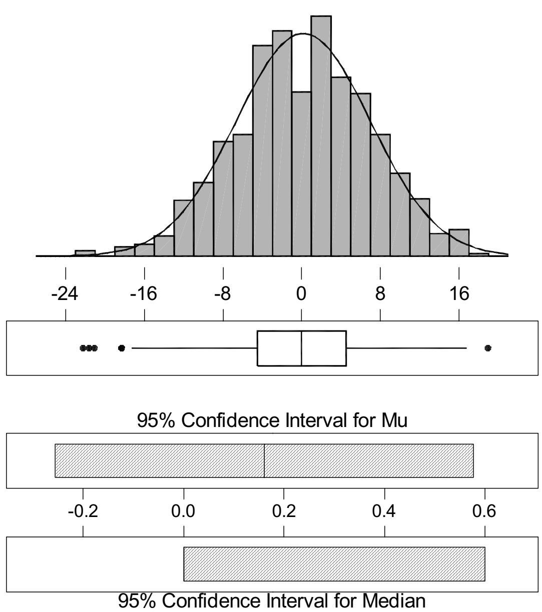
95% Confidence Interval for Sigma

5.9536 6.4910

95% Confidence Interval for Median

0.0000 0.6000

Descriptive Statistics



Variable:
MaxT(0)-MaxT(-3)

Anderson-Darling Normality Test

A-Squared:	0.530
P-Value:	0.175
Mean	0.16066
StDev	6.82170
Variance	46.5356
Skewness	-9.7E-02
Kurtosis	-2.0E-01
N	1032
Minimum	-22.2000
1st Quartile	-4.5000
Median	0.0000
3rd Quartile	4.5000
Maximum	18.9000

95% Confidence Interval for Mu

-0.2560 0.5773

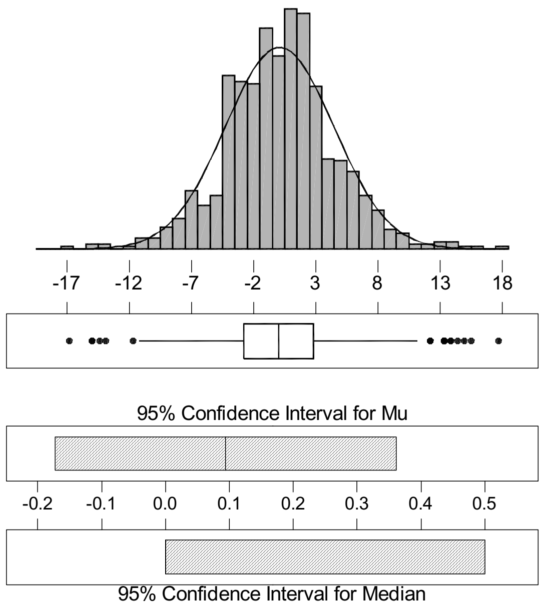
95% Confidence Interval for Sigma

6.5396 7.1295

95% Confidence Interval for Median

0.0000 0.6000

Descriptive Statistics



Variable:
MinT(0)-MinT(-1)

Anderson-Darling Normality Test

A-Squared:	2.134
P-Value:	0.000
Mean	0.09437
StDev	4.36718
Variance	19.0723
Skewness	7.58E-02
Kurtosis	0.997888
N	1030
Minimum	-16.8000
1st Quartile	-2.8000
Median	0.0000
3rd Quartile	2.8000
Maximum	17.7000

95% Confidence Interval for Mu

-0.1726	0.3614

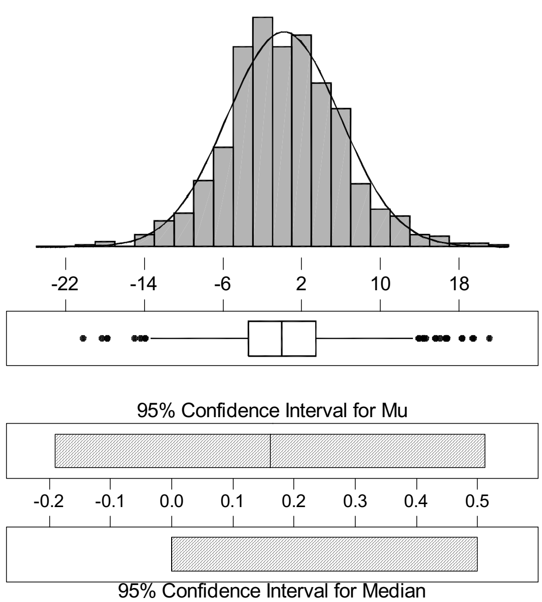
95% Confidence Interval for Sigma

4.1864	4.5644

95% Confidence Interval for Median

0.0000	0.5000

Descriptive Statistics



Variable:
MinT(0)-MinT(-2)

Anderson-Darling Normality Test

A-Squared:	1.697
P-Value:	0.000
Mean	0.16074
StDev	5.74022
Variance	32.9501
Skewness	0.165473
Kurtosis	0.670517
N	1029
Minimum	-20.2000
1st Quartile	-3.4000
Median	0.0000
3rd Quartile	3.4000
Maximum	21.1000

95% Confidence Interval for Mu

-0.1904	0.5119

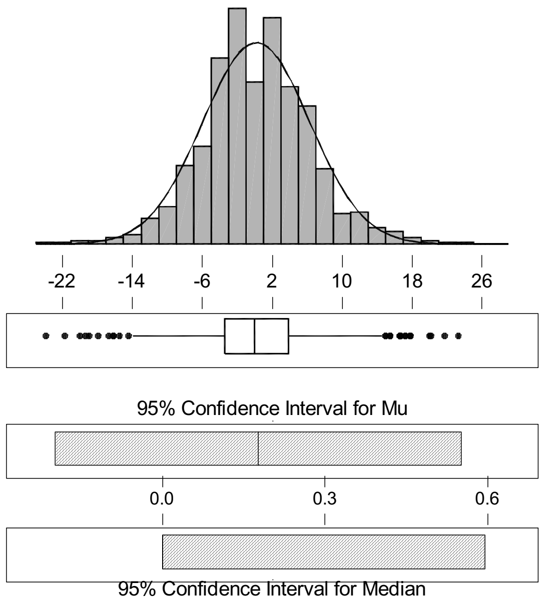
95% Confidence Interval for Sigma

5.5025	5.9996

95% Confidence Interval for Median

0.0000	0.5000

Descriptive Statistics



Variable:
MinT(0)-MinT(-3)

Anderson-Darling Normality Test

A-Squared:	1.728
P-Value:	0.000
Mean	0.17680
StDev	6.12178
Variance	37.4762
Skewness	9.00E-02
Kurtosis	0.867060
N	1030
Minimum	-23.9000
1st Quartile	-3.4000
Median	0.0000
3rd Quartile	3.9000
Maximum	23.3000

95% Confidence Interval for Mu

-0.1975 0.5511

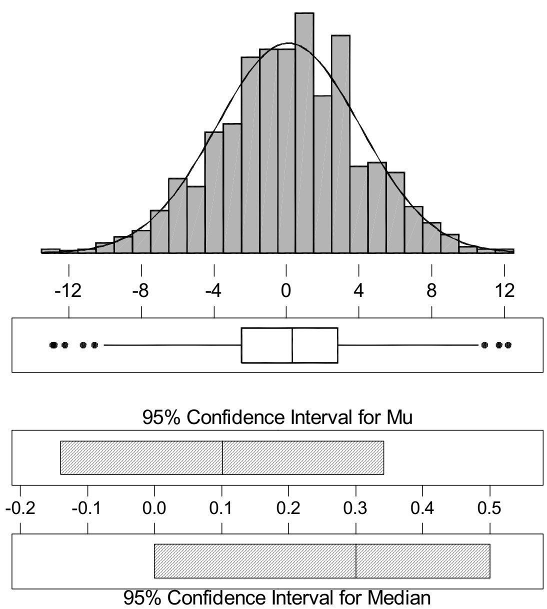
95% Confidence Interval for Sigma

5.8684 6.3983

95% Confidence Interval for Median

0.0000 0.5948

Descriptive Statistics



Variable:
AvgT(0)-AvgT(-1)

Anderson-Darling Normality Test

A-Squared:	0.542
P-Value:	0.164
Mean	0.10117
StDev	3.94461
Variance	15.5599
Skewness	-9.6E-02
Kurtosis	8.60E-02
N	1030
Minimum	-12.9000
1st Quartile	-2.5000
Median	0.3000
3rd Quartile	2.8000
Maximum	12.2000

95% Confidence Interval for Mu

-0.1400 0.3423

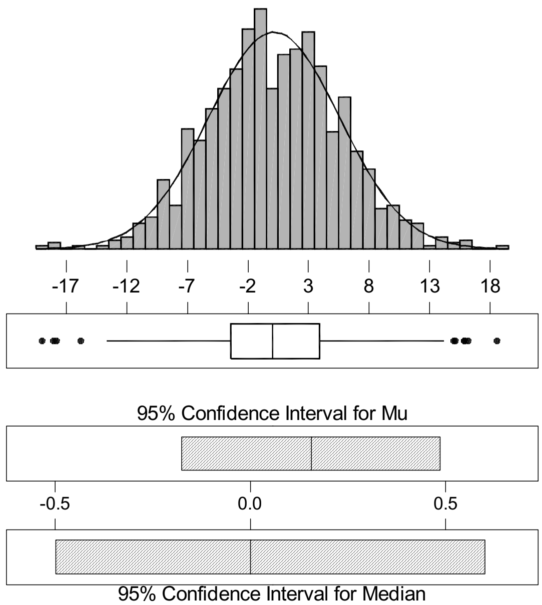
95% Confidence Interval for Sigma

3.7813 4.1228

95% Confidence Interval for Median

0.0000 0.5000

Descriptive Statistics



Variable:
AvgT(0)-AvgT(-2)

Anderson-Darling Normality Test

A-Squared:	0.307
P-Value:	0.563
Mean	0.15481
StDev	5.41180
Variance	29.2875
Skewness	2.01E-02
Kurtosis	0.127619
N	1029
Minimum	-19.0000
1st Quartile	-3.4000
Median	0.0000
3rd Quartile	3.9000
Maximum	18.6000

95% Confidence Interval for Mu

-0.1762 0.4859

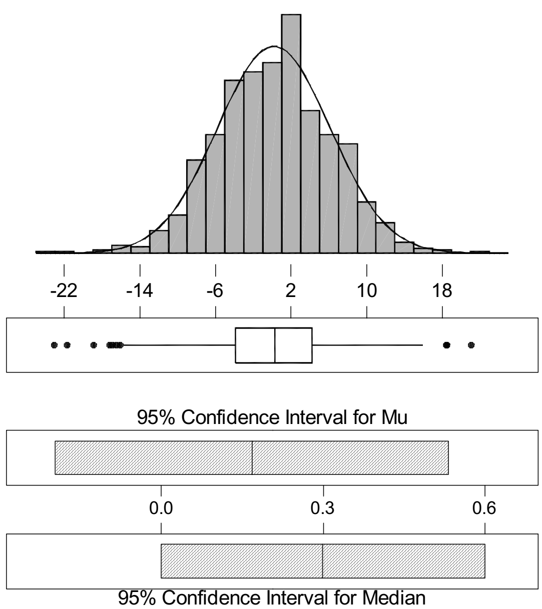
95% Confidence Interval for Sigma

5.1877 5.6563

95% Confidence Interval for Median

-0.5000 0.6000

Descriptive Statistics



Variable:
AvgT(0)-AvgT(-3)

Anderson-Darling Normality Test

A-Squared:	0.422
P-Value:	0.321
Mean	0.16786
StDev	5.95843
Variance	35.5029
Skewness	-6.6E-02
Kurtosis	0.288145
N	1030
Minimum	-23.1000
1st Quartile	-3.9000
Median	0.3000
3rd Quartile	4.2000
Maximum	21.1000

95% Confidence Interval for Mu

-0.1964 0.5322

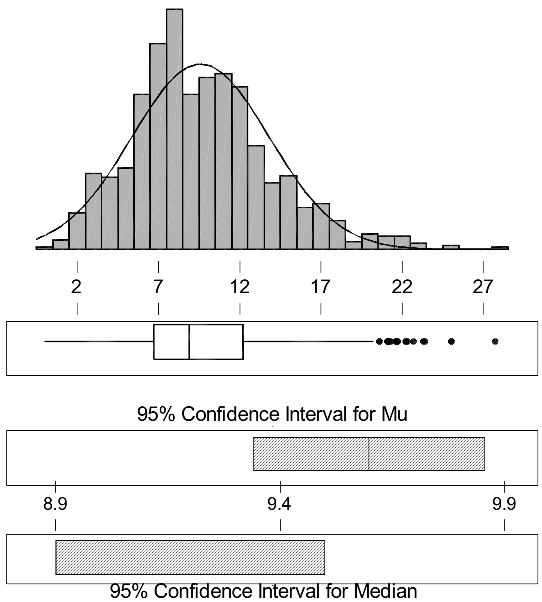
95% Confidence Interval for Sigma

5.7118 6.2275

95% Confidence Interval for Median

0.0000 0.6000

Descriptive Statistics



Variable:
MaxT(0)-MinT(0)

Anderson-Darling Normality Test

A-Squared:	5.552
P-Value:	0.000
Mean	9.59836
StDev	4.22080
Variance	17.8152
Skewness	0.662944
Kurtosis	0.639511
N	1038
Minimum	0.0000
1st Quartile	6.7000
Median	8.9000
3rd Quartile	12.2000
Maximum	27.7000

95% Confidence Interval for Mu

9.3413 9.8554

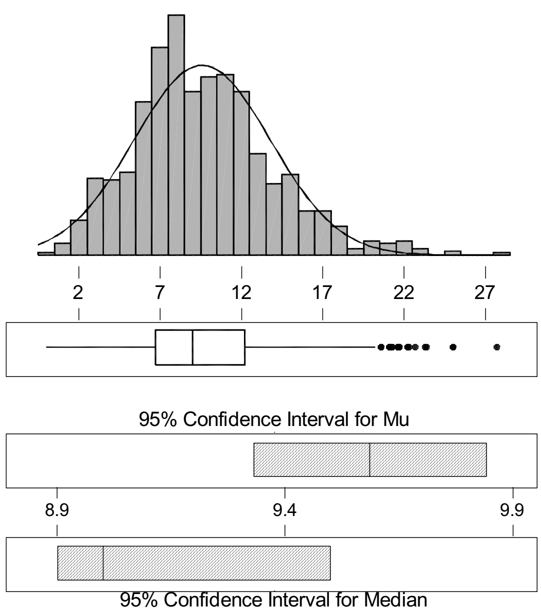
95% Confidence Interval for Sigma

4.0467 4.4107

95% Confidence Interval for Median

8.9000 9.5000

Descriptive Statistics



Variable:
MaxT(-1)-MinT(-1)

Anderson-Darling Normality Test

A-Squared:	4.883
P-Value:	0.000
Mean	9.58691
StDev	4.19176
Variance	17.5709
Skewness	0.634705
Kurtosis	0.640176
N	1039
Minimum	0.0000
1st Quartile	6.7000
Median	9.0000
3rd Quartile	12.2000
Maximum	27.7000

95% Confidence Interval for Mu

9.3317 9.8421

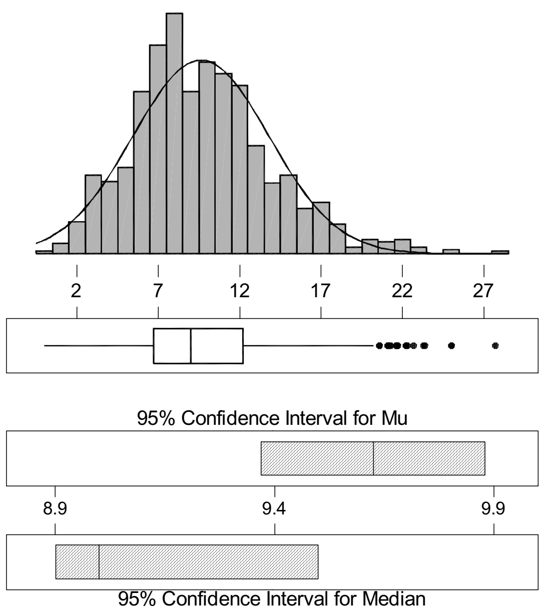
95% Confidence Interval for Sigma

4.0190 4.3802

95% Confidence Interval for Median

8.9000 9.5000

Descriptive Statistics



Variable:
MaxT(-2)-MinT(-2)

Anderson-Darling Normality Test

A-Squared:	5.092
P-Value:	0.000
Mean	9.62493
StDev	4.18305
Variance	17.4979
Skewness	0.643266
Kurtosis	0.630343
N	1039
Minimum	0.0000
1st Quartile	6.7000
Median	9.0000
3rd Quartile	12.2000
Maximum	27.7000

95% Confidence Interval for Mu

9.3703	9.8796

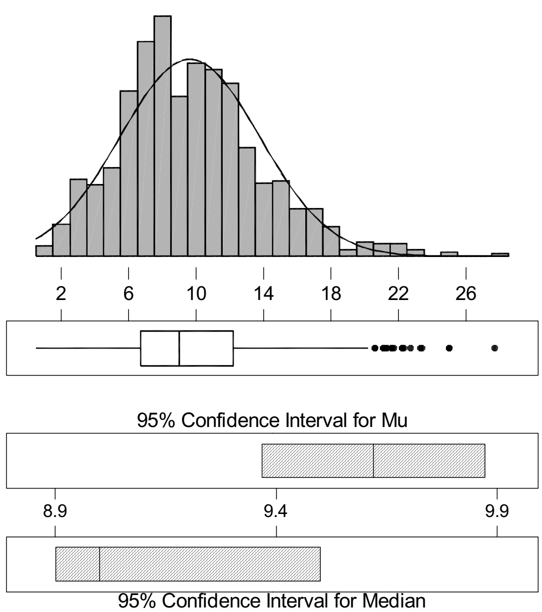
95% Confidence Interval for Sigma

4.0106	4.3711

95% Confidence Interval for Median

8.9000	9.5000

Descriptive Statistics



Variable:
MaxT(-3)-MinT(-3)

Anderson-Darling Normality Test

A-Squared:	4.959
P-Value:	0.000
Mean	9.61983
StDev	4.14273
Variance	17.1622
Skewness	0.648431
Kurtosis	0.657700
N	1039
Minimum	0.5000
1st Quartile	6.7000
Median	9.0000
3rd Quartile	12.2000
Maximum	27.7000

95% Confidence Interval for Mu

9.3676	9.8720

95% Confidence Interval for Sigma

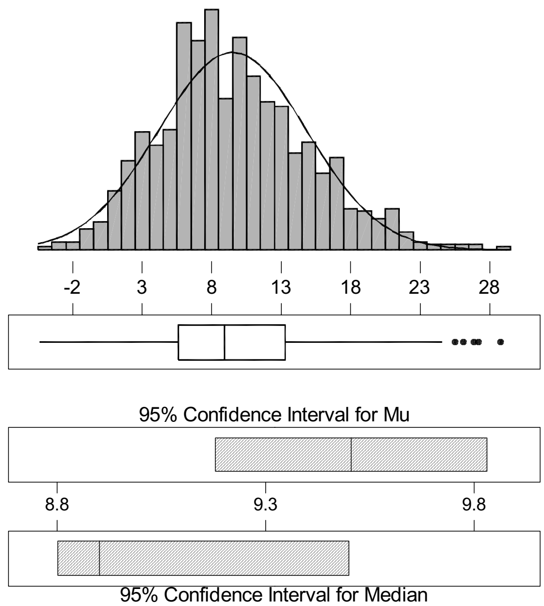
3.9719	4.3290

95% Confidence Interval for Median

8.9000	9.5000

Descriptive Statistics

Variable: MaxT(-1) - MinT(0)



Anderson-Darling Normality Test

A-Squared:	3.483
P-Value:	0.000
Mean	9.50514
StDev	5.31957
Variance	28.2978
Skewness	0.424700
Kurtosis	6.94E-02
N	1031
Minimum	-4.4000
1st Quartile	5.6000
Median	8.9000
3rd Quartile	13.3000
Maximum	28.8000

95% Confidence Interval for Mu

9.1800 9.8302

95% Confidence Interval for Sigma

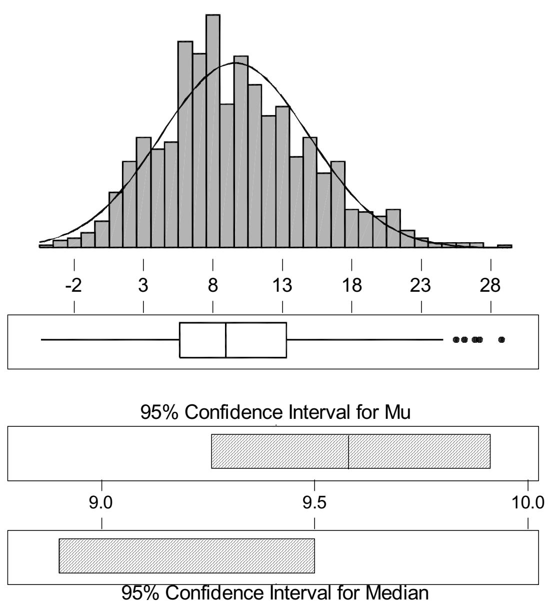
5.0995 5.5597

95% Confidence Interval for Median

8.8000 9.5000

Descriptive Statistics

Variable: MaxT(-2)-MinT(-1)



Anderson-Darling Normality Test

A-Squared:	3.369
P-Value:	0.000
Mean	9.57917
StDev	5.34537
Variance	28.5730
Skewness	0.411218
Kurtosis	3.93E-02
N	1032
Minimum	-4.4000
1st Quartile	5.6000
Median	8.9000
3rd Quartile	13.3000
Maximum	28.8000

95% Confidence Interval for Mu

9.2527 9.9057

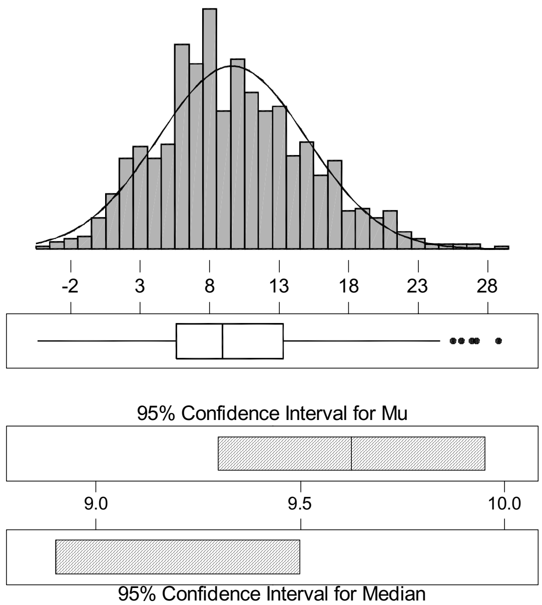
95% Confidence Interval for Sigma

5.1243 5.5865

95% Confidence Interval for Median

8.9000 9.5000

Descriptive Statistics



Variable: MaxT(-3)-MinT(-2)

Anderson-Darling Normality Test

A-Squared:	3.175
P-Value:	0.000
Mean	9.62478
StDev	5.35939
Variance	28.7230
Skewness	0.394994
Kurtosis	1.28E-02
N	1033
Minimum	-4.4000
1st Quartile	5.6000
Median	8.9000
3rd Quartile	13.3000
Maximum	28.8000

95% Confidence Interval for Mu

9.2976	9.9520

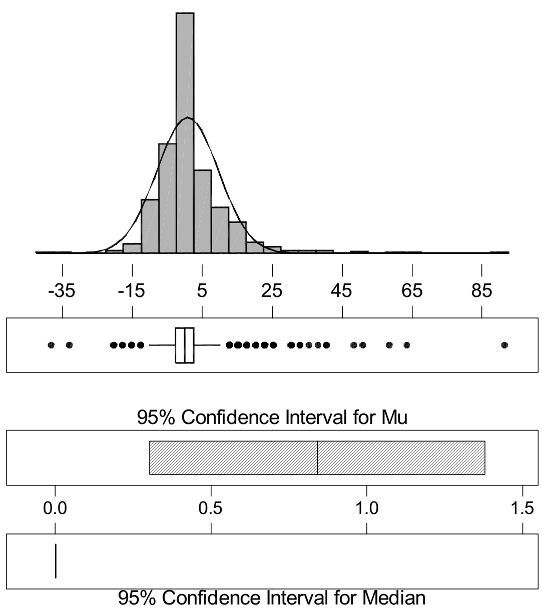
95% Confidence Interval for Sigma

5.1378	5.6011

95% Confidence Interval for Median

8.9000	9.5000

Descriptive Statistics



Variable: HS(0)-HS(-1)

Anderson-Darling Normality Test

A-Squared:	48.446
P-Value:	0.000
Mean	0.84135
StDev	8.82697
Variance	77.9154
Skewness	2.64595
Kurtosis	17.8414
N	1040
Minimum	-38.1000
1st Quartile	-2.6000
Median	0.0000
3rd Quartile	2.6000
Maximum	91.4000

95% Confidence Interval for Mu

0.3043	1.3784

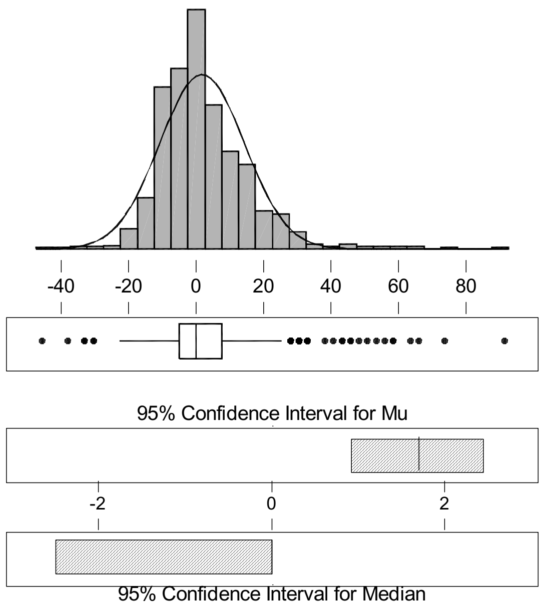
95% Confidence Interval for Sigma

8.4632	9.2236

95% Confidence Interval for Median

0.0000	0.0000

Descriptive Statistics



Variable:
HS(0)-HS(-2)

Anderson-Darling Normality Test

A-Squared:	25.392
P-Value:	0.000
Mean	1.7003
StDev	12.5683
Variance	157.963
Skewness	1.54264
Kurtosis	6.19342
N	1040
Minimum	-45.7000
1st Quartile	-5.1000
Median	0.0000
3rd Quartile	7.6000
Maximum	91.4000

95% Confidence Interval for Mu

0.9355 2.4650

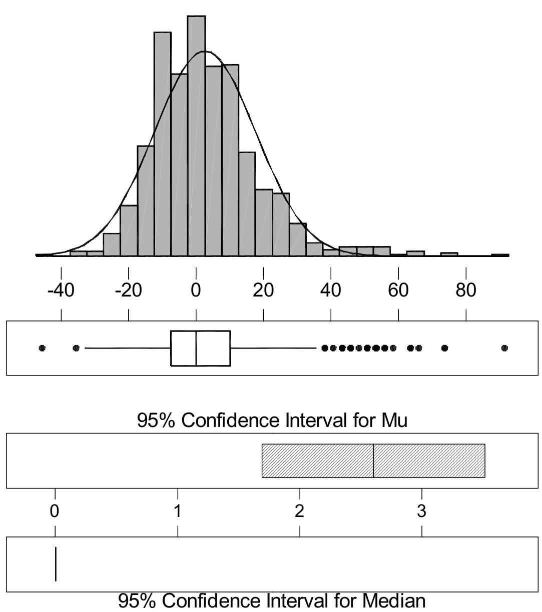
95% Confidence Interval for Sigma

12.0504 13.1331

95% Confidence Interval for Median

-2.5000 0.0000

Descriptive Statistics



Variable:
HS(0)-HS(-3)

Anderson-Darling Normality Test

A-Squared:	16.391
P-Value:	0.000
Mean	2.5995
StDev	14.9965
Variance	224.894
Skewness	1.24298
Kurtosis	3.49827
N	1040
Minimum	-45.7000
1st Quartile	-7.6000
Median	0.0000
3rd Quartile	10.1000
Maximum	91.4000

95% Confidence Interval for Mu

1.6870 3.5120

95% Confidence Interval for Sigma

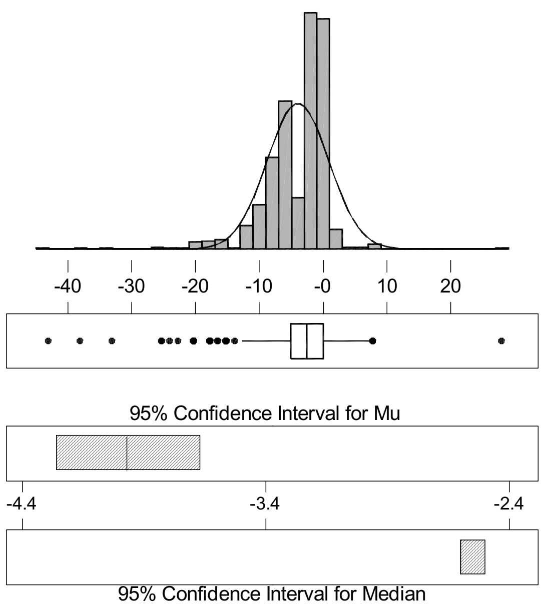
14.3785 15.6703

95% Confidence Interval for Median

0.0000 0.0000

Descriptive Statistics

Variable: Stl(0,-1)



Anderson-Darling Normality Test

A-Squared:	40.153
P-Value:	0.000
Mean	-3.96885
StDev	4.83583
Variance	23.3853
Skewness	-1.74091
Kurtosis	10.7306
N	1037
Minimum	-43.1000
1st Quartile	-5.1000
Median	-2.6000
3rd Quartile	0.0000
Maximum	28.0000

95% Confidence Interval for Mu

-4.2635	-3.6742

95% Confidence Interval for Sigma

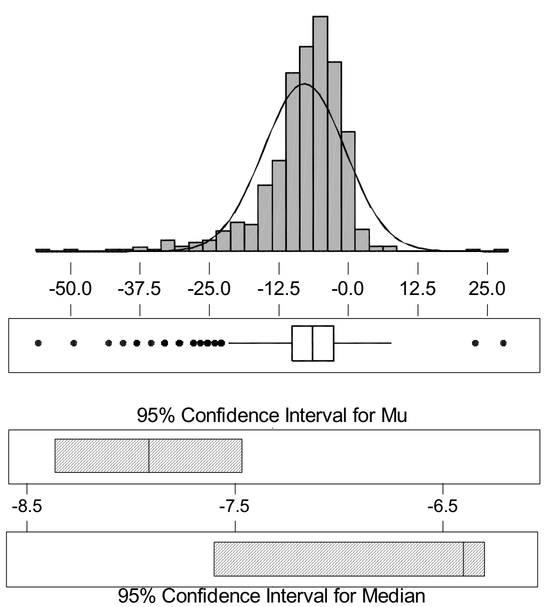
4.6363	5.0535

95% Confidence Interval for Median

-2.6000	-2.5000

Descriptive Statistics

Variable: Stl(0,-1,-2)



Anderson-Darling Normality Test

A-Squared:	28.502
P-Value:	0.000
Mean	-7.91500
StDev	7.35854
Variance	54.1482
Skewness	-1.45911
Kurtosis	5.57396
N	1033
Minimum	-55.8000
1st Quartile	-10.2000
Median	-6.4000
3rd Quartile	-2.6000
Maximum	27.9000

95% Confidence Interval for Mu

-8.3643	-7.4657

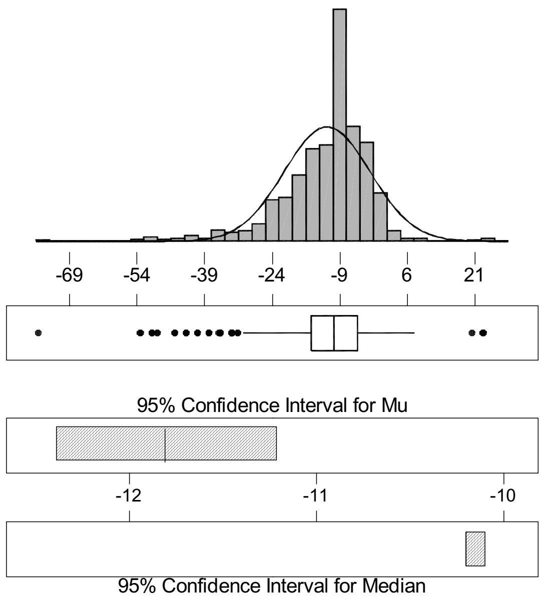
95% Confidence Interval for Sigma

7.0543	7.6904

95% Confidence Interval for Median

-7.6000	-6.3000

Descriptive Statistics



Variable: Stl(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	21.798
P-Value:	0.000
Mean	-11.8073
StDev	9.5928
Variance	92.0223
Skewness	-1.30964
Kurtosis	4.47897
N	1029
Minimum	-76.1000
1st Quartile	-15.3000
Median	-10.2000
3rd Quartile	-5.1000
Maximum	22.9000

95% Confidence Interval for Mu

-12.3941 -11.2205

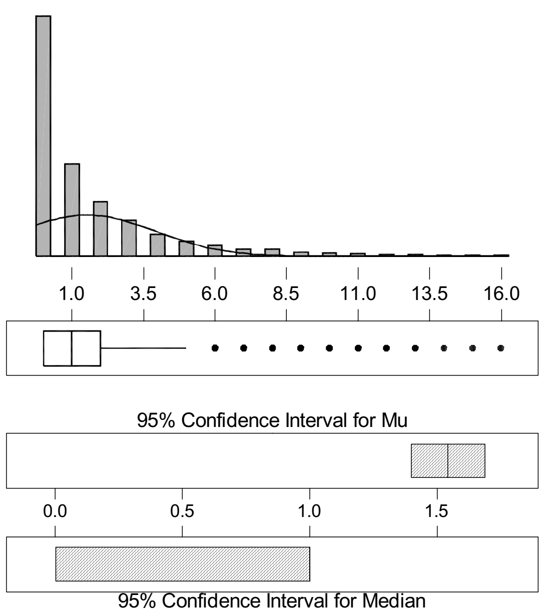
95% Confidence Interval for Sigma

9.1955 10.0263

95% Confidence Interval for Median

-10.2000 -10.1000

Descriptive Statistics



Variable: HNA(0)

Anderson-Darling Normality Test

A-Squared:	107.623
P-Value:	0.000
Mean	1.54398
StDev	2.38205
Variance	5.67414
Skewness	2.31152
Kurtosis	6.37242
N	1046
Minimum	0.0000
1st Quartile	0.0000
Median	1.0000
3rd Quartile	2.0000
Maximum	16.0000

95% Confidence Interval for Mu

1.3995 1.6885

95% Confidence Interval for Sigma

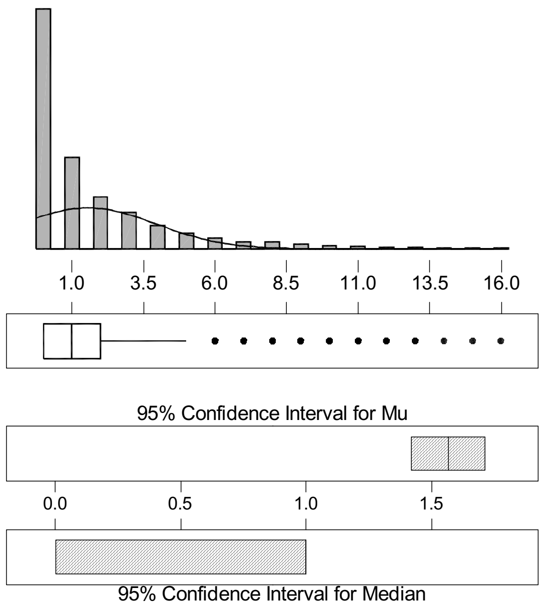
2.2842 2.4888

95% Confidence Interval for Median

0.0000 1.0000

Descriptive Statistics

Variable: HNA(-1)



Anderson-Darling Normality Test

A-Squared:	106.719
P-Value:	0.000
Mean	1.56597
StDev	2.40115
Variance	5.76550
Skewness	2.26722
Kurtosis	6.09445
N	1046
Minimum	0.0000
1st Quartile	0.0000
Median	1.0000
3rd Quartile	2.0000
Maximum	16.0000

95% Confidence Interval for Mu

1.4203 1.7116

95% Confidence Interval for Sigma

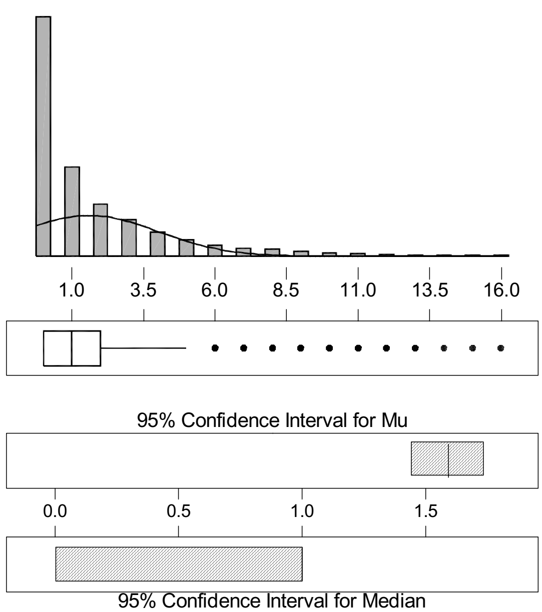
2.3025 2.5087

95% Confidence Interval for Median

0.0000 1.0000

Descriptive Statistics

Variable: HNA(-2)



Anderson-Darling Normality Test

A-Squared:	105.331
P-Value:	0.000
Mean	1.59082
StDev	2.41939
Variance	5.85347
Skewness	2.21953
Kurtosis	5.80915
N	1046
Minimum	0.0000
1st Quartile	0.0000
Median	1.0000
3rd Quartile	2.0000
Maximum	16.0000

95% Confidence Interval for Mu

1.4440 1.7376

95% Confidence Interval for Sigma

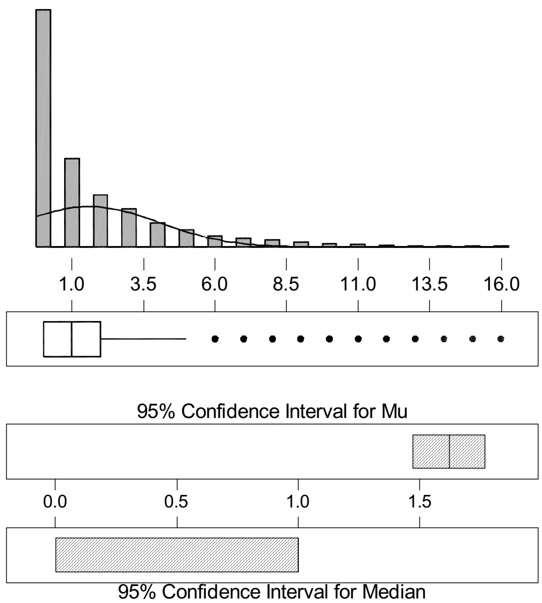
2.3200 2.5278

95% Confidence Interval for Median

0.0000 1.0000

Descriptive Statistics

Variable: HNA(-3)



Anderson-Darling Normality Test

A-Squared:	102.524
P-Value:	0.000
Mean	1.62046
StDev	2.43034
Variance	5.90653
Skewness	2.17512
Kurtosis	5.58199
N	1046
Minimum	0.0000
1st Quartile	0.0000
Median	1.0000
3rd Quartile	2.0000
Maximum	16.0000

95% Confidence Interval for Mu

1.4730 1.7679

95% Confidence Interval for Sigma

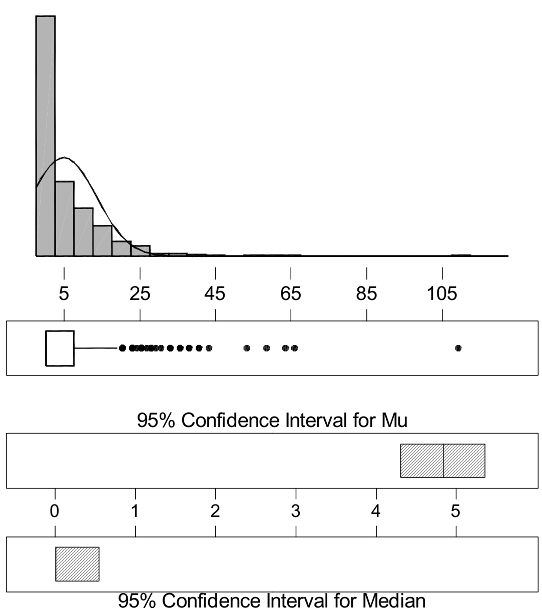
2.3305 2.5392

95% Confidence Interval for Median

0.0000 1.0000

Descriptive Statistics

Variable: HN(0)



Anderson-Darling Normality Test

A-Squared:	120.187
P-Value:	0.000
Mean	4.83157
StDev	8.59273
Variance	73.8351
Skewness	3.92157
Kurtosis	28.6708
N	1042
Minimum	0.000
1st Quartile	0.000
Median	0.000
3rd Quartile	7.600
Maximum	109.200

95% Confidence Interval for Mu

4.309 5.354

95% Confidence Interval for Sigma

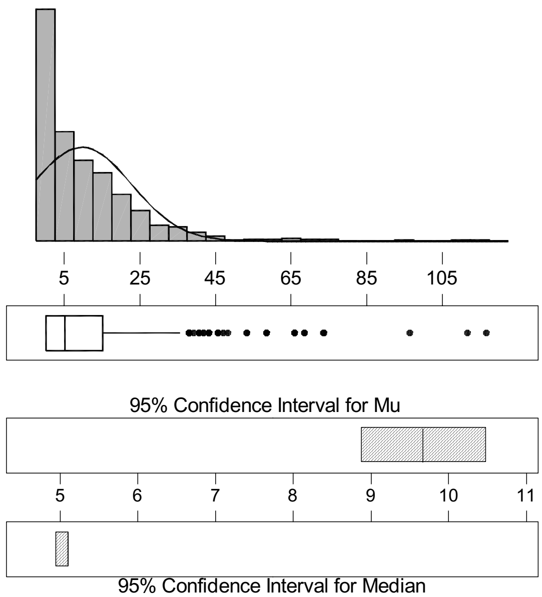
8.239 8.978

95% Confidence Interval for Median

0.000 0.538

Descriptive Statistics

Variable: HN(0,-1)



Anderson-Darling Normality Test

A-Squared:	69.639
P-Value:	0.000
Mean	9.6645
StDev	13.1359
Variance	172.551
Skewness	2.68254
Kurtosis	12.0932
N	1038
Minimum	0.000
1st Quartile	0.000
Median	5.100
3rd Quartile	15.200
Maximum	116.800

95% Confidence Interval for Mu

8.864 10.464

95% Confidence Interval for Sigma

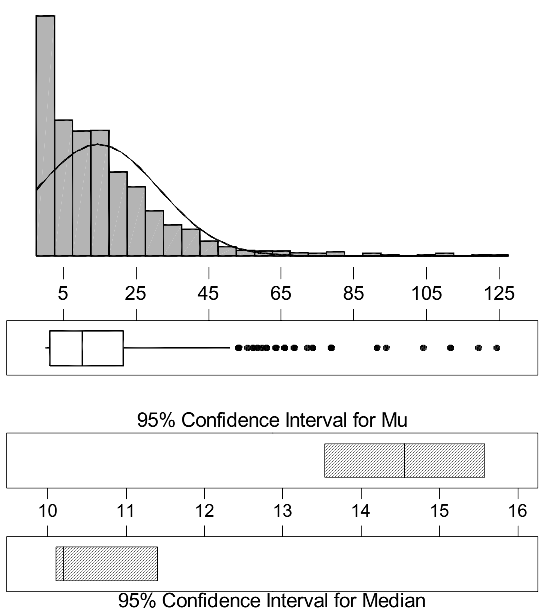
12.594 13.727

95% Confidence Interval for Median

4.938 5.100

Descriptive Statistics

Variable: HN(0,-1,-2)



Anderson-Darling Normality Test

A-Squared:	46.430
P-Value:	0.000
Mean	14.5556
StDev	16.7094
Variance	279.205
Skewness	2.22944
Kurtosis	7.84144
N	1034
Minimum	0.000
1st Quartile	1.300
Median	10.200
3rd Quartile	21.500
Maximum	124.400

95% Confidence Interval for Mu

13.536 15.575

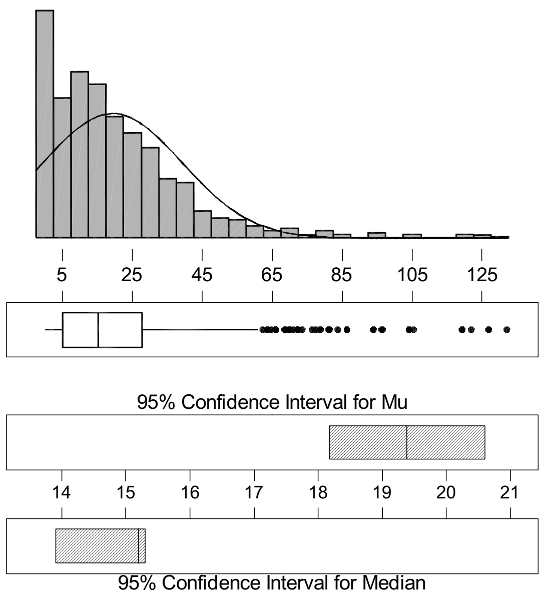
95% Confidence Interval for Sigma

16.019 17.463

95% Confidence Interval for Median

10.100 11.400

Descriptive Statistics



Variable: HN(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	36.259
P-Value:	0.000
Mean	19.3849
StDev	19.8537
Variance	394.169
Skewness	1.94690
Kurtosis	5.71267
N	1030
Minimum	0.000
1st Quartile	5.100
Median	15.200
3rd Quartile	27.900
Maximum	132.000

95% Confidence Interval for Mu

18.171 20.599

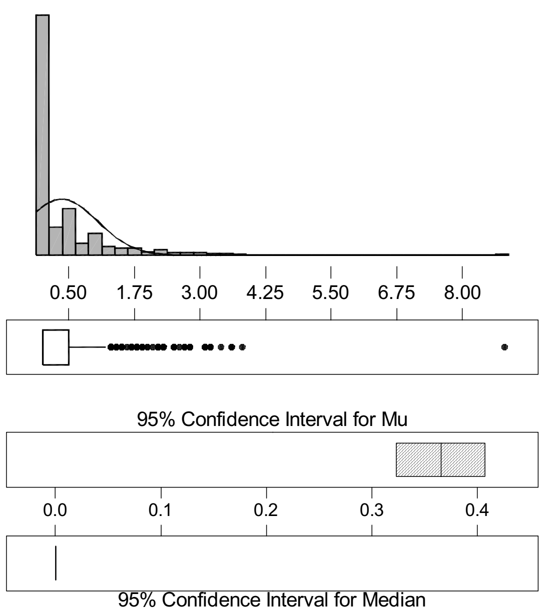
95% Confidence Interval for Sigma

19.032 20.750

95% Confidence Interval for Median

13.900 15.300

Descriptive Statistics



Variable: HNW(0)

Anderson-Darling Normality Test

A-Squared:	138.475
P-Value:	0.000
Mean	0.365049
StDev	0.685730
Variance	0.470225
Skewness	3.72277
Kurtosis	26.2696
N	1030
Minimum	0.00000
1st Quartile	0.00000
Median	0.00000
3rd Quartile	0.50000
Maximum	8.80000

95% Confidence Interval for Mu

0.32312 0.40698

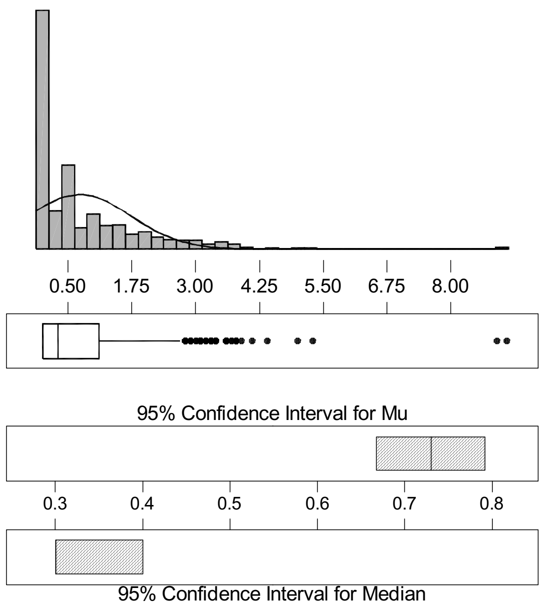
95% Confidence Interval for Sigma

0.65734 0.71670

95% Confidence Interval for Median

0.00000 0.00000

Descriptive Statistics



Variable: HNW(0,-1)

Anderson-Darling Normality Test

A-Squared:	79.480
P-Value:	0.000
Mean	0.72958
StDev	1.00813
Variance	1.01632
Skewness	2.35103
Kurtosis	9.84622
N	1021
Minimum	0.00000
1st Quartile	0.00000
Median	0.30000
3rd Quartile	1.10000
Maximum	9.10000

95% Confidence Interval for Mu

0.66767 0.79149

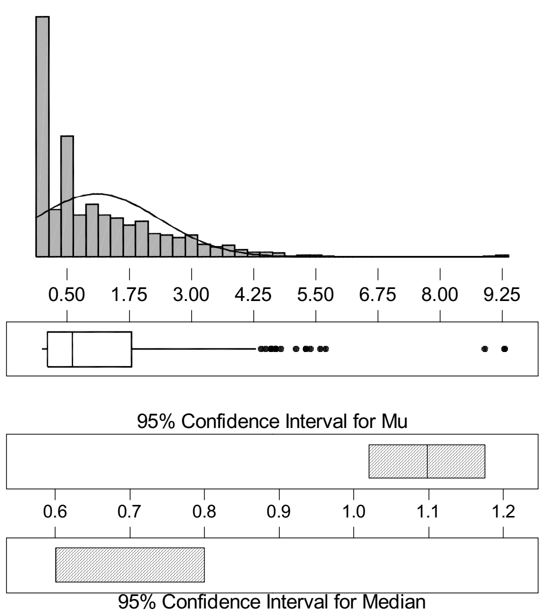
95% Confidence Interval for Sigma

0.96622 1.05387

95% Confidence Interval for Median

0.30000 0.40000

Descriptive Statistics



Variable:
HNW(0,-1,-2)

Anderson-Darling Normality Test

A-Squared:	50.265
P-Value:	0.000
Mean	1.09773
StDev	1.25907
Variance	1.58525
Skewness	1.77055
Kurtosis	5.09143
N	1015
Minimum	0.00000
1st Quartile	0.10000
Median	0.60000
3rd Quartile	1.80000
Maximum	9.30000

95% Confidence Interval for Mu

1.02018 1.17528

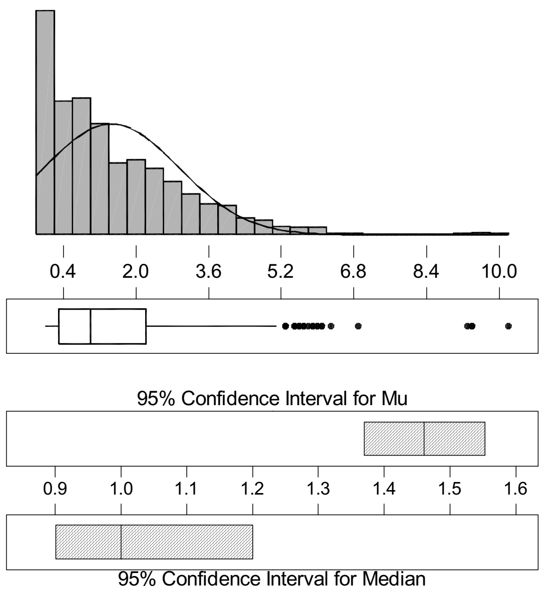
95% Confidence Interval for Sigma

1.20658 1.31637

95% Confidence Interval for Median

0.60000 0.80000

Descriptive Statistics



Variable: HNW(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	36.049
P-Value:	0.000
Mean	1.46119
StDev	1.48718
Variance	2.21169
Skewness	1.51066
Kurtosis	3.38609
N	1010
Minimum	0.0000
1st Quartile	0.3000
Median	1.0000
3rd Quartile	2.2250
Maximum	10.2000

95% Confidence Interval for Mu

1.3694 1.5530

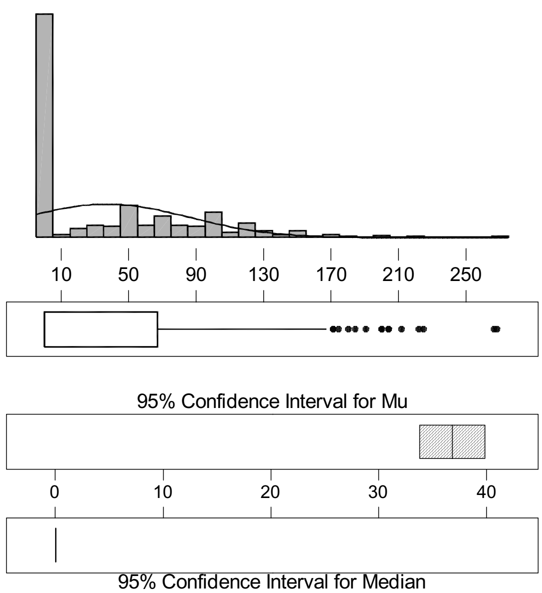
95% Confidence Interval for Sigma

1.4250 1.5550

95% Confidence Interval for Median

0.9000 1.2000

Descriptive Statistics



Variable: HND(0)

Anderson-Darling Normality Test

A-Squared:	95.166
P-Value:	0.000
Mean	36.8375
StDev	49.2230
Variance	2422.91
Skewness	1.26886
Kurtosis	1.16765
N	1026
Minimum	0.000
1st Quartile	0.000
Median	0.000
3rd Quartile	67.100
Maximum	268.400

95% Confidence Interval for Mu

33.822 39.853

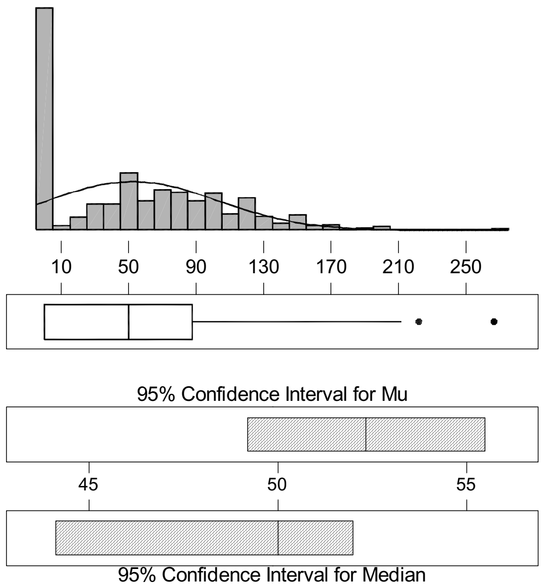
95% Confidence Interval for Sigma

47.182 51.451

95% Confidence Interval for Median

0.000 0.000

Descriptive Statistics



Variable: HND(0,-1)

Anderson-Darling Normality Test

A-Squared:	36.829
P-Value:	0.000
Mean	52.3379
StDev	50.9822
Variance	2599.19
Skewness	0.721128
Kurtosis	7.22E-03
N	1013
Minimum	0.000
1st Quartile	0.000
Median	50.000
3rd Quartile	87.500
Maximum	266.700

95% Confidence Interval for Mu

49.195 55.481

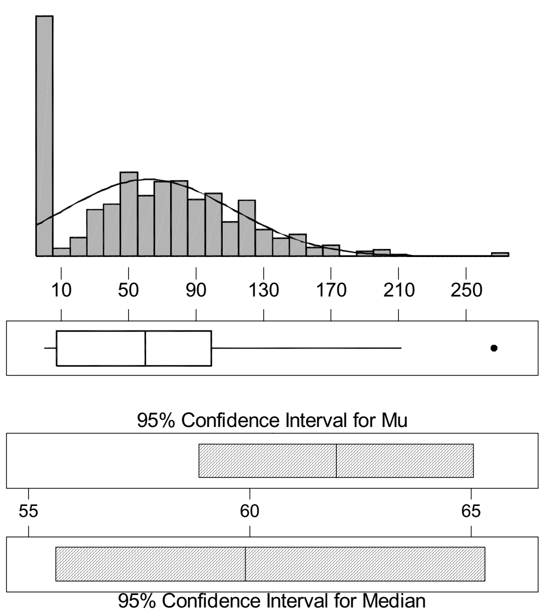
95% Confidence Interval for Sigma

48.855 53.305

95% Confidence Interval for Median

44.110 52.000

Descriptive Statistics



Variable:
HND(0,-1,-2)

Anderson-Darling Normality Test

A-Squared:	16.216
P-Value:	0.000
Mean	61.9458
StDev	50.0227
Variance	2502.27
Skewness	0.528141
Kurtosis	5.96E-02
N	1003
Minimum	0.000
1st Quartile	7.000
Median	59.900
3rd Quartile	99.000
Maximum	266.700

95% Confidence Interval for Mu

58.846 65.045

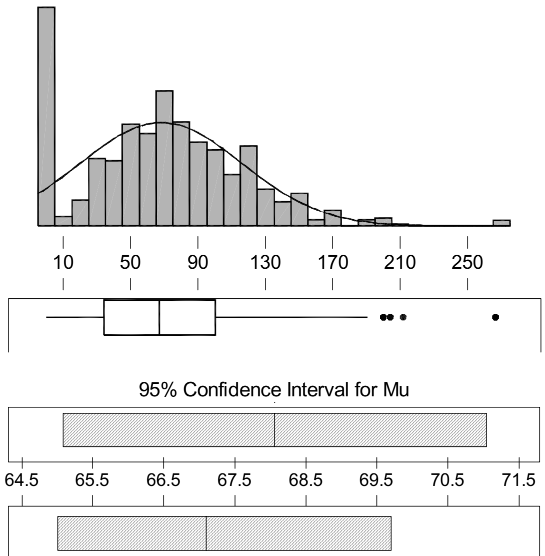
95% Confidence Interval for Sigma

47.925 52.313

95% Confidence Interval for Median

55.600 65.303

Descriptive Statistics



Variable:
HND(0,-1,-2,-3)

Anderson-Darling Normality Test

A-Squared:	7.915
P-Value:	0.000
Mean	68.0620
StDev	47.8884
Variance	2293.30
Skewness	0.486685
Kurtosis	0.467204
N	994
Minimum	0.000
1st Quartile	34.200
Median	67.100
3rd Quartile	100.000
Maximum	266.700

95% Confidence Interval for Mu

65.081	71.043

95% Confidence Interval for Sigma

45.872	50.092

95% Confidence Interval for Median

65.000	69.700

APPENDIX B:

HYPOTHESIS TESTING AND MODEL SELECTION RESULTS

"OLD SNOW HYPOTHESIS TESTING RESULTS"

The following tables provide the old snow hypothesis testing results. For each variable, up to three transformations were made to correct non-normal and/or unequal variance. The asterisk denotes which form of the variable was used in the model selection phase of the study.

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
Day of Year						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	0.5	-	No	Yes	Mann-Whitney	Yes
Optimal	0.337	-	No	Yes	Mann-Whitney	Yes
Alternate	0.281	-	No	Yes	Mann-Whitney	Yes
MaxT(0)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 16	No	Yes	Mann-Whitney	Yes
Optimal*	1.235	add 16	Yes	Yes	2-Sample T-Test	Yes
MaxT(-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 21	No	Yes	Mann-Whitney	Yes
Optimal	1.236	add 21	No	Yes	Mann-Whitney	Yes
Alternate	1.293	add 21	No	Yes	Mann-Whitney	Yes
MaxT(-2)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 21	No	Yes	Mann-Whitney	Yes
Optimal	1.012	add 21	No	Yes	Mann-Whitney	Yes
Alternate	0.955	add 21	No	Yes	Mann-Whitney	Yes
MaxT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
AvgMaxT(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1.5	add 15	No	Yes	Mann-Whitney	Yes
Optimal	1.348	add 15	No	Yes	Mann-Whitney	Yes
Alternate	1.291	add 15	No	Yes	Mann-Whitney	Yes

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
AvgMaxT(0,-1,-2)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 16	No	Yes	Mann-Whitney	Yes
Optimal*	1.235	add 16	Yes	Yes	2-Sample T-Test	Yes
AvgMaxT(0,-1,-2,-3)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 14	No	Yes	Mann-Whitney	Yes
Optimal	1.124	add 14	No	Yes	Mann-Whitney	Yes
Alternate	1.8	add 14	No	Yes	Mann-Whitney	Yes
MinT(0)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1.75	add 24	No	Yes	Mann-Whitney	Yes
Optimal	1.686	add 24	No	Yes	Mann-Whitney	Yes
Alternate	2	add 24	No	Yes	Mann-Whitney	Yes
MinT(-1)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.75	add 27	Yes	Yes	2-Sample T-Test	Yes
MinT(-2)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.5	add 27	Yes	Yes	2-Sample T-Test	Yes
MinT(-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1.5	add 27	No	Yes	Mann-Whitney	No
Optimal	1.461	add 27	No	Yes	Mann-Whitney	No
Alternate	1.6	add 27	No	Yes	Mann-Whitney	No
AvgMinT(0,-1)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	1.75	add 25	No	Yes	Mann-Whitney	Yes
Optimal*	1.798	add 25	Yes	Yes	2-Sample T-Test	Yes
AvgMinT(0,-1,-2)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.75	add 24	Yes	Yes	2-Sample T-Test	Yes
AvgMinT(0,-1,-2,-3)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.75	add 23	Yes	Yes	2-Sample T-Test	Yes

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
AvgT(0)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.75	add 20	Yes	Yes	2-Sample T-Test	Yes
AvgT(-1)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.5	add 23	Yes	Yes	2-Sample T-Test	Yes
AvgT(-2)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.25	add 23	Yes	Yes	2-Sample T-Test	Yes
AvgT(-3)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Common*	1.25	add 21	Yes	Yes	2-Sample T-Test	No
AvgAvgT(0,-1)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.75	add 20	Yes	Yes	2-Sample T-Test	Yes
AvgAvgT(0,-1,-2)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.5	add 20	Yes	Yes	2-Sample T-Test	Yes
AvgAvgT(0,-1,-2,-3)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.5	add 18	Yes	Yes	2-Sample T-Test	Yes
DDMaxT(0)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 16	No	Yes	Mann-Whitney	Yes
Optimal*	1.235	add 16	Yes	Yes	2-Sample T-Test	Yes
DDMaxT(0,-1)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	1.25	add 28	No	Yes	Mann-Whitney	Yes
Optimal*	1.236	add 28	Yes	Yes	2-Sample T-Test	Yes
DDMaxT(0,-1,-2)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 46	No	Yes	Mann-Whitney	Yes
Optimal*	1.124	add 46	Yes	Yes	2-Sample T-Test	Yes

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
DDMaxT(0,-1,-2,-3)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 53	No	Yes	Mann-Whitney	Yes
Optimal*	1.124	add 53	Yes	Yes	2-Sample T-Test	Yes
DDAvgT(0)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1	add 20	Yes	Yes	2-Sample T-Test	Yes
DDAvgT(0,-1)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.75	add 39	Yes	Yes	2-Sample T-Test	Yes
DDAvgT(0,-1,-2)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.5	add 58	Yes	Yes	2-Sample T-Test	Yes
DDAvgT(0,-1,-2,-3)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	1.25	add 71	No	Yes	Mann-Whitney	Yes
Optimal*	1.349	add 71	Yes	Yes	2-Sample T-Test	Yes
MaxT(0)-MaxT(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 17	No	Yes	Mann-Whitney	No
Optimal	1.235	add 17	No	Yes	Mann-Whitney	No
Alternate	1.292	add 17	No	Yes	Mann-Whitney	No
MaxT(0)-MaxT(-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	1.25	add 14	Yes	Yes	2-Sample T-Test	No
MaxT(0)-MaxT(-3)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common*	1.25	add 15	Yes	Yes	2-Sample T-Test	No
MinT(0)-MinT(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 12	No	Yes	Mann-Whitney	No
Optimal	0.899	add 12	No	Yes	Mann-Whitney	No
Alternate	0.843	add 12	No	Yes	Mann-Whitney	No

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
MinT(0)-MinT(-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	0.75	add 11	Yes	Yes	2-Sample T-Test	No
MinT(0)-MinT(-3)						
None	-	-	No	Yes	Mann-Whitney	No
Common	1	add 11	No	Yes	Mann-Whitney	No
Optimal*	0.899	add 11	Yes	Yes	2-Sample T-Test	No
AvgT(0)-AvgT(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 10	No	Yes	Mann-Whitney	No
Optimal	1.124	add 10	No	Yes	Mann-Whitney	No
Alternate	1.067	add 10	No	Yes	Mann-Whitney	No
AvgT(0)-AvgT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
AvgT(0)-AvgT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
MaxT(0)-MinT(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0.75	-	No	Yes	Mann-Whitney	No
Optimal	0.786	-	No	Yes	Mann-Whitney	No
Alternate	0.843	-	No	Yes	Mann-Whitney	No
MaxT(-1)-MinT(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0.5	-	No	Yes	Mann-Whitney	No
Optimal	0.562	-	No	Yes	Mann-Whitney	No
Alternate	0.618	-	No	Yes	Mann-Whitney	No
MaxT(-2)-MinT(-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	0.5	-	Yes	Yes	2-Sample T-Test	No
MaxT(-3)-MinT(-3)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	0.5	-	Yes	Yes	2-Sample T-Test	No
MaxT(-1)-MinT(0)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Common*	0.5	add 3	Yes	No	2-Sample T-Test	No

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
MaxT(-2)-MinT(-1)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	0.5	add 4	Yes	Yes	2-Sample T-Test	No
MaxT(-3)-MinT(-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	0.75	add 3	Yes	Yes	2-Sample T-Test	No
HS(0)-HS(-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	4.5	add 39	No	Yes	Mann-Whitney	Yes
Optimal	4.494	add 39	No	Yes	Mann-Whitney	Yes
Alternate	4.437	add 39	No	Yes	Mann-Whitney	Yes
HS(0)-HS(-2)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	3	add 39	No	No	Kolomogorov-Smirnov	-
Optimal	2.808	add 39	No	No	Kolomogorov-Smirnov	-
Alternate	3.2	add 39	No	No	Kolomogorov-Smirnov	-
HS(0)-HS(-3)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 36	No	Yes	Mann-Whitney	Yes
Optimal	1.124	add 36	No	Yes	Mann-Whitney	Yes
Alternate	1.18	add 36	No	Yes	Mann-Whitney	Yes
Stl(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	4.5	add 39	No	Yes	Mann-Whitney	Yes
Optimal	4.494	add 39	No	Yes	Mann-Whitney	Yes
Alternate	4.437	add 39	No	Yes	Mann-Whitney	No
Stl(0,-1-2)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	3	add 39	No	No	Kolomogorov-Smirnov	-
Optimal	2.809	add 39	No	No	Kolomogorov-Smirnov	-
Alternate	2.416	add 39	No	No	Kolomogorov-Smirnov	-
Stl(0,-1-2,-3)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	2.25	add 51	No	No	Kolomogorov-Smirnov	-
Optimal	2.36	add 51	No	No	Kolomogorov-Smirnov	-
Alternate	2.416	add 51	No	No	Kolomogorov-Smirnov	-

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
HNA(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-0.5	-	No	Yes	Mann-Whitney	No
Optimal	-0.562	-	No	Yes	Mann-Whitney	No
Alternate	-0.618	-	No	Yes	Mann-Whitney	No
HNA(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-0.25	-	No	Yes	Mann-Whitney	No
Optimal	-0.224	-	No	Yes	Mann-Whitney	No
Alternate	-0.168	-	No	Yes	Mann-Whitney	No
HNA(-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-0.25	add 1	No	Yes	Mann-Whitney	No
Optimal	-0.224	add 1	No	Yes	Mann-Whitney	No
Alternate	-0.168	add 1	No	Yes	Mann-Whitney	No
HNA(-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-0.25	add 1	No	Yes	Mann-Whitney	No
Optimal	-0.337	add 1	No	Yes	Mann-Whitney	No
Alternate	-0.393	add 1	No	Yes	Mann-Whitney	No
HN(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 1	No	Yes	Mann-Whitney	No
Optimal	5	add 1	No	Yes	Mann-Whitney	No
Alternate	4.944	add 1	No	Yes	Mann-Whitney	No
HN(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 1	No	Yes	Mann-Whitney	No
Optimal	5	add 1	No	Yes	Mann-Whitney	No
Alternate	4.944	add 1	No	Yes	Mann-Whitney	No
HN(0,-1,-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-1	add 1	No	Yes	Mann-Whitney	No
Optimal	-1.124	add 1	No	Yes	Mann-Whitney	No
Alternate	-1.18	add 1	No	Yes	Mann-Whitney	No

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
HN(0,-1-2,-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-0.25	add 1	No	Yes	Mann-Whitney	No
Optimal	-0.225	add 1	No	Yes	Mann-Whitney	No
Alternate	-0.169	add 1	No	Yes	Mann-Whitney	No
HNW(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 1	No	Yes	Mann-Whitney	No
Optimal	5	add 1	No	Yes	Mann-Whitney	No
Alternate	-	add 1	No	Yes	Mann-Whitney	No
HNW(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 1	No	Yes	Mann-Whitney	No
Optimal	5	add 1	No	Yes	Mann-Whitney	No
Alternate	-	add 1	No	Yes	Mann-Whitney	No
HNW(0,-1,-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-5	add 1	No	Yes	Mann-Whitney	No
Optimal	-4.944	add 1	No	Yes	Mann-Whitney	No
Alternate	-4.5	add 1	No	Yes	Mann-Whitney	No
HNW(0,-1,-2-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-2	add 1	No	Yes	Mann-Whitney	No
Optimal	-1.911	add 1	No	Yes	Mann-Whitney	No
Alternate	-1.854	add 1	No	Yes	Mann-Whitney	No
HND(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 1	No	Yes	Mann-Whitney	No
Optimal	5	add 1	No	Yes	Mann-Whitney	No
Alternate	-	add 1	No	Yes	Mann-Whitney	No
HND(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 1	No	Yes	Mann-Whitney	No
Optimal	5	add 1	No	Yes	Mann-Whitney	No
Alternate	-	add 1	No	Yes	Mann-Whitney	No

Old Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
HND(0-1,-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-0.5	add 1	No	Yes	Mann-Whitney	No
Optimal	-0.562	add 1	No	Yes	Mann-Whitney	No
Alternate	-0.618	add 1	No	Yes	Mann-Whitney	No
HND(0-1,-2-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0	add 1	No	Yes	Mann-Whitney	No
Optimal	0.056	add 1	No	Yes	Mann-Whitney	No
Alternate	-0.056	add 1	No	Yes	Mann-Whitney	No

"NEW SNOW HYPOTHESIS TESTING RESULTS"

The following tables provide the new snow hypothesis testing results. For each variable, up to three transformations were made to correct non-normal and/or unequal variance. The asterisk denotes which form of the variable was used in the model selection phase of the study.

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
Day of Year						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	-	No	Yes	Mann-Whitney	No
Optimal	1.461	-	No	Yes	Mann-Whitney	No
Alternate	1.517	-	No	Yes	Mann-Whitney	No
MaxT(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 21	No	Yes	Mann-Whitney	No
Optimal	1.124	add 21	No	Yes	Mann-Whitney	No
Alternate	1.067	add 21	No	Yes	Mann-Whitney	No
MaxT(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 18	No	Yes	Mann-Whitney	No
Optimal	1.011	add 18	No	Yes	Mann-Whitney	No
Alternate	1.067	add 18	No	Yes	Mann-Whitney	No
MaxT(-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 16	No	Yes	Mann-Whitney	No
Optimal	1.011	add 16	No	Yes	Mann-Whitney	No
Alternate	1.067	add 16	No	Yes	Mann-Whitney	No
MaxT(-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 21	No	Yes	Mann-Whitney	No
Optimal	0.899	add 21	No	Yes	Mann-Whitney	No
Alternate	0.843	add 21	No	Yes	Mann-Whitney	No
AvgMaxT(0,-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	No

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
AvgMaxT(0,-1,-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
AvgMaxT(0,-1,-2,-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
MinT(0)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1.5	add 27	No	Yes	Mann-Whitney	Yes
Optimal	1.574	add 27	No	Yes	Mann-Whitney	Yes
Alternate	1.63	add 27	No	Yes	Mann-Whitney	Yes
MinT(-1)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	1.5	add 27	Yes	Yes	2-Sample T-Test	No
MinT(-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1.5	add 25	No	Yes	Mann-Whitney	No
Optimal	1.349	add 25	No	Yes	Mann-Whitney	No
Alternate	1.405	add 25	No	Yes	Mann-Whitney	No
MinT(-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1.5	add 26	No	Yes	Mann-Whitney	No
Optimal	1.461	add 26	No	Yes	Mann-Whitney	No
Alternate	1.517	add 26	No	Yes	Mann-Whitney	No
AvgMinT(0,-1)						
None	-	-	No	Yes	Mann-Whitney	No
Common	1.5	add 26	No	Yes	Mann-Whitney	Yes
Optimal*	1.685	add 26	Yes	Yes	2-Sample T-Test	Yes
AvgMinT(0,-1,-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common	1.5	add 25	No	Yes	Mann-Whitney	No
Optimal	1.573	add 25	No	Yes	Mann-Whitney	No
Alternate*	1.629	add 25	Yes	Yes	2-Sample T-Test	No
AvgMinT(0,-1,-2,-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1.5	add 24	No	Yes	Mann-Whitney	No
Optimal	1.461	add 24	No	Yes	Mann-Whitney	No
Alternate	1.517	add 24	No	Yes	Mann-Whitney	No

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
AvgT(0)						
None	-	-	No	No	Kolomogorob-Smirnov	-
Common*	1.5	add 23	Yes	No	2-Sample T-Test	Yes
AvgT(-1)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	1.25	add 21	Yes	Yes	2-Sample T-Test	No
AvgT(-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	1.25	add 21	Yes	Yes	2-Sample T-Test	No
AvgT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
AvgAvgT(0,-1)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Common*	1.5	add 22	Yes	Yes	2-Sample T-Test	No
AvgAvgT(0,-1,-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	1.5	add 20	Yes	Yes	2-Sample T-Test	No
AvgAvgT(0,-1,-2,-3)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	1.25	add 19	Yes	Yes	2-Sample T-Test	No
DDMaxT(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1	add 21	No	Yes	Mann-Whitney	No
Optimal	1.124	add 21	No	Yes	Mann-Whitney	No
Alternate	1.067	add 21	No	Yes	Mann-Whitney	No
DDMaxT(0,-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
DDMaxT(0,-1,-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
DDMaxT(0,-1,-2,-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
DDAvgT(0)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Common*	1.5	add 23	Yes	No	2-Sample T-Test	Yes
DDAvgT(0,-1)						
None	-	-	No	No	Kolomorogov-Smirnov	-
Common*	1.5	add 43	Yes	Yes	2-Sample T-Test	No
DDAvgT(0,-1,-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	1.5	add 60	Yes	Yes	2-Sample T-Test	No
DDAvgT(0,-1,-2,-3)						
None	-	-	No	Yes	Mann-Whitney	No
Common	1	add 74	No	Yes	Mann-Whitney	No
Optimal*	1.236	add 74	Yes	Yes	2-Sample T-Test	no
MaxT(0)-MaxT(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	1.5	add 18	No	Yes	Mann-Whitney	No
Optimal	1.348	add 18	No	Yes	Mann-Whitney	No
Alternate	1.291	add 18	No	Yes	Mann-Whitney	No
MaxT(0)-MaxT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(0)-MaxT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
MinT(0)-MinT(-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 17	No	Yes	Mann-Whitney	Yes
Optimal	1.011	add 17	No	Yes	Mann-Whitney	Yes
Alternate	0.954	add 17	No	Yes	Mann-Whitney	Yes
MinT(0)-MinT(-2)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	1	add 21	No	Yes	Mann-Whitney	Yes
Optimal	0.899	add 21	No	Yes	Mann-Whitney	Yes
Alternate	0.843	add 21	No	Yes	Mann-Whitney	Yes

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
MinT(0)-MinT(-3)						
None	-	-	No	Yes	Mann-Whitney	No
Common	1	add 24	No	Yes	Mann-Whitney	No
Optimal*	1.124	add 24	No	Yes	Mann-Whitney	Yes
Alternate	1.067	add 24	No	Yes	Mann-Whitney	Yes
AvgT(0)-AvgT(-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgT(0)-AvgT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgT(0)-AvgT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(0)-MinT(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0.5	add 1	No	Yes	Mann-Whitney	No
Optimal	0.337	add 1	No	Yes	Mann-Whitney	No
Alternate	0.281	add 1	No	Yes	Mann-Whitney	No
MaxT(-1)-MinT(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0.5	add 1	No	Yes	Mann-Whitney	No
Optimal	0.562	add 1	No	Yes	Mann-Whitney	No
Alternate	0.506	add 1	No	Yes	Mann-Whitney	No
MaxT(-2)-MinT(-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	0.5	add 1	Yes	Yes	2-Sample T-Test	No
MaxT(-3)-MinT(-3)						
None	-	-	No	Yes	Mann-Whitney	No
Common*	0.5	add 1	Yes	Yes	2-Sample T-Test	No
MaxT(-1)-MinT(0)						
None	-	-	No	Yes	Mann-Whitney	Yes
Common	0.5	add 5	No	Yes	Mann-Whitney	Yes
Optimal*	0.674	add 5	Yes	Yes	2-Sample T-Test	Yes
MaxT(-2)-MinT(-1)						
None	-	-	No	Yes	Mann-Whitney	No
Common	0.75	add 5	No	Yes	Mann-Whitney	No
Optimal*	0.674	add 5	Yes	Yes	2-Sample T-Test	No

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
MaxT(-3)-MinT(-2)						
None	-	-	No	Yes	Mann-Whitney	No
Common	0.5	add 5	No	Yes	Mann-Whitney	No
Optimal*	0.562	add 5	Yes	Yes	2-Sample T-Test	No
HS(0)-HS(-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0.25	add 34	No	Yes	Mann-Whitney	No
Optimal	0.337	add 34	No	Yes	Mann-Whitney	No
Alternate	0.393	add 34	No	Yes	Mann-Whitney	No
HS(0)-HS(-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0.5	add 46	No	Yes	Mann-Whitney	No
Optimal	0.562	add 46	No	Yes	Mann-Whitney	No
Alternate	0.618	add 46	No	No	Mann-Whitney	No
HS(0)-HS(-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0.5	add 46	No	Yes	Mann-Whitney	No
Optimal	0.562	add 46	No	Yes	Mann-Whitney	No
Alternate	0.618	add 46	No	No	Mann-Whitney	No
Stl(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	2	add 45	No	Yes	Mann-Whitney	Yes
Optimal	2.022	add 45	No	Yes	Mann-Whitney	Yes
Alternate	2.079	add 45	No	Yes	Mann-Whitney	Yes
Stl(0,-1-2)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	2	add 56	No	Yes	Mann-Whitney	Yes
Optimal	2.022	add 56	No	Yes	Mann-Whitney	Yes
Alternate	2.079	add 56	No	Yes	Mann-Whitney	Yes
Stl(0,-1-2,-3)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	2	add 7	No	Yes	Mann-Whitney	Yes
Optimal	2.134	add 7	No	Yes	Mann-Whitney	Yes
Alternate	2.191	add 7	No	Yes	Mann-Whitney	Yes

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
HNA(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-4	add 1	No	Yes	Mann-Whitney	No
Optimal	-4.494	add 1	No	Yes	Mann-Whitney	No
Alternate	-4.551	add 1	No	Yes	Mann-Whitney	No
HNA(-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	-2.5	add 1	No	No	Kolomogorov-Smirnov	-
Optimal	-2.471	add 1	No	No	Kolomogorov-Smirnov	-
Alternate	-2.415	add 1	No	No	Kolomogorov-Smirnov	-
HNA(-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-1	add 1	No	Yes	Mann-Whitney	No
Optimal	-1.012	add 1	No	Yes	Mann-Whitney	No
Alternate	-1.068	add 1	No	Yes	Mann-Whitney	No
HNA(-3)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-1	add 1	No	Yes	Mann-Whitney	No
Optimal	-0.899	add 1	No	Yes	Mann-Whitney	No
Alternate	-0.843	add 1	No	Yes	Mann-Whitney	No
HN(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0	add 1	No	Yes	Mann-Whitney	No
Optimal	-0.056	add 1	No	Yes	Mann-Whitney	No
Alternate	0.056	add 1	No	Yes	Mann-Whitney	No
HN(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0	add 1	No	Yes	Mann-Whitney	No
Optimal	0.113	add 1	No	Yes	Mann-Whitney	No
Alternate	0.17	add 1	No	Yes	Mann-Whitney	No
HN(0,-1,-2)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	0.25	add 1	No	No	Kolomogorov-Smirnov	-
Optimal	0.225	add 1	No	No	Kolomogorov-Smirnov	-
Alternate	0.282	add 1	No	Yes	Mann-Whitney	Yes

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
HN(0,-1-2,-3)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	0.25	add 1	No	Yes	Mann-Whitney	Yes
Optimal	0.337	add 1	No	Yes	Mann-Whitney	Yes
Alternate	0.393	add 1	No	Yes	Mann-Whitney	Yes
HNW(0)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	-1.5	add 1	No	Yes	Mann-Whitney	No
Optimal	-1.573	add 1	No	Yes	Mann-Whitney	No
Alternate	-1.629	add 1	No	Yes	Mann-Whitney	No
HNW(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	-0.5	add 1	No	Yes	Mann-Whitney	Yes
Optimal	-0.562	add 1	No	Yes	Mann-Whitney	Yes
Alternate	-0.618	add 1	No	Yes	Mann-Whitney	Yes
HNW(0,-1,-2)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	0	add 1	No	Yes	Mann-Whitney	No
Optimal	-0.225	add 1	No	No	Kolomogorov-Smirnov	-
Alternate	-0.282	add 1	No	No	Kolomogorov-Smirnov	-
HNW(0,-1,-2-3)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	0	add 1	No	Yes	Mann-Whitney	Yes
Optimal	-0.056	add 1	No	No	Kolomogorov-Smirnov	-
Alternate	0.056	add 1	No	No	Kolomogorov-Smirnov	-
HND(0)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Common	0.25	add 1	No	No	Kolomogorov-Smirnov	-
Optimal	0.337	add 1	No	No	Kolomogorov-Smirnov	-
Alternate	0.393	add 1	No	No	Kolomogorov-Smirnov	-

*Used non-transformed data for a 2-Sample T-Test with unequal variance, results were 'not significant'

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
HND(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	0.5	add 1	No	Yes	Mann-Whitney	Yes
Optimal	0.674	add 1	No	Yes	Mann-Whitney	Yes
Alternate	0.73	add 1	No	Yes	Mann-Whitney	Yes

New Snow Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significant Predictor?
HND(0-1,-2)						
None*	-	-	No	Yes	Mann-Whitney	No
Common	0.5	add 1	No	Yes	Mann-Whitney	No
Optimal	0.674	add 1	No	Yes	Mann-Whitney	No
Alternate	0.73	add 1	No	Yes	Mann-Whitney	No
HND(0-1,-2-3)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Common	0.5	add 1	No	Yes	Mann-Whitney	Yes
Optimal	0.674	add 1	No	Yes	Mann-Whitney	Yes
Alternate	0.73	add 1	No	Yes	Mann-Whitney	Yes

"OLD SNOW AND NEW SNOW WET AVALANCHE DAY HYPOTHESIS TESTING RESULTS"

The following tables provide the old snow and new snow wet avalanche day hypothesis testing results. For each variable, up to three transformations were made to correct non-normal and/or unequal variance. The asterisk denotes which form of the variable was used in the model selection phase of the study.

Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significantly Different?
Day of Year						
None*	-	-	No	Yes	Mann-Whitney	No
Optimal	1.686	-	No	Yes	Mann-Whitney	No
Lower Alternate	1.629	-	No	Yes	Mann-Whitney	No
Upper Alternate	1.743	-	No	Yes	Mann-Whitney	No
MaxT(0)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
AvgMaxT(0,-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgMaxT(0,-1,-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgMaxT(0,-1,-2,-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MinT(0)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MinT(-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes

Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significantly Different?
MinT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MinT(-3)						
None	-	-	No	Yes	Mann-Whitney	Yes
Optimal*	1.348	add 21	Yes	Yes	2-Sample T-Test	Yes
AvgMinT(0,-1)						
None*	-	-	Yes	No	2-Sample T-Test	Yes
Optimal	1.124	add 18	Yes	No	2-Sample T-Test	Yes
Lower Alternate	1.067	add 18	Yes	No	2-Sample T-Test	Yes
Upper Alternate	1.18	add 18	Yes	No	2-Sample T-Test	Yes
AvgMinT(0,-1,-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgMinT(0,-1,-2,-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgT(0)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgT(-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgAvgT(0,-1)						
None*	-	-	Yes	No	2-Sample T-Test	Yes
Optimal	0.899	add 12	Yes	No	2-Sample T-Test	Yes
Lower Alternate	0.843	add 12	Yes	No	2-Sample T-Test	Yes
Upper Alternate	0.955	add 12	Yes	No	2-Sample T-Test	Yes
AvgAvgT(0,-1,-2)						
None	-	-	Yes	No	2-Sample T-Test	Yes
Optimal*	0.899	add 11	Yes	No	2-Sample T-Test	Yes
Lower Alternate	0.843	add 11	Yes	Yes	2-Sample T-Test	Yes
AvgAvgT(0,-1,-2,-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes

Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significantly Different?
DDMaxT(0)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
DDMaxT(0,-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
DDMaxT(0,-1,-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
DDMaxT(0,-1,-2,-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
DDAvgT(0)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
DDAvgT(0,-1)						
None*	-	-	Yes	No	2-Sample T-Test	Yes
Optimal	0.899	add 23	Yes	No	2-Sample T-Test	Yes
Lower Alternate	0.843	add 23	Yes	No	2-Sample T-Test	Yes
Upper Alternate	0.955	add 23	Yes	No	2-Sample T-Test	Yes
DDAvgT(0,-1,-2)						
None	-	-	Yes	No	2-Sample T-Test	Yes
Optimal	0.899	add 32	Yes	No	2-Sample T-Test	Yes
Lower Alternate*	0.843	add 32	Yes	Yes	2-Sample T-Test	Yes
DDAvgT(0,-1,-2,-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(0)-MaxT(-1)						
None	-	-	Yes	No	2-Sample T-Test	No
Optimal*	1.124	add 12	Yes	Yes	2-Sample T-Test	No
MaxT(0)-MaxT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(0)-MaxT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
MinT(0)-MinT(-1)						
None*	-	-	Yes	No	2-Sample T-Test	No
Optimal	1.236	add 12	Yes	No	2-Sample T-Test	No
Lower Alternative	1.18	add 12	Yes	No	2-Sample T-Test	No
Upper Alternative	1.293	add 12	Yes	No	2-Sample T-Test	No

Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significantly Different?
MinT(0)-MinT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
MinT(0)-MinT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
AvgT(0)-AvgT(-1)						
None	-	-	No	No	Kolomogorov-Smirnov	Yes
Optimal*	1.348	add 10	Yes	No	2-Sample T-Test	No
Lower Alternate	1.291	add 10	Yes	No	2-Sample T-Test	No
Upper Alternate	1.404	add 10	Yes	No	2-Sample T-Test	No
AvgT(0)-AvgT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
AvgT(0)-AvgT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(0)-MinT(0)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(-1)-MinT(-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	Yes
MaxT(-2)-MinT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
MaxT(-3)-MinT(-3)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
MaxT(-1)-MinT(0)						
None*	-	-	Yes	No	2-Sample T-Test	Yes
Optimal	1.011	add 5	Yes	No	2-Sample T-Test	Yes
Lower Alternate	0.954	add 5	Yes	No	2-Sample T-Test	Yes
Upper Alternate	1.067	add 5	Yes	No	2-Sample T-Test	Yes
MaxT(-2)-MinT(-1)						
None*	-	-	Yes	Yes	2-Sample T-Test	No
MaxT(-3)-MinT(-2)						
None*	-	-	Yes	Yes	2-Sample T-Test	No

Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significantly Different?
HS(0)-HS(-1)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	0.674	add 16	No	No	Kolomogorov-Smirnov	-
Lower Alternate	0.617	add 16	No	No	Kolomogorov-Smirnov	-
Upper Alternate	0.73	add 16	No	No	Kolomogorov-Smirnov	-
*Used optimal transformation, 2-Sample T-Test with unequla variance, 'significant' result						
HS(0)-HS(-2)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal*	0.337	add 21	Yes	No	2-Sample T-Test	Yes
Lower Alternate	0.281	add 21	Yes	No	2-Sample T-Test	Yes
Upper Alternate	0.393	add 46	Yes	No	2-Sample T-Test	Yes
HS(0)-HS(-3)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal*	0.562	add 23	Yes	Yes	2-Sample T-Test	Yes
Stl(0,-1)						
None*	-	-	No	Yes	Mann-Whitney	No
Optimal	1.461	add 21	No	Yes	Mann-Whitney	No
Lower Alternate	1.404	add 21	No	Yes	Mann-Whitney	No
Upper Alternate	1.517	add 21	No	Yes	Mann-Whitney	No
Stl(0,-1-2)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	1.573	add 34	No	No	Kolomogorov-Smirnov	-
Lower Alternate	1.516	add 34	No	No	Kolomogorov-Smirnov	-
Upper Alternate	1.629	add 34	No	No	Kolomogorov-Smirnov	-
*Used upper alternative transformation, 2-Sample T-Test with unequal variance, 'significant' results						
Stl(0,-1-2,-3)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal*	2.472	add 77	Yes	No	2-Sample T-Test	No
Lower Alternate	2.416	add 77	Yes	No	2-Sample T-Test	No
Upper Alternate	2.529	add 77	Yes	No	2-Sample T-Test	No
HNA(0)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal*	-0.337	add 1	No	Yes	Mann-Whitney	Yes
Lower Alternate	-0.393	add 1	No	Yes	Mann-Whitney	Yes
Upper Alternate	-0.281	add 1	No	Yes	Mann-Whitney	Yes

Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significantly Different?
HNA(-1)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	-0.675	add 1	No	No	Kolomogorov-Smirnov	-
Lower Alternate	-0.731	add 1	No	No	Kolomogorov-Smirnov	-
Upper Alternate	-0.618	add 1	No	No	Kolomogorov-Smirnov	-
*Used non-transformed data, 2-Sample T-Test with unequal variance, could not compute						
HNA(-2)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal*	-0.786	add 1	No	Yes	Mann-Whitney	Yes
Lower Alternate	-0.843	add 1	No	Yes	Mann-Whitney	Yes
Upper Alternate	-0.729	add 1	No	Yes	Mann-Whitney	Yes
HNA(-3)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal*	-1.012	add 1	No	Yes	Mann-Whitney	No
Lower Alternative	-1.068	add 1	No	Yes	Mann-Whitney	No
Upper Alternative	-0.955	add 1	No	Yes	Mann-Whitney	No
HN(0)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	-1.124	add 1	No	No	Kolomogorov-Smirnov	-
Lower Alternate	-1.18	add 1	No	No	Kolomogorov-Smirnov	-
Upper Alternate	-1.067	add 1	No	No	Kolomogorov-Smirnov	-
*Used non-transformed data, 2-Sample T-Test with unequal variance, could not compute, likely signficant						
HN(0,-1)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	-0.113	add 1	No	No	Kolomogorov-Smirnov	-
Lower Alternate	-0.17	add 1	No	No	Kolomogorov-Smirnov	-
Upper Alternate	-0.056	add 1	No	No	Kolomogorov-Smirnov	-
*Used non-transformed data, 2-Sample T-Test with unequal variance, could not compute, likely signficant						
HN(0,-1,-2)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal*	0.113	add 1	No	Yes	Mann-Whitney	Yes
Lower Alternate	0.056	add 1	No	Yes	Mann-Whitney	Yes
Upper Alternate	0.17	add 1	No	Yes	Mann-Whitney	Yes
HN(0,-1-2,-3)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal*	0.337	add 1	No	Yes	Mann-Whitney	Yes
Lower Alternate	0.281	add 1	No	Yes	Mann-Whitney	Yes
Upper Alternate	0.393	add 1	No	Yes	Mann-Whitney	Yes

Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significantly Different?
HNW(0)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Common	-3.82	add 1	No	No	Kolomogorov-Smirnov	-
Optimal	-3.876	add 1	No	No	Kolomogorov-Smirnov	-
Alternate	-3.764	add 1	No	No	Kolomogorov-Smirnov	-
*Used non-transformed data, 2-Sample T-Test with unequal variance, could not compute, likely significant						
HNW(0,-1)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Common	-1.236	add 1	No	No	Kolomogorov-Smirnov	-
Optimal	-1.293	add 1	No	No	Kolomogorov-Smirnov	-
Alternate	-1.18	add 1	No	No	Kolomogorov-Smirnov	-
*Used non-transformed data, 2-Sample T-Test with unequal variance, could not compute, likely significant						
HNW(0,-1,-2)						
None	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	-0.337	add 1	No	No	Kolomogorov-Smirnov	-
Lower Alternate*	-0.393	add 1	No	Yes	Mann-Whitney	Yes
Upper Alternate	-0.281	add 1	No	No	Kolomogorov-Smirnov	-
HNW(0,-1,-2-3)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Optimal	0.113	add 1	No	Yes	Mann-Whitney	Yes
Lower Alternate	0.056	add 1	No	Yes	Mann-Whitney	Yes
Upper Alternate	0.17	add 1	No	Yes	Mann-Whitney	Yes
HND(0)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	-0.562	add 1	No	No	Kolomogorov-Smirnov	-
Lower Alternate	-0.618	add 1	No	No	Kolomogorov-Smirnov	-
Upper Alternate	-0.506	add 1	No	No	Kolomogorov-Smirnov	-
*Used non-transformed data, 2-Sample T-Test with unequal variance, could not compute, likely significant						
HND(0,-1)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	0	add 1	No	No	Kolomogorov-Smirnov	-
Lower Alternate	-0.056	add 1	No	No	Kolomogorov-Smirnov	-
Upper Alternate	0.056	add 1	No	No	Kolomogorov-Smirnov	-
*Used non-transformed data, 2-Sample T-Test with unequal variance, could not compute, likely significant						

Old Snow and New Snow Wet Avalanche Day Hypothesis Testing Results

Transformation	Lambda	Constant (values>zero)	Normal Distribution?	Equal Variance?	Mean/Median Test	Significantly Different?
HND(0-1,-2)						
None*	-	-	No	Yes	Mann-Whitney	Yes
Optimal	0.225	add 1	No	Yes	Mann-Whitney	Yes
Lower Alternate	0.169	add 1	No	Yes	Mann-Whitney	No
Upper Alternate	0.282	add 1	No	Yes	Mann-Whitney	No
HND(0-1,-2-3)						
None*	-	-	No	No	Kolomogorov-Smirnov	-
Optimal	0.562	add 1	No	No	Kolomogorov-Smirnov	-
Lower Alternate	0.506	add 1	No	No	Kolomogorov-Smirnov	-
Upper Alternate	0.618	add 1	No	No	Kolomogorov-Smirnov	-

*Used non-transformed data, 2-Sample T-Test with unequal variance, could not compute, 'significant' result

"OLD SNOW BINOMIAL LOGISTIC REGRESSION RESULTS"

The following charts provide the old snow binomial logistic regression results. Each significant old snow variable was entered into the binomial logistic regression equation individually and in groups of two and the resulting p-values, odds ratios and percent concordant pairs are tabulated in the charts.

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	Variable P-Value	Variable Odds Ratio	Percent Concordant Pairs
Day (of year)	0.021	1.05	62.70%
MaxT(0)	0	1.07	72.60%
MaxT(-1)	0.013	1.1	64.00%
MaxT(-2)	0.189	1.04	55.50%
AvgMaxT(0,-1)	0.001	1.17	70.20%
AvgMaxT(0,-1,-2)	0.004	1.05	66.60%
AvgMaxT(0,-1,-2,-3)	0.019	1.11	62.80%
MinT(0)	0.007	1.18	67.60%
MinT(-1)	0.009	1.01	63.80%
MinT(-2)	0.066	1.01	59.80%
AvgMinT(0,-1)	0.002	1.01	68.10%
AvgMinT(0,-1,-2)	0.004	1.01	66.50%
AvgMinT(0,-1,-2,-3)	0.013	1.01	64.10%
AvgT(0)	0	1.01	73.30%
AvgT(-1)	0.006	1.02	65.40%
AvgT(-2)	0.09	1.03	58.10%
AvgAvgT(0,-1)	0	1.01	70.30%
AvgAvgT(0,-1,-2)	0.003	1.02	67.60%
AvgAvgT(0,-1,-2,-3)	0.011	1.02	64.60%
DDMaxT(0)	0	1.07	72.60%
DDMaxT(0,-1)	0.001	1.03	70.10%
DDMaxT(0,-1,-2)	0.005	1.02	66.70%
DDMaxT(0,-1,-2,-3)	0.019	1.03	62.90%
DDAvgT(0)	0	1.01	73.30%
DDAvgT(0,-1)	0	1.01	70.30%
DDAvgT(0,-1,-2)	0.003	1	67.60%
DDAvgT(0,-1,-2,-3)	0.011	1.01	64.80%
HS(0)-HS(-1)	0.009	0.88	55.60%
HS(0)-HS(-2)	0.001	0.9	68.10%
HS(0)-HS(-3)	0.006	0.93	65.00%
Stl(0,-1)	0.009	0.88	55.60%
Stl(0,-1,-2)	0.005	0.92	66.70%
Stl(0,-1,-2,-3)	0.035	0.95	63.70%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
Day, MaxT(0)	0.19	1.03	0.002	1.06	74.20%
Day, MaxT(-1)	0.052	1.05	0.03	1.08	66.70%
Day, MaxT(-2)	0.031	1.05	0.312	1.03	63.40%
Day, AvgMaxT(0,-1)	0.083	1.04	0.005	1.15	71.00%
Day, AvgMaxT(0,-1-2)	0.05	1.05	0.014	1.05	69.20%
Day, AvgMaxT(0,-1,-2,-3)	0.042	1.05	0.056	1.09	67.30%
Day, MinT(0)	0.038	1.05	0.016	1.16	71.20%
Day, MinT(-1)	0.04	1.05	0.016	1.01	67.60%
Day, MinT(-2)	0.027	1.05	0.088	1.01	65.60%
Day, AvgMinT(0,-1)	0.032	1.05	0.004	1.01	70.70%
Day, AvgMinT(0,-1,-2)	0.025	1.05	0.007	1.01	70.50%
Day, AvgMinT(0,-1,-2,-3)	0.024	1.05	0.022	1.01	68.60%
Day, AvgT(0)	0.154	1.04	0.001	1.01	73.80%
Day, AvgT(-1)	0.053	1.05	0.013	1.02	67.30%
Day, AvgT(-2)	0.031	1.05	0.146	1.02	64.10%
Day, AvgAvgT(0,-1)	0.069	1.04	0.002	1.01	71.50%
Day, AvgAvgT(0,-1,-2)	0.042	1.05	0.008	1.02	69.50%
Day, AvgAvgT(0,-1,-2,-3)	0.037	1.05	0.027	1.02	68.50%
Day, DDMaxT(0)	0.19	1.03	0.002	1.06	74.20%
Day, DDMaxT(0,-1)	0.087	1.04	0.004	1.02	71.10%
Day, DDMaxT(0,-1,-2)	0.05	1.05	0.015	1.02	69.40%
Day, DDMaxT(0,-1,-2,-3)	0.043	1.05	0.054	1.02	67.30%
Day, DDAvgT(0)	0.154	1.04	0.001	1.01	73.80%
Day, DDAvgT(0,-1)	0.069	1.04	0.002	1	71.50%
Day, DDAvgT(0,-1,-2)	0.042	1.05	0.008	1	69.50%
Day, DDAvgT(0,-1,-2,-3)	0.037	1.05	0.028	1.01	68.30%
Day, HS(0)-HS(-1)	0.039	1.05	0.018	0.89	67.30%
Day, HS(0)-HS(-2)	0.035	1.05	0.002	0.9	72.60%
Day, HS(0)-HS(-3)	0.033	1.05	0.01	0.94	69.50%
Day, Stl(0,-1)	0.039	1.05	0.018	0.89	67.30%
Day, Stl(0,-1,-2)	0.018	1.06	0.004	0.91	70.90%
Day, Stl(0,-1,-2,-3)	0.02	1.05	0.034	0.95	67.80%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MaxT(0), AvgMaxT(0,-1)	0.068	1.07	0.986	1	72.60%
MaxT(0), AvgMaxT(0,-1-2)	0.01	1.08	0.672	0.99	74.10%
MaxT(0), AvgMaxT(0,-1,-2,-3)	0.002	1.09	0.367	0.94	74.00%
MaxT(0), MinT(0)	0.007	1.06	0.573	1.04	73.70%
MaxT(0), AvgMinT(0,-1)	0.015	1.06	0.443	1	73.60%
MaxT(0), AvgMinT(0,-1,-2)	0.008	1.06	0.609	1	73.60%
MaxT(0), AvgMinT(0,-1,-2,-3)	0.003	1.07	0.84	1	73.30%
MaxT(0), AvgT(0)	0.719	1.02	0.228	1.01	73.80%
MaxT(0), AvgAvgT(0,-1)	0.121	1.05	0.474	1	73.20%
MaxT(0), AvgAvgT(0,-1,-2)	0.017	1.07	0.929	1	73.40%
MaxT(0), AvgAvgT(0,-1,-2,-3)	0.004	1.08	0.763	1	73.50%
MaxT(0), DDMaxT(0)	na	na	na	na	na
MaxT(0), DDMaxT(0,-1)	0.088	1.07	0.891	1	73.60%
MaxT(0), DDMaxT(0,-1,-2)	0.01	1.08	0.642	0.99	74.00%
MaxT(0), DDMaxT(0,-1,-2,-3)	0.002	1.09	0.378	0.98	73.90%
MaxT(0), DDAvgT(0)	0.719	1.02	0.228	1.01	73.80%
MaxT(0), DDAvgT(0,-1)	0.124	1.05	0.467	1	73.20%
MaxT(0), DDAvgT(0,-1,-2)	0.017	1.07	0.922	1	73.20%
MaxT(0), DDAvgT(0,-1,-2,-3)	0.004	1.08	0.75	1	73.60%
MaxT(0), Day	0.002	1.02	0.19	0.98	74.20%
MaxT(0), MaxT(-1)	0.003	1.07	0.987	1	72.60%
MaxT(0), MaxT(-2)	0	1.08	0.401	0.96	73.90%
MaxT(0), MinT(-1)	0.004	1.02	0.781	0.99	73.50%
MaxT(0), MinT(-2)	0.001	1.07	0.948	1	73.20%
MaxT(0), AvgT(-1)	0.006	1.07	0.821	1	73.50%
MaxT(0), AvgT(-2)	0.001	1.08	0.685	0.99	73.80%
MaxT(0), HS(0)-HS(-1)	0.001	1.06	0.033	0.89	75.10%
MaxT(0), HS(0)-HS(-2)	0.001	1.07	0.005	0.9	77.30%
MaxT(0), HS(0)-HS(-3)	0.002	1.06	0.12	0.96	74.20%
MaxT(0), Stl(0,-1)	0.001	1.06	0.033	0.89	75.10%
MaxT(0), Stl(0,-1,-2)	0	1.07	0.015	0.92	76.40%
MaxT(0), Stl(0,-1,-2,-3)	0	1.07	0.102	0.96	74.60%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MaxT(-1), AvgMaxT(0,-1)	0.079	0.84	0.004	1.41	73.70%
MaxT(-1), AvgMaxT(0,-1-2)	0.667	0.96	0.104	1.07	67.10%
MaxT(-1), AvgMaxT(0,-1,-2,-3)	0.375	1.07	0.637	1.04	65.10%
MaxT(-1), MinT(-1)	0.35	1.05	0.231	1	65.80%
MaxT(-1), AvgMinT(0,-1)	0.615	1.03	0.044	1.01	68.40%
MaxT(-1), AvgMinT(0,-1,-2)	0.559	1.03	0.101	1.01	67.20%
MaxT(-1), AvgMinT(0,-1,-2,-3)	0.279	1.06	0.265	1.01	66.00%
MaxT(-1), AvgT(-1)	0.718	0.96	0.196	1.02	65.60%
MaxT(-1), AvgAvgT(0,-1)	0.179	0.9	0.004	1.02	71.90%
MaxT(-1), AvgAvgT(0,-1,-2)	0.664	0.97	0.058	1.03	67.90%
MaxT(-1), AvgAvgT(0,-1,-2,-3)	0.527	1.04	0.315	1.01	65.50%
MaxT(-1), DDMaxT(0,-1)	0.057	0.83	0.002	1.06	73.50%
MaxT(-1), DDMaxT(0,-1,-2)	0.694	0.97	0.115	1.03	66.80%
MaxT(-1), DDMaxT(0,-1,-2,-3)	0.385	1.06	0.62	1.01	64.80%
MaxT(-1), DDAvgT(0,-1)	0.177	0.9	0.003	1.01	71.80%
MaxT(-1), DDAvgT(0,-1,-2)	0.658	0.97	0.057	1.01	68.10%
MaxT(-1), DDAvgT(0,-1,-2,-3)	0.523	1.04	0.321	1	65.40%
MaxT(-1), Day	0.03	1.08	0.052	1.05	66.70%
MaxT(-1), MaxT(0)	0.987	1	0.003	1.07	72.60%
MaxT(-1), MaxT(-2)	0.027	1.13	0.424	0.96	65.90%
MaxT(-1), MinT(0)	0.245	1.05	0.069	1.13	70.30%
MaxT(-1), MinT(-2)	0.087	1.08	0.724	1	64.80%
MaxT(-1), AvgT(0)	0.877	0.99	0.002	1.01	73.40%
MaxT(-1), AvgT(-2)	0.068	1.1	0.83	1	64.90%
MaxT(-1), DDMaxT(0)	0.987	1	0.003	1.07	72.60%
MaxT(-1), DDAvgT(0)	0.877	0.99	0.002	1.01	73.40%
MaxT(-1), HS(0)-HS(-1)	0.004	1.12	0.002	0.85	70.30%
MaxT(-1), HS(0)-HS(-2)	0.01	1.1	0.001	0.89	74.70%
MaxT(-1), HS(0)-HS(-3)	0.054	1.08	0.031	0.94	68.60%
MaxT(-1), Stl(0,-1)	0.004	1.12	0.002	0.85	70.30%
MaxT(-1), Stl(0,-1,-2)	0.01	1.1	0.004	0.91	72.70%
MaxT(-1), Stl(0,-1,-2,-3)	0.013	1.1	0.044	0.95	69.10%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MaxT(-2), MinT(-2)	0.967	1	0.197	1.01	60.30%
MaxT(-2), AvgT(-2)	0.39	0.92	0.174	1.06	60.50%
MaxT(-2), Day	0.312	1.03	0.031	1.05	63.40%
MaxT(-2), MaxT(0)	0.401	0.96	0	1.08	73.90%
MaxT(-2), MaxT(-1)	0.424	0.96	0.027	1.13	65.90%
MaxT(-2), AvgMaxT(0,-1)	0.165	0.93	0.001	1.25	71.50%
MaxT(-2), AvgMaxT(0,-1-2)	0.016	0.83	0.001	1.15	71.50%
MaxT(-2), AvgMaxT(0,-1,-2,-3)	0.065	0.86	0.009	1.34	67.60%
MaxT(-2), MinT(0)	0.827	1.01	0.013	1.17	70.00%
MaxT(-2), MinT(-1)	0.685	0.98	0.022	1.01	65.10%
MaxT(-2), AvgMinT(0,-1)	0.623	0.98	0.004	1.01	67.80%
MaxT(-2), AvgMinT(0,-1,-2)	0.414	0.96	0.008	1.01	66.60%
MaxT(-2), AvgMinT(0,-1,-2,-3)	0.529	0.97	0.03	1.01	64.20%
MaxT(-2), AvgT(0)	0.384	0.96	0	1.01	73.00%
MaxT(-2), AvgT(-1)	0.256	0.94	0.009	1.03	66.40%
MaxT(-2), AvgAvgT(0,-1)	0.136	0.93	0	1.02	70.70%
MaxT(-2), AvgAvgT(0,-1,-2)	0.036	0.87	0.001	1.05	69.40%
MaxT(-2), AvgAvgT(0,-1,-2,-3)	0.089	0.88	0.007	1.05	66.90%
MaxT(-2), DDMaxT(0)	0.401	0.96	0	1.08	73.90%
MaxT(-2), DDMaxT(0,-1)	0.142	0.93	0.001	1.04	71.40%
MaxT(-2), DDMaxT(0,-1,-2)	0.018	0.83	0.001	1.06	71.50%
MaxT(-2), DDMaxT(0,-1,-2,-3)	0.061	0.85	0.008	1.07	67.50%
MaxT(-2), DDAvgT(0)	0.384	0.96	0	1.01	73.00%
MaxT(-2), DDAvgT(0,-1)	0.134	0.84	0	1	70.70%
MaxT(-2), DDAvgT(0,-1,-2)	0.036	0.86	0.001	1.01	69.30%
MaxT(-2), DDAvgT(0,-1,-2,-3)	0.091	0.88	0.007	1.01	66.80%
MaxT(-2), HS(0)-HS(-1)	0.061	1.07	0.003	0.86	67.80%
MaxT(-2), HS(0)-HS(-2)	0.031	1.08	0	0.88	73.70%
MaxT(-2), HS(0)-HS(-3)	0.255	1.04	0.008	0.93	68.60%
MaxT(-2), Stl(0,-1)	0.061	1.07	0.003	0.86	67.80%
MaxT(-2), Stl(0,-1,-2)	0.054	1.07	0.002	0.9	71.70%
MaxT(-2), Stl(0,-1,-2,-3)	0.124	1.05	0.026	0.95	67.70%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgMaxT(0,-1), MaxT(0)	0.986	1	0.068	1.07	72.60%
AvgMaxT(0,-1), MaxT(-1)	0.004	1.41	0.079	0.84	73.70%
AvgMaxT(0,-1), AvgMaxT(0,-1-2)	0.029	1.39	0.224	0.93	71.60%
AvgMaxT(0,-1), AvgMaxT(0,-1,-2,-3)	0.005	1.34	0.14	0.86	72.10%
AvgMaxT(0,-1), MinT(0)	0.036	1.13	0.375	1.07	71.50%
AvgMaxT(0,-1), MinT(-1)	0.023	1.17	0.923	1	70.50%
AvgMaxT(0,-1), AvgMinT(0,-1)	0.095	1.12	0.355	1	70.70%
AvgMaxT(0,-1), AvgMinT(0,-1,-2)	0.053	1.14	0.616	1	70.10%
AvgMaxT(0,-1), AvgMinT(0,-1,-2,-3)	0.017	1.17	0.919	1	70.20%
AvgMaxT(0,-1), AvgT(0)	0.981	1	0.036	1.01	73.30%
AvgMaxT(0,-1), AvgT(-1)	0.029	1.26	0.432	0.99	71.50%
AvgMaxT(0,-1), AvgAvgT(0,-1)	0.991	1	0.212	1.01	70.40%
AvgMaxT(0,-1), AvgAvgT(0,-1,-2)	0.117	1.18	0.909	1	70.30%
AvgMaxT(0,-1), AvgAvgT(0,-1,-2,-3)	0.02	1.22	0.566	0.99	71.20%
AvgMaxT(0,-1), DDMaxT(0)	0.986	1	0.068	1.07	72.60%
AvgMaxT(0,-1), DDMaxT(0,-1)	0.085	0.29	0.055	1.27	70.20%
AvgMaxT(0,-1), DDMaxT(0,-1,-2)	0.025	1.41	0.195	0.97	71.80%
AvgMaxT(0,-1), DDMaxT(0,-1,-2,-3)	0.006	1.33	0.148	0.97	72.00%
AvgMaxT(0,-1), DDAvgT(0)	0.981	1	0.036	1.01	73.30%
AvgMaxT(0,-1), DDAvgT(0,-1)	0.98	1	0.206	1	70.40%
AvgMaxT(0,-1), DDAvgT(0,-1,-2)	0.119	1.18	0.92	1	70.30%
AvgMaxT(0,-1), DDAvgT(0,-1,-2,-3)	0.02	1.22	0.551	1	71.20%
AvgMaxT(0,-1), Day	0.005	1.15	0.083	1.04	71.00%
AvgMaxT(0,-1), MaxT(-2)	0.001	1.25	0.165	0.93	71.50%
AvgMaxT(0,-1), MinT(-2)	0.005	1.18	0.848	1	70.50%
AvgMaxT(0,-1), AvgT(-2)	0.003	1.22	0.383	0.98	71.40%
AvgMaxT(0,-1), HS(0)-HS(-1)	0.001	1.17	0.007	0.86	73.90%
AvgMaxT(0,-1), HS(0)-HS(-2)	0.002	1.16	0.003	0.9	76.20%
AvgMaxT(0,-1), HS(0)-HS(-3)	0.008	1.14	0.09	0.95	72.00%
AvgMaxT(0,-1), Stl(0,-1)	0.001	1.17	0.007	0.86	73.90%
AvgMaxT(0,-1), Stl(0,-1,-2)	0.001	1.17	0.01	0.92	74.60%
AvgMaxT(0,-1), Stl(0,-1,-2,-3)	0.001	1.17	0.068	0.96	72.90%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgMaxT(0,-1,-2), MaxT(0)	0.672	0.99	0.01	1.08	74.10%
AvgMaxT(0,-1,-2), MaxT(-1)	0.104	1.07	0.667	0.96	67.10%
AvgMaxT(0,-1,-2), AvgMaxT(0,-1)	0.224	0.93	0.029	1.39	71.60%
AvgMaxT(0,-1,-2), AvgMaxT(0,-1,-2,-3)	0.017	1.19	0.082	0.73	69.80%
AvgMaxT(0,-1,-2), MinT(0)	0.131	1.03	0.153	1.11	70.30%
AvgMaxT(0,-1,-2), MinT(-1)	0.129	1.04	0.508	1	67.20%
AvgMaxT(0,-1,-2), AvgMinT(0,-1)	0.357	1.02	0.122	1.01	69.40%
AvgMaxT(0,-1,-2), AvgMinT(0,-1,-2)	0.298	1.03	0.298	1.01	67.70%
AvgMaxT(0,-1,-2), AvgMinT(0,-1,-2,-3)	0.113	1.04	0.66	1	66.70%
AvgMaxT(0,-1,-2), AvgT(0)	0.67	0.99	0.005	1.01	73.00%
AvgMaxT(0,-1,-2), AvgT(-1)	0.341	1.04	0.724	1.01	66.90%
AvgMaxT(0,-1,-2), AvgAvgT(0,-1)	0.316	0.016	0.016	1.02	70.50%
AvgMaxT(0,-1,-2), AvgAvgT(0,-1,-2)	0.91	0.99	0.296	1.03	67.50%
AvgMaxT(0,-1,-2), AvgAvgT(0,-1,-2,-3)	0.179	1.06	0.848	1	66.90%
AvgMaxT(0,-1,-2), DDMaxT(0)	0.672	0.99	0.01	1.08	74.10%
AvgMaxT(0,-1,-2), DDMaxT(0,-1)	0.145	0.92	0.016	1.07	71.60%
AvgMaxT(0,-1,-2), DDMaxT(0,-1,-2)	0.2	3.04	0.22	0.62	67.40%
AvgMaxT(0,-1,-2), DDMaxT(0,-1,-2,-3)	0.019	1.18	0.09	0.93	69.70%
AvgMaxT(0,-1,-2), DDAvgT(0)	0.67	0.99	0.005	1.01	73.00%
AvgMaxT(0,-1,-2), DDAvgT(0,-1)	0.31	0.96	0.015	1.01	70.30%
AvgMaxT(0,-1,-2), DDAvgT(0,-1,-2)	0.897	0.99	0.288	1.01	67.60%
AvgMaxT(0,-1,-2), DDAvgT(0,-1,-2,-3)	0.174	1.06	0.834	1	66.90%
AvgMaxT(0,-1.-2), Day	0.014	1.05	0.05	1.05	69.20%
AvgMaxT(0,-1,-2), MaxT(-2)	0.001	1.15	0.016	0.83	71.50%
AvgMaxT(0,-1,-2), MinT(-2)	0.029	1.06	0.895	1	66.80%
AvgMaxT(0,-1,-2), AvgT(-2)	0.008	1.1	0.166	0.96	69.30%
AvgMaxT(0,-1,-2), HS(0)-HS(-1)	0.002	1.06	0.004	0.85	73.00%
AvgMaxT(0,-1,-2), HS(0)-HS(-2)	0.002	1.06	0.001	0.89	75.80%
AvgMaxT(0,-1,-2), HS(0)-HS(-3)	0.021	1.04	0.047	0.95	70.30%
AvgMaxT(0,-1,-2), Stl(0,-1)	0.002	1.06	0.004	0.85	73.00%
AvgMaxT(0,-1,-2), Stl(0,-1,-2)	0.003	1.06	0.005	0.91	73.60%
AvgMaxT(0,-1,-2), Stl(0,-1,-2,-3)	0.004	1.05	0.048	0.95	70.80%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgMaxT(0,-1,-2,-3), MaxT(0)	0.367	0.94	0.002	1.09	74.00%
AvgMaxT(0,-1,-2,-3), MaxT(-1)	0.637	1.04	0.375	1.07	65.10%
AvgMaxT(0,-1,-2,-3), AvgMaxT(0,-1)	0.14	0.86	0.005	1.34	72.10%
AvgMaxT(0,-1,-2,-3), AvgMaxT(0,-1-2)	0.082	0.73	0.017	1.19	69.80%
AvgMaxT(0,-1,-2,-3), MinT(0)	0.356	1.05	0.067	1.13	69.80%
AvgMaxT(0,-1,-2,-3), AvgMinT(0,-1)	0.789	1.02	0.035	1.01	68.10%
AvgMaxT(0,-1,-2,-3), AvgMinT(0,-1,-2)	0.834	1.02	0.089	1.01	66.70%
AvgMaxT(0,-1,-2,-3), AvgMinT(0,-1,-2,-3)	0.532	1.05	0.316	1.01	64.70%
AvgMaxT(0,-1,-2,-3), AvgT(0)	0.368	0.94	0.001	1.02	73.10%
AvgMaxT(0,-1,-2,-3), AvgT(-1)	0.985	1	0.149	1.02	65.40%
AvgMaxT(0,-1,-2,-3), AvgAvgT(0,-1)	0.151	0.88	0.002	1.02	70.40%
AvgMaxT(0,-1,-2,-3), AvgAvgT(0,-1,-2)	0.187	0.85	0.019	1.05	68.50%
AvgMaxT(0,-1,-2,-3), AvgAvgT(0,-1,-2,-3)	0.702	0.94	0.702	1.03	65.00%
AvgMaxT(0,-1,-2,-3), DDMaxT(0)	0.367	0.94	0.002	1.09	74.00%
AvgMaxT(0,-1,-2,-3), DDMaxT(0,-1)	0.108	0.85	0.003	1.05	71.90%
AvgMaxT(0,-1,-2,-3), DDMaxT(0,-1,-2)	0.091	0.73	0.02	1.08	69.80%
AvgMaxT(0,-1,-2,-3), DDMaxT(0,-1,-2,-3)	0.083	0	0.08	14.83	65.80%
AvgMaxT(0,-1,-2,-3), DDAvgT(0)	0.368	0.94	0.001	1.02	73.10%
AvgMaxT(0,-1,-2,-3), DDAvgT(0,-1)	0.149	0.88	0.002	1.01	70.40%
AvgMaxT(0,-1,-2,-3), DDAvgT(0,-1,-2)	0.183	0.85	0.018	1.01	68.50%
AvgMaxT(0,-1,-2,-3), DDAvgT(0,-1,-2,-3)	0.707	0.94	0.271	1.01	65.10%
AvgMaxT(0,-1,-2,-3), Day	0.056	1.09	0.042	1.05	67.30%
AvgMaxT(0,-1,-2,-3), MaxT(-2)	0.009	1.34	0.065	0.86	67.60%
AvgMaxT(0,-1,-2,-3), MinT(-1)	0.44	1.05	0.199	1	65.40%
AvgMaxT(0,-1,-2,-3), MinT(-2)	0.16	1.1	0.738	1	63.50%
AvgMaxT(0,-1,-2,-3), AvgT(-2)	0.084	1.18	0.483	0.98	64.30%
AvgMaxT(0,-1,-2,-3), HS(0)-HS(-1)	0.006	1.14	0.003	0.85	71.60%
AvgMaxT(0,-1,-2,-3), HS(0)-HS(-2)	0.006	1.14	0	0.88	75.00%
AvgMaxT(0,-1,-2,-3), HS(0)-HS(-3)	0.043	1.1	0.02	0.94	69.30%
AvgMaxT(0,-1,-2,-3), Stl(0,-1)	0.006	1.14	0.003	0.85	71.60%
AvgMaxT(0,-1,-2,-3), Stl(0,-1,-2)	0.008	1.14	0.003	0.9	73.10%
AvgMaxT(0,-1,-2,-3), Stl(0,-1,-2,-3)	0.015	1.12	0.031	0.95	70.20%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MinT(0), MaxT(0)	0.573	1.04	0.007	1.06	73.70%
MinT(0), AvgMaxT(0,-1)	0.375	1.07	0.036	1.13	71.50%
MinT(0), AvgMaxT(0,-1-2)	0.153	1.11	0.131	1.03	70.30%
MinT(0), AvgMaxT(0,-1,-2,-3)	0.067	1.13	0.356	1.05	69.80%
MinT(0), AvgMinT(0,-1)	0.929	1.01	0.191	1.01	68.50%
MinT(0), AvgMinT(0,-1,-2)	0.375	1.09	0.331	1.01	68.70%
MinT(0), AvgMinT(0,-1,-2,-3)	0.137	1.13	0.608	1	68.50%
MinT(0), AvgT(0)	0.176	0.86	0.002	1.02	74.40%
MinT(0), AvgAvgT(0,-1)	0.899	0.99	0.023	1.01	70.40%
MinT(0), AvgAvgT(0,-1,-2)	0.362	1.08	0.154	1.02	69.50%
MinT(0), AvgAvgT(0,-1,-2,-3)	0.135	1.12	0.385	1.01	69.20%
MinT(0), DDMaxT(0)	0.573	1.04	0.007	1.06	73.70%
MinT(0), DDMaxT(0,-1)	0.394	1.06	0.028	1.02	71.50%
MinT(0), DDMaxT(0,-1,-2)	0.151	1.11	0.139	1.01	70.30%
MinT(0), DDMaxT(0,-1,-2,-3)	0.069	1.13	0.348	1.01	69.90%
MinT(0), DDAvgT(0)	0.176	0.86	0.002	1.02	74.40%
MinT(0), DDAvgT(0,-1)	0.894	0.99	0.023	1	70.30%
MinT(0), DDAvgT(0,-1,-2)	0.364	1.08	0.151	1	69.40%
MinT(0), DDAvgT(0,-1,-2,-3)	0.134	1.12	0.392	1	69.30%
MinT(0), Day	0.016	1.16	0.038	1.05	71.20%
MinT(0), MaxT(-1)	0.069	1.13	0.245	1.05	70.30%
MinT(0), MaxT(-2)	0.013	1.17	0.827	1.01	70.00%
MinT(0), MinT(-1)	0.143	1.12	0.43	1	68.60%
MinT(0), MinT(-2)	0.031	1.16	0.621	1	69.00%
MinT(0), AvgT(-1)	0.162	1.11	0.227	1.01	69.10%
MinT(0), AvgT(-2)	0.023	1.16	0.676	1.01	69.50%
MinT(0), HS(0)-HS(-1)	0.008	1.16	0.013	0.88	70.90%
MinT(0), HS(0)-HS(-2)	0.013	1.16	0.004	0.9	75.00%
MinT(0), HS(0)-HS(-3)	0.02	1.15	0.031	0.94	72.30%
MinT(0), Stl(0,-1)	0.008	1.16	0.013	0.88	70.90%
MinT(0), Stl(0,-1,-2)	0.008	1.17	0.01	0.92	73.80%
MinT(0), Stl(0,-1,-2,-3)	0.008	1.17	0.058	0.96	71.90%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MinT(-1), MaxT(-1)	0.231	1	0.35	1.05	65.80%
MinT(-1), AvgMaxT(0,-1)	0.923	1	0.023	1.17	70.50%
MinT(-1), AvgMaxT(0,-1-2)	0.508	1	0.129	1.04	67.20%
MinT(-1), AvgMinT(0,-1)	0.25	0.99	0.036	1.02	69.20%
MinT(-1), AvgMinT(0,-1,-2)	0.728	1	0.16	1.01	66.70%
MinT(-1), AvgMinT(0,-1,-2,-3)	0.415	1	0.595	1	65.20%
MinT(-1), AvgT(-1)	0.851	1	0.303	1.02	65.40%
MinT(-1), AvgAvgT(0,-1)	0.149	0.99	0.004	1.02	72.00%
MinT(-1), AvgAvgT(0,-1,-2)	0.804	1	0.083	1.03	68.00%
MinT(-1), AvgAvgT(0,-1,-2,-3)	0.442	1	0.4	1.01	65.30%
MinT(-1), DDMaxT(0,-1)	0.978	1	0.017	1.03	70.10%
MinT(-1), DDMaxT(0,-1,-2)	0.497	1	0.138	1.02	67.20%
MinT(-1), DDMaxT(0,-1,-2,-3)	0.203	1	0.43	1.01	65.30%
MinT(-1), DDAvgT(0,-1)	0.146	0.99	0.004	1.01	72.00%
MinT(-1), DDAvgT(0,-1,-2)	0.796	1	0.081	1.01	68.00%
MinT(-1), DDAvgT(0,-1,-2,-3)	0.437	1	0.406	1	65.20%
MinT(-1), Day	0.016	1.01	0.04	1.05	67.60%
MinT(-1), MaxT(0)	0.781	1	0.004	1.07	73.50%
MinT(-1), MaxT(-2)	0.022	1.01	0.685	0.98	65.10%
MinT(-1), AvgMaxT(0,-1,-2,-3)	0.199	1	0.44	1.05	65.40%
MinT(-1), MinT(0)	0.43	1	0.143	1.12	68.60%
MinT(-1), MinT(-2)	0.068	1.01	0.942	1	64.40%
MinT(-1), AvgT(0)	0.616	1	0.002	1.01	73.80%
MinT(-1), AvgT(-2)	0.048	1.01	0.807	0.99	64.70%
MinT(-1), DDMaxT(0)	0.781	1	0.004	1.07	73.50%
MinT(-1), DDAvgT(0)	0.616	1	0.002	1.01	73.80%
MinT(-1), HS(0)-HS(-1)	0.005	1.01	0.005	0.86	69.40%
MinT(-1), HS(0)-HS(-2)	0.007	1.01	0.001	0.89	73.50%
MinT(-1), HS(0)-HS(-3)	0.038	1.01	0.031	0.94	69.30%
MinT(-1), Stl(0,-1)	0.005	1.01	0.005	0.86	69.40%
MinT(-1), Stl(0,-1,-2)	0.006	1.01	0.004	0.91	71.50%
MinT(-1), Stl(0,-1,-2,-3)	0.008	1.01	0.043	0.95	69.00%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MinT(-2), MaxT(-2)	0.197	1.01	0.967	1	60.30%
MinT(-2), AvgT(-2)	0.47	1.01	0.974	1	60.00%
MinT(-2), Day	0.088	1.01	0.027	1.05	65.60%
MinT(-2), MaxT(0)	0.948	1	0.001	1.07	73.20%
MinT(-2), MaxT(-1)	0.724	1	0.087	1.08	64.80%
MinT(-2), AvgMaxT(0,-1)	0.848	1	0.005	1.18	70.50%
MinT(-2), AvgMaxT(0,-1-2)	0.895	1	0.029	1.06	66.80%
MinT(-2), AvgMaxT(0,-1,-2,-3)	0.738	1	0.16	1.1	63.50%
MinT(-2), MinT(0)	0.621	1	0.031	1.16	69.00%
MinT(-2), MinT(-1)	0.942	1	0.068	1.01	64.40%
MinT(-2), AvgMinT(0,-1)	0.768	1	0.013	1.01	68.30%
MinT(-2), AvgMinT(0,-1,-2)	0.206	0.98	0.014	1.02	68.40%
MinT(-2), AvgMinT(0,-1,-2,-3)	0.541	0.99	0.091	1.01	64.60%
MinT(-2), AvgT(0)	0.682	1	0	1.01	73.50%
MinT(-2), AvgT(-1)	0.767	1	0.038	1.02	65.80%
MinT(-2), AvgAvgT(0,-1)	0.393	0.99	0.002	1.01	71.20%
MinT(-2), AvgAvgT(0,-1,-2)	0.254	0.99	0.009	1.04	69.30%
MinT(-2), AvgAvgT(0,-1,-2,-3)	0.64	0.99	0.073	1.03	65.40%
MinT(-2), DDMaxT(0)	0.948	1	0.001	1.07	73.20%
MinT(-2), DDMaxT(0,-1)	0.811	1	0.004	1.03	70.70%
MinT(-2), DDMaxT(0,-1,-2)	0.907	1	0.031	1.02	66.80%
MinT(-2), DDMaxT(0,-1,-2,-3)	0.747	1	0.155	1.02	63.40%
MinT(-2), DDAvgT(0)	0.682	1	0	1.01	73.50%
MinT(-2), DDAvgT(0,-1)	0.389	0.99	0.002	1	71.20%
MinT(-2), DDAvgT(0,-1,-2)	0.251	0.99	0.009	1.01	69.50%
MinT(-2), DDAvgT(0,-1,-2,-3)	0.647	0.99	0.075	1.01	65.30%
MinT(-2), HS(0)-HS(-1)	0.025	1.01	0.003	0.86	66.10%
MinT(-2), HS(0)-HS(-2)	0.016	1.02	0	0.88	72.50%
MinT(-2), HS(0)-HS(-3)	0.083	1.01	0.007	0.93	68.30%
MinT(-2), Stl(0,-1)	0.025	1.01	0.003	0.86	66.10%
MinT(-2), Stl(0,-1,-2)	0.03	1.01	0.002	0.91	70.70%
MinT(-2), Stl(0,-1,-2,-3)	0.059	1.01	0.032	0.95	67.20%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgMinT(0,-1), MaxT(0)	0.443	1	0.015	1.06	73.60%
AvgMinT(0,-1), MaxT(-1)	0.044	1.01	0.615	1.03	68.40%
AvgMinT(0,-1), AvgMaxT(0,-1)	0.355	1	0.095	1.12	70.70%
AvgMinT(0,-1), AvgMaxT(0,-1-2)	0.122	1.01	0.357	1.02	69.40%
AvgMinT(0,-1), AvgMaxT(0,-1,-2,-3)	0.035	1.01	0.789	1.02	68.10%
AvgMinT(0,-1), MinT(0)	0.191	1.01	0.929	1.01	68.50%
AvgMinT(0,-1), MinT(-1)	0.036	1.02	0.25	0.99	69.20%
AvgMinT(0,-1), AvgMinT(0,-1,-2)	0.201	1.01	0.774	1	68.30%
AvgMinT(0,-1), AvgMinT(0,-1,-2,-3)	0.04	1.01	0.527	1	68.80%
AvgMinT(0,-1), AvgT(0)	0.57	1	0.009	1.02	73.80%
AvgMinT(0,-1), AvgT(-1)	0.129	1.01	0.883	1	68.00%
AvgMinT(0,-1), AvgAvgT(0,-1)	0.596	1	0.052	1.02	70.80%
AvgMinT(0,-1), AvgAvgT(0,-1,-2)	0.34	1.01	0.5	1.01	68.50%
AvgMinT(0,-1), AvgAvgT(0,-1,-2,-3)	0.07	1.01	0.987	1	67.80%
AvgMinT(0,-1), DDMaxT(0)	0.443	1	0.015	1.06	73.60%
AvgMinT(0,-1), DDMaxT(0,-1)	0.39	1	0.075	1.02	70.80%
AvgMinT(0,-1), DDMaxT(0,-1,-2)	0.118	1.01	0.375	1.01	69.40%
AvgMinT(0,-1), DDMaxT(0,-1,-2,-3)	0.035	1.01	0.776	1	68.10%
AvgMinT(0,-1), DDAvgT(0)	0.57	1	0.009	1.02	73.80%
AvgMinT(0,-1), DDAvgT(0,-1)	0.586	1	0.05	1	70.60%
AvgMinT(0,-1), DDAvgT(0,-1,-2)	0.345	1.01	0.493	1	68.50%
AvgMinT(0,-1), DDAvgT(0,-1,-2,-3)	0.069	1.01	0.995	1	67.80%
AvgMinT(0,-1), Day	0.004	1.01	0.032	1.05	70.70%
AvgMinT(0,-1), MaxT(-2)	0.004	1.01	0.623	0.98	67.80%
AvgMinT(0,-1), MinT(-2)	0.013	1.01	0.768	1	68.30%
AvgMinT(0,-1), AvgT(-2)	0.009	1.01	0.689	0.99	68.10%
AvgMinT(0,-1), HS(0)-HS(-1)	0.002	1.01	0.008	0.87	71.60%
AvgMinT(0,-1), HS(0)-HS(-2)	0.003	1.01	0.003	0.9	74.20%
AvgMinT(0,-1), HS(0)-HS(-3)	0.01	1.01	0.051	0.95	71.60%
AvgMinT(0,-1), Stl(0,-1)	0.002	1.01	0.008	0.87	71.60%
AvgMinT(0,-1), Stl(0,-1,-2)	0.002	1.01	0.008	0.92	72.80%
AvgMinT(0,-1), Stl(0,-1,-2,-3)	0.002	1.01	0.054	0.95	71.50%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgMinT(0,-1,-2), MaxT(0)	0.609	1	0.008	1.06	73.60%
AvgMinT(0,-1,-2), MaxT(-1)	0.101	1.01	0.559	1.01	67.20%
AvgMinT(0,-1,-2), AvgMaxT(0,-1)	0.616	1	0.053	1.14	70.10%
AvgMinT(0,-1,-2), AvgMaxT(0,-1-2)	0.298	1.01	0.298	1.03	67.70%
AvgMinT(0,-1,-2), AvgMaxT(0,-1,-2,-3)	0.089	1.01	0.834	1.02	66.70%
AvgMinT(0,-1,-2), MinT(0)	0.331	1.01	0.375	1.09	68.70%
AvgMinT(0,-1,-2), MinT(-1)	0.16	1.01	0.728	1	66.70%
AvgMinT(0,-1,-2), AvgMinT(0,-1)	0.774	1	0.201	1.01	68.30%
AvgMinT(0,-1,-2), AvgMinT(0,-1,-2,-3)	0.055	1.02	0.241	0.98	68.10%
AvgMinT(0,-1,-2), AvgT(0)	0.579	1	0.004	1.02	73.60%
AvgMinT(0,-1,-2), AvgT(-1)	0.309	1.01	0.643	1.01	66.80%
AvgMinT(0,-1,-2), AvgAvgT(0,-1)	0.356	0.99	0.015	1.02	71.10%
AvgMinT(0,-1,-2), AvgAvgT(0,-1,-2)	0.923	1	0.294	1.02	67.50%
AvgMinT(0,-1,-2), AvgAvgT(0,-1,-2,-3)	0.184	1.01	0.936	1	66.50%
AvgMinT(0,-1,-2), DDMaxT(0)	0.609	1	0.008	1.06	73.60%
AvgMinT(0,-1,-2), DDMaxT(0,-1)	0.665	1	0.04	1.02	70.30%
AvgMinT(0,-1,-2), DDMaxT(0,-1,-2)	0.289	1.01	0.315	1.01	67.60%
AvgMinT(0,-1,-2), DDMaxT(0,-1,-2,-3)	0.092	1.01	0.819	1	66.80%
AvgMinT(0,-1,-2), DDAvgT(0)	0.579	1	0.004	1.02	73.60%
AvgMinT(0,-1,-2), DDAvgT(0,-1)	0.349	0.99	0.014	1.01	70.80%
AvgMinT(0,-1,-2), DDAvgT(0,-1,-2)	0.934	1	0.287	1	67.60%
AvgMinT(0,-1,-2), DDAvgT(0,-1,-2,-3)	0.18	1.01	0.926	1	66.60%
AvgMinT(0,-1,-2), Day	0.007	1.01	0.025	1.05	70.50%
AvgMinT(0,-1,-2), MaxT(-2)	0.008	1.01	0.414	0.96	66.60%
AvgMinT(0,-1,-2), MinT(-2)	0.014	1.02	0.206	0.98	68.40%
AvgMinT(0,-1,-2), AvgT(-2)	0.012	1.02	0.281	0.97	66.90%
AvgMinT(0,-1,-2), HS(0)-HS(-1)	0.002	1.01	0.004	0.86	70.40%
AvgMinT(0,-1,-2), HS(0)-HS(-2)	0.003	1.01	0.001	0.89	74.20%
AvgMinT(0,-1,-2), HS(0)-HS(-3)	0.014	1.01	0.029	0.94	70.50%
AvgMinT(0,-1,-2), Stl(0,-1)	0.002	1.01	0.004	0.86	70.40%
AvgMinT(0,-1,-2), Stl(0,-1,-2)	0.003	1.01	0.005	0.91	72.40%
AvgMinT(0,-1,-2), Stl(0,-1,-2,-3)	0.004	1.01	0.044	0.95	70.00%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgMinT(0,-1,-2,-3), MaxT(0)	0.84	1	0.003	1.07	73.30%
AvgMinT(0,-1,-2,-3), MaxT(-1)	0.265	1.01	0.279	1.06	66.00%
AvgMinT(0,-1,-2,-3), AvgMaxT(0,-1)	0.919	1	0.017	1.17	70.20%
AvgMinT(0,-1,-2,-3), AvgMaxT(0,-1-2)	0.66	1	0.113	1.04	66.70%
AvgMinT(0,-1,-2,-3), AvgMaxT(0,-1,-2,-3)	0.316	1.01	0.532	1.05	64.70%
AvgMinT(0,-1,-2,-3), MinT(0)	0.608	1	0.137	1.13	68.50%
AvgMinT(0,-1,-2,-3), MinT(-1)	0.595	1	0.415	1	65.20%
AvgMinT(0,-1,-2,-3), AvgMinT(0,-1)	0.527	1	0.04	1.01	68.80%
AvgMinT(0,-1,-2,-3), AvgMinT(0,-1,-2)	0.241	0.98	0.055	1.02	68.10%
AvgMinT(0,-1,-2,-3), AvgT(0)	0.443	1	0.001	1.02	73.70%
AvgMinT(0,-1,-2,-3), AvgT(-1)	0.709	1	0.204	1.01	65.30%
AvgMinT(0,-1,-2,-3), AvgAvgT(0,-1)	0.259	0.99	0.004	1.02	71.00%
AvgMinT(0,-1,-2,-3), AvgAvgT(0,-1,-2)	0.471	0.99	0.046	1.04	68.10%
AvgMinT(0,-1,-2,-3), AvgAvgT(0,-1,-2,-3)	0.86	1	0.462	1.02	65.20%
AvgMinT(0,-1,-2,-3), DDMaxT(0)	0.84	1	0.003	1.07	73.30%
AvgMinT(0,-1,-2,-3), DDMaxT(0,-1)	0.963	1	0.013	1.03	70.10%
AvgMinT(0,-1,-2,-3), DDMaxT(0,-1,-2)	0.649	1	0.122	1.02	66.90%
AvgMinT(0,-1,-2,-3), DDMaxT(0,-1,-2,-3)	0.323	1.01	0.518	1.01	64.90%
AvgMinT(0,-1,-2,-3), DDAvgT(0)	0.443	1	0.001	1.02	73.70%
AvgMinT(0,-1,-2,-3), DDAvgT(0,-1)	0.255	0.99	0.004	1.01	70.90%
AvgMinT(0,-1,-2,-3), DDAvgT(0,-1,-2)	0.464	0.99	0.044	1.01	68.00%
AvgMinT(0,-1,-2,-3), DDAvgT(0,-1,-2,-3)	0.845	1	0.472	1	65.20%
AvgMinT(0,-1,-2,-3), Day	0.022	1.01	0.024	1.05	68.60%
AvgMinT(0,-1,-2,-3), MaxT(-2)	0.03	1.01	0.529	0.97	64.20%
AvgMinT(0,-1,-2,-3), MinT(-2)	0.091	1.01	0.541	0.99	64.60%
AvgMinT(0,-1,-2,-3), AvgT(-2)	0.062	1.01	0.49	0.98	64.50%
AvgMinT(0,-1,-2,-3), HS(0)-HS(-1)	0.005	1.01	0.003	0.85	70.00%
AvgMinT(0,-1,-2,-3), HS(0)-HS(-2)	0.005	1.01	0.001	0.88	74.40%
AvgMinT(0,-1,-2,-3), HS(0)-HS(-3)	0.021	1.01	0.014	0.94	70.10%
AvgMinT(0,-1,-2,-3), Stl(0,-1)	0.005	1.01	0.003	0.85	70.00%
AvgMinT(0,-1,-2,-3), Stl(0,-1,-2)	0.006	1.01	0.003	0.9	72.40%
AvgMinT(0,-1,-2,-3), Stl(0,-1,-2,-3)	0.011	1.01	0.031	0.95	70.10%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgT(0), MaxT(0)	0.228	1.01	0.719	1.02	73.80%
AvgT(0), AvgMaxT(0,-1)	0.036	1.01	0.981	1	73.30%
AvgT(0), AvgMaxT(0,-1-2)	0.005	1.01	0.67	0.99	73.00%
AvgT(0), AvgMaxT(0,-1,-2,-3)	0.001	1.02	0.368	0.94	73.10%
AvgT(0), MinT(0)	0.002	1.02	0.176	0.86	74.40%
AvgT(0), AvgMinT(0,-1)	0.009	1.02	0.57	1	73.80%
AvgT(0), AvgMinT(0,-1,-2)	0.004	1.02	0.579	1	73.60%
AvgT(0), AvgMinT(0,-1,-2,-3)	0.001	1.02	0.443	1	73.70%
AvgT(0), AvgAvgT(0,-1)	0.08	1.01	0.919	1	73.50%
AvgT(0), AvgAvgT(0,-1,-2)	0.008	1.02	0.99	0.96	73.40%
AvgT(0), AvgAvgT(0,-1,-2,-3)	0.002	1.02	0.99	0.96	73.50%
AvgT(0), DDMaxT(0)	0.228	1.01	0.719	1.02	73.80%
AvgT(0), DDMaxT(0,-1)	0.046	1.01	0.904	1	73.40%
AvgT(0), DDMaxT(0,-1,-2)	0.005	1.02	0.641	0.99	73.00%
AvgT(0), DDMaxT(0,-1,-2,-3)	0.001	1.02	0.377	0.99	73.20%
AvgT(0), DDAvgT(0)	na	na	na	na	na
AvgT(0), DDAvgT(0,-1)	0.082	1.01	0.931	1	73.50%
AvgT(0), DDAvgT(0,-1,-2)	0.008	1.02	0.578	1	73.40%
AvgT(0), DDAvgT(0,-1,-2,-3)	0.002	1.02	0.365	1	73.40%
AvgT(0), Day	0.001	1.01	0.154	1.04	73.80%
AvgT(0), MaxT(-1)	0.002	1.01	0.877	0.99	73.40%
AvgT(0), MaxT(-2)	0	1.01	0.384	0.96	73.00%
AvgT(0), MinT(-1)	0.002	1.01	0.616	1	73.80%
AvgT(0), MinT(-2)	0	1.01	0.682	1	73.50%
AvgT(0), AvgT(-1)	0.004	1.01	0.79	1	73.30%
AvgT(0), AvgT(-2)	0	1.01	0.493	0.99	73.20%
AvgT(0), HS(0)-HS(-1)	0	1.01	0.037	0.89	75.00%
AvgT(0), HS(0)-HS(-2)	0	1.01	0.008	0.91	76.20%
AvgT(0), HS(0)-HS(-3)	0.001	1.01	0.127	0.96	74.40%
AvgT(0), Stl(0,-1)	0	1.01	0.037	0.89	75.00%
AvgT(0), Stl(0,-1,-2)	0	1.01	0.018	0.92	75.80%
AvgT(0), Stl(0,-1,-2,-3)	0	1.01	0.113	0.96	73.90%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgT(-1), MaxT(-1)	0.196	1.02	0.718	0.96	65.60%
AvgT(-1), AvgMaxT(0,-1)	0.432	0.99	0.029	1.26	71.50%
AvgT(-1), AvgMaxT(0,-1-2)	0.724	1.01	0.341	1.04	66.90%
AvgT(-1), AvgMaxT(0,-1,-2,-3)	0.149	1.02	0.985	1	65.40%
AvgT(-1), MinT(-1)	0.303	1.02	0.851	1	65.40%
AvgT(-1), AvgMinT(0,-1)	0.883	1	0.129	1.01	68.00%
AvgT(-1), AvgMinT(0,-1,-2)	0.643	1.01	0.309	1.01	66.80%
AvgT(-1), AvgMinT(0,-1,-2,-3)	0.204	1.01	0.709	1	65.30%
AvgT(-1), AvgAvgT(0,-1)	0.042	0.96	0.002	1.03	73.50%
AvgT(-1), AvgAvgT(0,-1,-2)	0.668	0.99	0.145	1.03	68.10%
AvgT(-1), AvgAvgT(0,-1,-2,-3)	0.31	1.01	0.762	1.01	65.50%
AvgT(-1), DDMaxT(0,-1)	0.351	0.99	0.019	1.04	71.60%
AvgT(-1), DDMaxT(0,-1,-2)	0.697	1.01	0.365	1.02	66.80%
AvgT(-1), DDMaxT(0,-1,-2,-3)	0.154	1.02	0.996	1	65.40%
AvgT(-1), DDAvgT(0,-1)	0.041	0.96	0.002	1.01	73.60%
AvgT(-1), DDAvgT(0,-1,-2)	0.656	0.99	0.141	1.01	68.20%
AvgT(-1), DDAvgT(0,-1,-2,-3)	0.305	1.01	0.772	1	65.50%
AvgT(-1), Day	0.013	1.02	0.053	1.05	67.30%
AvgT(-1), MaxT(0)	0.821	1	0.006	1.07	73.50%
AvgT(-1), MaxT(-2)	0.009	1.03	0.256	0.94	66.40%
AvgT(-1), MinT(0)	0.227	1.01	0.162	1.11	69.10%
AvgT(-1), MinT(-2)	0.038	1.02	0.767	1	65.80%
AvgT(-1), AvgT(0)	0.79	1	0.004	1.01	73.30%
AvgT(-1), AvgT(-2)	0.022	1.02	0.403	0.98	66.50%
AvgT(-1), DDMaxT(0)	0.821	1	0.006	1.07	73.50%
AvgT(-1), DDAvgT(0)	0.79	1	0.004	1.01	73.30%
AvgT(-1), HS(0)-HS(-1)	0.002	1.02	0.003	0.85	71.00%
AvgT(-1), HS(0)-HS(-2)	0.004	1.02	0.001	0.89	74.10%
AvgT(-1), HS(0)-HS(-3)	0.029	1.01	0.04	0.95	69.30%
AvgT(-1), Stl(0,-1)	0.002	1.02	0.003	0.85	71.00%
AvgT(-1), Stl(0,-1,-2)	0.004	1.02	0.004	0.91	72.60%
AvgT(-1), Stl(0,-1,-2,-3)	0.005	1.02	0.043	0.95	69.60%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgT(-2), MaxT(-2)	0.174	1.06	0.39	0.92	60.50%
AvgT(-2), MinT(-2)	0.974	1	0.47	1.01	60.00%
AvgT(-2), Day	0.146	1.02	0.031	1.05	64.10%
AvgT(-2), MaxT(0)	0.685	0.99	0.001	1.08	73.80%
AvgT(-2), MaxT(-1)	0.83	1	0.068	1.1	64.90%
AvgT(-2), AvgMaxT(0,-1)	0.383	0.98	0.003	1.22	71.40%
AvgT(-2), AvgMaxT(0,-1-2)	0.166	0.96	0.008	1.1	69.30%
AvgT(-2), AvgMaxT(0,-1,-2,-3)	0.483	0.98	0.084	1.18	64.30%
AvgT(-2), MinT(0)	0.676	1.01	0.023	1.16	69.50%
AvgT(-2), MinT(-1)	0.807	0.99	0.048	1.01	64.70%
AvgT(-2), AvgMinT(0,-1)	0.689	0.99	0.009	1.01	68.10%
AvgT(-2), AvgMinT(0,-1,-2)	0.281	0.97	0.012	1.02	66.90%
AvgT(-2), AvgMinT(0,-1,-2,-3)	0.49	0.98	0.062	1.01	64.50%
AvgT(-2), AvgT(0)	0.493	0.99	0	1.01	73.20%
AvgT(-2), AvgT(-1)	0.403	0.98	0.022	1.02	66.50%
AvgT(-2), AvgAvgT(0,-1)	0.181	0.97	0.001	1.02	71.10%
AvgT(-2), AvgAvgT(0,-1,-2)	0.03	0.92	0.002	1.06	71.10%
AvgT(-2), AvgAvgT(0,-1,-2,-3)	0.121	0.94	0.016	1.05	67.60%
AvgT(-2), DDMaxT(0)	0.685	0.99	0.001	1.08	73.80%
AvgT(-2), DDMaxT(0,-1)	0.344	0.98	0.002	1.04	71.40%
AvgT(-2), DDMaxT(0,-1,-2)	0.177	0.96	0.009	1.04	69.40%
AvgT(-2), DDMaxT(0,-1,-2,-3)	0.468	0.98	0.08	1.04	64.50%
AvgT(-2), DDAvgT(0)	0.493	0.99	0	1.01	73.20%
AvgT(-2), DDAvgT(0,-1)	0.178	0.97	0.001	1.01	71.10%
AvgT(-2), DDAvgT(0,-1,-2)	0.029	0.92	0.001	1.01	71.00%
AvgT(-2), DDAvgT(0,-1,-2,-3)	0.125	0.94	0.017	1.01	67.50%
AvgT(-2), HS(0)-HS(-1)	0.027	1.04	0.003	0.85	68.20%
AvgT(-2), HS(0)-HS(-2)	0.013	1.04	0	0.87	73.30%
AvgT(-2), HS(0)-HS(-3)	0.125	1.02	0.008	0.93	68.40%
AvgT(-2), Stl(0,-1)	0.027	1.04	0.003	0.85	68.20%
AvgT(-2), Stl(0,-1,-2)	0.026	1.04	0.002	0.9	71.30%
AvgT(-2), Stl(0,-1,-2,-3)	0.063	1.03	0.026	0.95	67.60%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgAvgT(0,-1), MaxT(0)	0.474	1	0.121	1.05	73.20%
AvgAvgT(0,-1), MaxT(-1)	0.004	1.02	0.179	0.9	71.90%
AvgAvgT(0,-1), AvgMaxT(0,-1)	0.212	1.01	0.991	1	70.40%
AvgAvgT(0,-1), AvgMaxT(0,-1-2)	0.016	1.02	0.316	0.96	70.50%
AvgAvgT(0,-1), AvgMaxT(0,-1,-2,-3)	0.002	1.02	0.151	0.88	70.40%
AvgAvgT(0,-1), MinT(0)	0.023	1.01	0.899	0.99	70.40%
AvgAvgT(0,-1), MinT(-1)	0.004	1.02	0.149	0.99	72.00%
AvgAvgT(0,-1), AvgMinT(0,-1)	0.052	1.02	0.596	1	70.80%
AvgAvgT(0,-1), AvgMinT(0,-1,-2)	0.015	1.02	0.356	0.99	71.10%
AvgAvgT(0,-1), AvgMinT(0,-1,-2,-3)	0.004	1.02	0.259	0.99	71.10%
AvgAvgT(0,-1), AvgT(0)	0.919	1	0.08	1.01	73.50%
AvgAvgT(0,-1), AvgT(-1)	0.002	1.03	0.042	0.96	73.50%
AvgAvgT(0,-1), AvgAvgT(0,-1,-2)	0.013	1.03	0.129	0.96	71.30%
AvgAvgT(0,-1), AvgAvgT(0,-1,-2,-3)	0.003	1.02	0.125	0.97	71.10%
AvgAvgT(0,-1), DDMaxT(0)	0.474	1	0.121	1.05	73.20%
AvgAvgT(0,-1), DDMaxT(0,-1)	0.29	1.01	0.848	1	70.70%
AvgAvgT(0,-1), DDMaxT(0,-1,-2)	0.014	1.02	0.29	0.98	70.50%
AvgAvgT(0,-1), DDMaxT(0,-1,-2,-3)	0.002	1.02	0.158	0.97	70.50%
AvgAvgT(0,-1), DDAvgT(0)	0.919	1	0.08	1.01	73.50%
AvgAvgT(0,-1), DDAvgT(0,-1)	0.049	0.31	0.047	1.43	71.30%
AvgAvgT(0,-1), DDAvgT(0,-1,-2)	0.014	1.03	0.133	0.99	71.10%
AvgAvgT(0,-1), DDAvgT(0,-1,-2,-3)	0.003	1.02	0.121	0.99	71.00%
AvgAvgT(0,-1), Day	0.002	1.01	0.069	1.04	71.50%
AvgAvgT(0,-1), MaxT(-2)	0	1.02	0.136	0.93	70.70%
AvgAvgT(0,-1), MinT(-2)	0.002	1.01	0.393	0.99	71.20%
AvgAvgT(0,-1), AvgT(-2)	0.001	1.02	0.181	0.97	71.10%
AvgAvgT(0,-1), HS(0)-HS(-1)	0	1.01	0.009	0.87	73.60%
AvgAvgT(0,-1), HS(0)-HS(-2)	0.001	1.01	0.003	0.9	75.20%
AvgAvgT(0,-1), HS(0)-HS(-3)	0.004	1.01	0.105	0.95	72.10%
AvgAvgT(0,-1), Stl(0,-1)	0	1.01	0.009	0.87	73.60%
AvgAvgT(0,-1), Stl(0,-1,-2)	0	1.01	0.01	0.92	74.20%
AvgAvgT(0,-1), Stl(0,-1,-2,-3)	0.001	1.01	0.069	0.96	72.60%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgAvgT(0,-1,-2), MaxT(0)	0.929	1	0.017	1.07	73.40%
AvgAvgT(0,-1,-2), MaxT(-1)	0.058	1.03	0.664	0.97	67.90%
AvgAvgT(0,-1,-2), AvgMaxT(0,-1)	0.909	1	0.117	1.18	70.30%
AvgAvgT(0,-1,-2), AvgMaxT(0,-1-2)	0.296	1.03	0.91	0.99	67.50%
AvgAvgT(0,-1,-2), AvgMaxT(0,-1,-2,-3)	0.019	1.05	0.187	0.85	68.50%
AvgAvgT(0,-1,-2), MinT(0)	0.154	1.02	0.362	1.08	69.50%
AvgAvgT(0,-1,-2), MinT(-1)	0.083	1.03	0.804	1	68.00%
AvgAvgT(0,-1,-2), AvgMinT(0,-1)	0.5	1.01	0.34	1.01	68.50%
AvgAvgT(0,-1,-2), AvgMinT(0,-1,-2)	0.294	1.02	0.923	1	67.50%
AvgAvgT(0,-1,-2), AvgMinT(0,-1,-2,-3)	0.046	1.04	0.471	0.99	68.10%
AvgAvgT(0,-1,-2), AvgT(0)	0.571	0.99	0.008	1.02	73.40%
AvgAvgT(0,-1,-2), AvgT(-1)	0.145	1.03	0.668	0.99	68.10%
AvgAvgT(0,-1,-2), AvgAvgT(0,-1)	0.129	0.96	0.013	1.03	71.30%
AvgAvgT(0,-1,-2), AvgAvgT(0,-1,-2,-3)	0.022	1.08	0.109	0.95	69.50%
AvgAvgT(0,-1,-2), DDMaxT(0)	0.929	1	0.017	1.07	73.40%
AvgAvgT(0,-1,-2), DDMaxT(0,-1)	0.791	1	0.082	1.03	70.50%
AvgAvgT(0,-1,-2), DDMaxT(0,-1,-2)	0.27	1.03	0.857	1	67.60%
AvgAvgT(0,-1,-2), DDMaxT(0,-1,-2,-3)	0.02	1.05	0.197	0.96	68.30%
AvgAvgT(0,-1,-2), DDAvgT(0)	0.571	0.99	0.008	1.02	73.40%
AvgAvgT(0,-1,-2), DDAvgT(0,-1)	0.124	0.96	0.013	1.01	71.20%
AvgAvgT(0,-1,-2), DDAvgT(0,-1,-2)	0.074	0.05	0.072	1.8	69.00%
AvgAvgT(0,-1,-2), DDAvgT(0,-1,-2,-3)	1.08	1.01	0.104	0.99	69.30%
AvgAvgT(0,-1,-2), Day	0.008	1.02	0.042	1.05	69.50%
AvgAvgT(0,-1,-2), MaxT(-2)	0.001	1.05	0.036	0.87	69.40%
AvgAvgT(0,-1,-2), MinT(-2)	0.009	1.04	0.254	0.99	69.30%
AvgAvgT(0,-1,-2), AvgT(-2)	0.002	1.06	0.03	0.92	71.10%
AvgAvgT(0,-1,-2), HS(0)-HS(-1)	0.001	1.03	0.004	0.85	72.50%
AvgAvgT(0,-1,-2), HS(0)-HS(-2)	0.002	1.03	0.001	0.89	75.30%
AvgAvgT(0,-1,-2), HS(0)-HS(-3)	0.012	1.02	0.045	0.95	71.00%
AvgAvgT(0,-1,-2), Stl(0,-1)	0.001	1.03	0.004	0.85	72.50%
AvgAvgT(0,-1,-2), Stl(0,-1,-2)	0.002	1.03	0.004	0.91	73.50%
AvgAvgT(0,-1,-2), Stl(0,-1,-2,-3)	0.003	1.02	0.044	0.95	71.30%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgAvgT(0,-1,-2,-3), MaxT(0)	0.763	1	0.004	1.08	73.50%
AvgAvgT(0,-1,-2,-3), MaxT(-1)	0.315	1.01	0.527	1.04	65.50%
AvgAvgT(0,-1,-2,-3), AvgMaxT(0,-1)	0.566	0.99	0.02	1.22	71.20%
AvgAvgT(0,-1,-2,-3), AvgMaxT(0,-1-2)	0.848	1	0.179	1.06	66.90%
AvgAvgT(0,-1,-2,-3), AvgMaxT(0,-1,-2,-3)	0.264	1.03	0.702	0.94	65.00%
AvgAvgT(0,-1,-2,-3), MinT(0)	0.385	1.01	0.135	1.12	69.20%
AvgAvgT(0,-1,-2,-3), MinT(-1)	0.4	1.01	0.442	1	65.30%
AvgAvgT(0,-1,-2,-3), AvgMinT(0,-1)	0.987	1	0.07	1.01	67.80%
AvgAvgT(0,-1,-2,-3), AvgMinT(0,-1,-2)	0.936	1	0.184	1.01	66.50%
AvgAvgT(0,-1,-2,-3), AvgMinT(0,-1,-2,-3)	0.462	1.02	0.86	1	65.20%
AvgAvgT(0,-1,-2,-3), AvgT(0)	0.374	0.99	0.002	1.02	73.50%
AvgAvgT(0,-1,-2,-3), AvgT(-1)	0.762	1.01	0.31	1.01	65.50%
AvgAvgT(0,-1,-2,-3), AvgAvgT(0,-1)	0.125	0.97	0.003	1.02	71.10%
AvgAvgT(0,-1,-2,-3), AvgAvgT(0,-1,-2)	0.109	0.95	0.022	1.08	69.50%
AvgAvgT(0,-1,-2,-3), DDMaxT(0)	0.763	1	0.004	1.08	73.50%
AvgAvgT(0,-1,-2,-3), DDMaxT(0,-1)	0.498	0.99	0.014	1.04	71.20%
AvgAvgT(0,-1,-2,-3), DDMaxT(0,-1,-2)	0.878	1	0.195	1.03	66.70%
AvgAvgT(0,-1,-2,-3), DDMaxT(0,-1,-2,-3)	0.28	1.03	0.732	0.99	64.80%
AvgAvgT(0,-1,-2,-3), DDAvgT(0)	0.374	0.99	0.002	1.02	73.50%
AvgAvgT(0,-1,-2,-3), DDAvgT(0,-1)	0.122	0.97	0.003	1.01	71.10%
AvgAvgT(0,-1,-2,-3), DDAvgT(0,-1,-2)	0.105	0.95	0.02	1.01	69.50%
AvgAvgT(0,-1,-2,-3), DDAvgT(0,-1,-2,-3)	0.77	1.11	0.818	0.98	64.90%
AvgAvgT(0,-1,-2,-3), Day	0.027	1.02	0.037	1.05	68.50%
AvgAvgT(0,-1,-2,-3), MaxT(-2)	0.007	1.05	0.089	0.88	66.90%
AvgAvgT(0,-1,-2,-3), MinT(-2)	0.073	1.03	0.64	0.99	65.40%
AvgAvgT(0,-1,-2,-3), AvgT(-2)	0.016	1.05	0.121	0.94	67.60%
AvgAvgT(0,-1,-2,-3), HS(0)-HS(-1)	0.003	1.03	0.002	0.85	71.50%
AvgAvgT(0,-1,-2,-3), HS(0)-HS(-2)	0.003	1.03	0	0.88	75.30%
AvgAvgT(0,-1,-2,-3), HS(0)-HS(-3)	0.022	1.02	0.019	0.94	70.10%
AvgAvgT(0,-1,-2,-3), Stl(0,-1)	0.003	1.03	0.002	0.85	71.50%
AvgAvgT(0,-1,-2,-3), Stl(0,-1,-2)	0.004	1.03	0.002	0.9	73.50%
AvgAvgT(0,-1,-2,-3), Stl(0,-1,-2,-3)	0.008	1.02	0.029	0.95	70.50%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDMaxT(0), MaxT(0)	na	na	na	na	na
DDMaxT(0), AvgMaxT(0,-1)	0.068	1.07	0.986	1	72.60%
DDMaxT(0), AvgMaxT(0,-1-2)	0.01	1.08	0.672	0.99	74.10%
DDMaxT(0), AvgMaxT(0,-1,-2,-3)	0.002	1.09	0.367	0.94	74.00%
DDMaxT(0), MinT(0)	0.007	1.06	0.573	1.04	73.70%
DDMaxT(0), AvgMinT(0,-1)	0.015	1.06	0.443	1	73.60%
DDMaxT(0), AvgMinT(0,-1,-2)	0.008	1.06	0.609	1	73.60%
DDMaxT(0), AvgMinT(0,-1,-2,-3)	0.003	1.07	0.84	1	73.30%
DDMaxT(0), AvgT(0)	0.719	1.02	0.228	1.01	73.80%
DDMaxT(0), AvgAvgT(0,-1)	0.121	1.05	0.474	1	73.20%
DDMaxT(0), AvgAvgT(0,-1,-2)	0.017	1.07	0.929	1	73.40%
DDMaxT(0), AvgAvgT(0,-1,-2,-3)	0.004	1.08	0.763	1	73.50%
DDMaxT(0), DDMaxT(0,-1)	0.088	1.07	0.891	1	73.60%
DDMaxT(0), DDMaxT(0,-1,-2)	0.01	1.08	0.642	0.99	74.00%
DDMaxT(0), DDMaxT(0,-1,-2,-3)	0.002	1.09	0.378	0.98	73.90%
DDMaxT(0), DDAvgT(0)	0.719	1.02	0.228	1.01	73.80%
DDMaxT(0), DDAvgT(0,-1)	0.124	1.05	0.467	1	73.20%
DDMaxT(0), DDAvgT(0,-1,-2)	0.017	1.07	0.922	1	73.20%
DDMaxT(0), DDAvgT(0,-1,-2,-3)	0.004	1.08	0.75	1	73.60%
DDMaxT(0), Day	0.002	1.06	0.19	1.03	74.20%
DDMaxT(0), MaxT(-1)	0.003	1.07	0.987	1	72.60%
DDMaxT(0), MaxT(-2)	0	1.08	0.401	0.96	73.90%
DDMaxT(0), MinT(-1)	0.004	1.07	0.781	1	73.50%
DDMaxT(0), MinT(-2)	0.001	1.07	0.948	1	73.20%
DDMaxT(0), AvgT(-1)	0.006	1.07	0.821	1	73.50%
DDMaxT(0), AvgT(-2)	0.001	1.08	0.685	0.99	73.80%
DDMaxT(0), HS(0)-HS(-1)	0.001	1.06	0.033	0.89	75.10%
DDMaxT(0), HS(0)-HS(-2)	0.001	1.07	0.005	0.9	77.30%
DDMaxT(0), HS(0)-HS(-3)	0.002	1.06	0.12	0.96	74.20%
DDMaxT(0), Stl(0,-1)	0.001	1.06	0.033	0.89	75.10%
DDMaxT(0), Stl(0,-1,-2)	0	1.07	0.015	0.92	76.40%
DDMaxT(0), Stl(0,-1,-2,-3)	0	1.07	0.102	0.96	74.60%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDMaxT(0,-1), MaxT(0)	0.891	1	0.088	1.07	73.60%
DDMaxT(0,-1), MaxT(-1)	0.002	1.06	0.057	0.83	73.50%
DDMaxT(0,-1), AvgMaxT(0,-1)	0.055	1.27	0.085	0.29	70.20%
DDMaxT(0,-1), AvgMaxT(0,-1-2)	0.016	1.07	0.145	0.92	71.60%
DDMaxT(0,-1), AvgMaxT(0,-1,-2,-3)	0.003	1.05	0.108	0.85	71.90%
DDMaxT(0,-1), MinT(0)	0.028	1.02	0.394	1.06	71.50%
DDMaxT(0,-1), MinT(-1)	0.017	1.03	0.978	1	70.10%
DDMaxT(0,-1), AvgMinT(0,-1)	0.075	1.02	0.39	1	70.80%
DDMaxT(0,-1), AvgMinT(0,-1,-2)	0.04	1.02	0.665	1	70.30%
DDMaxT(0,-1), AvgMinT(0,-1,-2,-3)	0.013	1.03	0.963	1	70.10%
DDMaxT(0,-1), AvgT(0)	0.904	1	0.046	1.01	73.40%
DDMaxT(0,-1), AvgT(-1)	0.019	1.04	0.351	0.99	71.60%
DDMaxT(0,-1), AvgAvgT(0,-1)	0.848	1	0.29	1.01	70.70%
DDMaxT(0,-1), AvgAvgT(0,-1,-2)	0.082	1.03	0.791	1	70.50%
DDMaxT(0,-1), AvgAvgT(0,-1,-2,-3)	0.014	1.04	0.498	0.99	71.20%
DDMaxT(0,-1), DDMaxT(0)	0.891	1	0.088	1.07	73.60%
DDMaxT(0,-1), DDMaxT(0,-1,-2)	0.013	1.07	0.125	0.96	71.40%
DDMaxT(0,-1), DDMaxT(0,-1,-2,-3)	0.004	1.05	0.114	0.96	71.90%
DDMaxT(0,-1), DDAvgT(0)	0.904	1	0.046	1.01	73.40%
DDMaxT(0,-1), DDAvgT(0,-1)	0.861	1	0.282	1	70.50%
DDMaxT(0,-1), DDAvgT(0,-1,-2)	0.084	1.03	0.802	1	70.50%
DDMaxT(0,-1), DDAvgT(0,-1,-2,-3)	0.014	1.04	0.486	1	71.00%
DDMaxT(0,-1), Day	0.004	1.02	0.087	1.04	71.10%
DDMaxT(0,-1), MaxT(-2)	0.001	1.04	0.142	0.93	71.40%
DDMaxT(0,-1), MinT(-2)	0.004	1.03	0.811	1	70.70%
DDMaxT(0,-1), AvgT(-2)	0.002	1.04	0.344	0.98	71.40%
DDMaxT(0,-1), HS(0)-HS(-1)	0.001	1.03	0.007	0.86	73.90%
DDMaxT(0,-1), HS(0)-HS(-2)	0.001	1.03	0.003	0.9	75.90%
DDMaxT(0,-1), HS(0)-HS(-3)	0.006	1.02	0.098	0.95	71.90%
DDMaxT(0,-1), Stl(0,-1)	0.001	1.03	0.007	0.86	73.90%
DDMaxT(0,-1), Stl(0,-1,-2)	0.001	1.03	0.01	0.92	74.60%
DDMaxT(0,-1), Stl(0,-1,-2,-3)	0.001	1.03	0.072	0.96	72.80%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDMaxT(0,-1,-2), MaxT(0)	0.642	0.99	0.01	1.08	74.00%
DDMaxT(0,-1,-2), MaxT(-1)	0.115	1.03	0.694	0.97	66.80%
DDMaxT(0,-1,-2), AvgMaxT(0,-1)	0.195	0.97	0.025	1.41	71.80%
DDMaxT(0,-1,-2), AvgMaxT(0,-1-2)	0.22	0.62	0.2	3.04	67.40%
DDMaxT(0,-1,-2), AvgMaxT(0,-1,-2,-3)	0.02	1.08	0.091	0.73	69.80%
DDMaxT(0,-1,-2), MinT(0)	0.139	1.01	0.151	1.11	70.30%
DDMaxT(0,-1,-2), MinT(-1)	0.138	1.02	0.497	1	67.20%
DDMaxT(0,-1,-2), AvgMinT(0,-1)	0.375	1.01	0.118	1.01	69.40%
DDMaxT(0,-1,-2), AvgMinT(0,-1,-2)	0.315	1.01	0.289	1.01	67.60%
DDMaxT(0,-1,-2), AvgMinT(0,-1,-2,-3)	0.122	1.02	0.649	1	66.90%
DDMaxT(0,-1,-2), AvgT(0)	0.641	0.99	0.005	1.02	73.00%
DDMaxT(0,-1,-2), AvgT(-1)	0.365	1.02	0.697	1.01	66.80%
DDMaxT(0,-1,-2), AvgAvgT(0,-1)	0.29	0.98	0.014	1.02	70.50%
DDMaxT(0,-1,-2), AvgAvgT(0,-1,-2)	0.857	1	0.27	1.03	67.60%
DDMaxT(0,-1,-2), AvgAvgT(0,-1,-2,-3)	0.195	1.03	0.878	1	66.70%
DDMaxT(0,-1,-2), DDMaxT(0)	0.642	0.99	0.01	1.08	74.00%
DDMaxT(0,-1,-2), DDMaxT(0,-1)	0.125	0.96	0.013	1.07	71.40%
DDMaxT(0,-1,-2), DDMaxT(0,-1,-2,-3)	0.023	1.08	0.101	0.93	69.70%
DDMaxT(0,-1,-2), DDAvgT(0)	0.641	0.99	0.005	1.02	73.00%
DDMaxT(0,-1,-2), DDAvgT(0,-1)	0.285	0.98	0.014	1.01	70.40%
DDMaxT(0,-1,-2), DDAvgT(0,-1,-2)	0.844	0.99	0.263	1.01	67.60%
DDMaxT(0,-1,-2), DDAvgT(0,-1,-2,-3)	0.191	1.03	0.863	1	66.70%
DDMaxT(0,-1,-2), Day	0.015	1.02	0.05	1.05	69.40%
DDMaxT(0,-1,-2), MaxT(-2)	0.001	1.06	0.018	0.83	71.50%
DDMaxT(0,-1,-2), MinT(-2)	0.031	1.02	0.907	1	66.80%
DDMaxT(0,-1,-2), AvgT(-2)	0.009	1.04	0.177	0.96	69.40%
DDMaxT(0,-1,-2), HS(0)-HS(-1)	0.002	1.03	0.004	0.85	73.30%
DDMaxT(0,-1,-2), HS(0)-HS(-2)	0.003	1.03	0.001	0.89	75.90%
DDMaxT(0,-1,-2), HS(0)-HS(-3)	0.022	1.02	0.046	0.95	70.20%
DDMaxT(0,-1,-2), Stl(0,-1)	0.002	1.03	0.004	0.85	73.30%
DDMaxT(0,-1,-2), Stl(0,-1,-2)	0.003	1.02	0.005	0.91	73.70%
DDMaxT(0,-1,-2), Stl(0,-1,-2,-3)	0.005	1.02	0.047	0.95	71.10%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDMaxT(0,-1,-2,-3), MaxT(0)	0.378	0.98	0.002	1.09	73.90%
DDMaxT(0,-1,-2,-3), MaxT(-1)	0.62	1.01	0.385	1.06	64.80%
DDMaxT(0,-1,-2,-3), AvgMaxT(0,-1)	0.148	0.97	0.006	1.33	72.00%
DDMaxT(0,-1,-2,-3), AvgMaxT(0,-1-2)	0.09	0.93	0.019	1.18	69.70%
DDMaxT(0,-1,-2,-3), AvgMaxT(0,-1,-2,-3)	0.08	14.83	0.083	0	65.80%
DDMaxT(0,-1,-2,-3), MinT(0)	0.348	1.01	0.069	1.13	69.90%
DDMaxT(0,-1,-2,-3), MinT(-1)	0.43	1.01	0.203	1	65.30%
DDMaxT(0,-1,-2,-3), AvgMinT(0,-1)	0.776	1	0.035	1.01	68.10%
DDMaxT(0,-1,-2,-3), AvgMinT(0,-1,-2)	0.819	1	0.092	1.01	66.80%
DDMaxT(0,-1,-2,-3), AvgMinT(0,-1,-2,-3)	0.518	1.01	0.323	1.01	64.90%
DDMaxT(0,-1,-2,-3), AvgT(0)	0.377	0.99	0.001	1.02	73.20%
DDMaxT(0,-1,-2,-3), AvgT(-1)	0.996	1	0.154	1.02	65.40%
DDMaxT(0,-1,-2,-3), AvgAvgT(0,-1)	0.158	0.97	0.002	1.02	70.50%
DDMaxT(0,-1,-2,-3), AvgAvgT(0,-1,-2)	0.197	0.96	0.02	1.05	68.30%
DDMaxT(0,-1,-2,-3), AvgAvgT(0,-1,-2,-3)	0.732	0.99	0.28	1.03	64.80%
DDMaxT(0,-1,-2,-3), DDMaxT(0)	0.378	0.98	0.002	1.09	73.90%
DDMaxT(0,-1,-2,-3), DDMaxT(0,-1)	0.114	0.96	0.004	1.05	71.90%
DDMaxT(0,-1,-2,-3), DDMaxT(0,-1,-2)	0.101	0.93	0.023	1.08	69.70%
DDMaxT(0,-1,-2,-3), DDAvgT(0)	0.377	0.99	0.001	1.02	73.20%
DDMaxT(0,-1,-2,-3), DDAvgT(0,-1)	0.155	0.97	0.002	1.01	70.40%
DDMaxT(0,-1,-2,-3), DDAvgT(0,-1,-2)	0.193	0.96	0.02	1.01	68.40%
DDMaxT(0,-1,-2,-3), DDAvgT(0,-1,-2,-3)	0.738	0.99	0.288	1.01	64.90%
DDMaxT(0,-1,-2,-3), Day	0.054	1.02	0.043	1.05	67.30%
DDMaxT(0,-1,-2,-3), MaxT(-2)	0.008	1.07	0.061	0.85	67.50%
DDMaxT(0,-1,-2,-3), MinT(-2)	0.155	1.02	0.747	1	63.40%
DDMaxT(0,-1,-2,-3), AvgT(-2)	0.08	1.04	0.468	0.98	64.50%
DDMaxT(0,-1,-2,-3), HS(0)-HS(-1)	0.006	1.03	0.003	0.85	71.40%
DDMaxT(0,-1,-2,-3), HS(0)-HS(-2)	0.006	1.03	0	0.88	75.10%
DDMaxT(0,-1,-2,-3), HS(0)-HS(-3)	0.042	1.02	0.02	0.94	69.20%
DDMaxT(0,-1,-2,-3), Stl(0,-1)	0.006	1.03	0.003	0.85	71.40%
DDMaxT(0,-1,-2,-3), Stl(0,-1,-2)	0.008	1.03	0.003	0.9	73.20%
DDMaxT(0,-1,-2,-3), Stl(0,-1,-2,-3)	0.015	1.03	0.031	0.95	70.20%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDAvgT(0), MaxT(0)	0.228	1.01	0.719	1.02	73.80%
DDAvgT(0), AvgMaxT(0,-1)	0.036	1.01	0.981	1	73.30%
DDAvgT(0), AvgMaxT(0,-1-2)	0.005	1.01	0.67	0.99	73.00%
DDAvgT(0), AvgMaxT(0,-1,-2,-3)	0.001	1.02	0.368	0.94	73.10%
DDAvgT(0), MinT(0)	0.002	1.02	0.176	0.86	74.40%
DDAvgT(0), AvgMinT(0,-1)	0.009	1.02	0.57	1	73.80%
DDAvgT(0), AvgMinT(0,-1,-2)	0.004	1.02	0.579	1	73.60%
DDAvgT(0), AvgMinT(0,-1,-2,-3)	0.001	1.02	0.443	1	73.70%
DDAvgT(0), AvgT(0)	na	na	na	na	na
DDAvgT(0), AvgAvgT(0,-1)	0.08	1.01	0.919	1	73.50%
DDAvgT(0), AvgAvgT(0,-1,-2)	0.008	1.02	0.571	0.99	73.40%
DDAvgT(0), AvgAvgT(0,-1,-2,-3)	0.002	1.02	0.374	0.99	73.50%
DDAvgT(0), DDMaxT(0)	0.228	1.01	0.719	1.02	73.80%
DDAvgT(0), DDMaxT(0,-1)	0.046	1.01	0.904	1	73.40%
DDAvgT(0), DDMaxT(0,-1,-2)	0.005	1.02	0.641	0.99	73.00%
DDAvgT(0), DDMaxT(0,-1,-2,-3)	0.001	1.02	0.377	0.99	73.20%
DDAvgT(0), DDAvgT(0,-1)	0.082	1.01	0.931	1	73.50%
DDAvgT(0), DDAvgT(0,-1,-2)	0.008	1.02	0.578	1	73.40%
DDAvgT(0), DDAvgT(0,-1,-2,-3)	0.002	1.02	0.365	1	73.40%
DDAvgT(0), Day	0.001	1.01	0.154	1.04	73.80%
DDAvgT(0), MaxT(-1)	0.002	1.01	0.877	0.99	73.40%
DDAvgT(0), MaxT(-2)	0	1.01	0.384	0.96	73.00%
DDAvgT(0), MinT(-1)	0.002	1.01	0.616	1	73.80%
DDAvgT(0), MinT(-2)	0	1.01	0.682	1	73.50%
DDAvgT(0), AvgT(-1)	0.004	1.01	0.79	1	73.30%
DDAvgT(0), AvgT(-2)	0	1.01	0.493	0.99	73.20%
DDAvgT(0), HS(0)-HS(-1)	0	1.01	0.037	0.89	75.00%
DDAvgT(0), HS(0)-HS(-2)	0	1.01	0.008	0.91	76.20%
DDAvgT(0), HS(0)-HS(-3)	0.001	1.01	0.127	0.96	74.40%
DDAvgT(0), Stl(0,-1)	0	1.01	0.037	0.89	75.00%
DDAvgT(0), Stl(0,-1,-2)	0	1.01	0.018	0.92	75.80%
DDAvgT(0), Stl(0,-1,-2,-3)	0	1.01	0.113	0.96	73.90%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDAvgT(0,-1), MaxT(0)	0.467	1	0.124	1.05	73.20%
DDAvgT(0,-1), MaxT(-1)	0.003	1.01	0.177	0.9	71.80%
DDAvgT(0,-1), AvgMaxT(0,-1)	0.206	1	0.98	1	70.40%
DDAvgT(0,-1), AvgMaxT(0,-1-2)	0.015	1.01	0.31	0.96	70.30%
DDAvgT(0,-1), AvgMaxT(0,-1,-2,-3)	0.002	1.01	0.149	0.88	70.40%
DDAvgT(0,-1), MinT(0)	0.023	1	0.894	0.99	70.30%
DDAvgT(0,-1), MinT(-1)	0.004	1.01	0.146	0.99	72.00%
DDAvgT(0,-1), AvgMinT(0,-1)	0.05	1	0.586	1	70.60%
DDAvgT(0,-1), AvgMinT(0,-1,-2)	0.014	1.01	0.349	0.99	70.80%
DDAvgT(0,-1), AvgMinT(0,-1,-2,-3)	0.004	1.01	0.255	0.99	70.90%
DDAvgT(0,-1), AvgT(0)	0.931	1	0.082	1.01	73.50%
DDAvgT(0,-1), AvgT(-1)	0.002	1.01	0.041	0.96	73.60%
DDAvgT(0,-1), AvgAvgT(0,-1)	0.047	1.43	0.049	0.31	71.30%
DDAvgT(0,-1), AvgAvgT(0,-1,-2)	0.013	1.01	0.124	0.96	71.20%
DDAvgT(0,-1), AvgAvgT(0,-1,-2,-3)	0.003	1.01	0.122	0.97	71.10%
DDAvgT(0,-1), DDMaxT(0)	0.467	1	0.124	1.05	73.20%
DDAvgT(0,-1), DDMaxT(0,-1)	0.282	1	0.861	1	70.50%
DDAvgT(0,-1), DDMaxT(0,-1,-2)	0.014	1.01	0.285	0.98	70.40%
DDAvgT(0,-1), DDMaxT(0,-1,-2,-3)	0.002	1.01	0.155	0.97	70.40%
DDAvgT(0,-1), DDAvgT(0)	0.931	1	0.082	1.01	73.50%
DDAvgT(0,-1), DDAvgT(0,-1,-2)	0.013	1.01	0.128	0.99	71.10%
DDAvgT(0,-1), DDAvgT(0,-1,-2,-3)	0.003	1.01	0.119	0.99	71.10%
DDAvgT(0,-1), Day	0.002	1	0.069	1.04	71.50%
DDAvgT(0,-1), MaxT(-2)	0	1.01	0.134	0.93	70.70%
DDAvgT(0,-1), MinT(-2)	0.002	1	0.389	0.99	71.20%
DDAvgT(0,-1), AvgT(-2)	0.001	1.01	0.178	0.97	71.10%
DDAvgT(0,-1), HS(0)-HS(-1)	0	1	0.009	0.87	73.70%
DDAvgT(0,-1), HS(0)-HS(-2)	0.001	1	0.003	0.9	75.20%
DDAvgT(0,-1), HS(0)-HS(-3)	0.003	1	0.105	0.95	72.20%
DDAvgT(0,-1), Stl(0,-1)	0	1	0.009	0.87	73.70%
DDAvgT(0,-1), Stl(0,-1,-2)	0	1	0.01	0.92	74.20%
DDAvgT(0,-1), Stl(0,-1,-2,-3)	0.001	1	0.069	0.96	72.70%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDAvgT(0,-1,-2), MaxT(0)	0.922	1	0.017	1.07	73.20%
DDAvgT(0,-1,-2), MaxT(-1)	0.057	1.01	0.658	0.97	68.10%
DDAvgT(0,-1,-2), AvgMaxT(0,-1)	0.92	1	0.119	1.18	70.30%
DDAvgT(0,-1,-2), AvgMaxT(0,-1-2)	0.288	1.01	0.897	0.99	67.60%
DDAvgT(0,-1,-2), AvgMaxT(0,-1,-2,-3)	0.018	1.01	0.183	0.85	68.50%
DDAvgT(0,-1,-2), MinT(0)	0.151	1	0.364	1.08	69.40%
DDAvgT(0,-1,-2), MinT(-1)	0.081	1.01	0.796	1	68.00%
DDAvgT(0,-1,-2), AvgMinT(0,-1)	0.493	1	0.345	1.01	68.50%
DDAvgT(0,-1,-2), AvgMinT(0,-1,-2)	0.287	1	0.934	1	67.60%
DDAvgT(0,-1,-2), AvgMinT(0,-1,-2,-3)	0.044	1.01	0.464	0.99	68.00%
DDAvgT(0,-1,-2), AvgT(0)	0.578	1	0.008	1.02	73.40%
DDAvgT(0,-1,-2), AvgT(-1)	0.141	1.01	0.656	0.99	68.20%
DDAvgT(0,-1,-2), AvgAvgT(0,-1)	0.133	0.99	0.014	1.03	71.10%
DDAvgT(0,-1,-2), AvgAvgT(0,-1,-2)	0.072	1.8	0.074	0.05	69.00%
DDAvgT(0,-1,-2), AvgAvgT(0,-1,-2,-3)	0.02	1.01	0.105	0.95	69.50%
DDAvgT(0,-1,-2), DDMaxT(0)	0.922	1	0.017	1.07	73.20%
DDAvgT(0,-1,-2), DDMaxT(0,-1)	0.802	1	0.084	1.03	70.50%
DDAvgT(0,-1,-2), DDMaxT(0,-1,-2)	0.263	1.01	0.844	0.99	67.60%
DDAvgT(0,-1,-2), DDMaxT(0,-1,-2,-3)	0.02	1.01	0.193	0.96	68.40%
DDAvgT(0,-1,-2), DDAvgT(0)	0.578	1	0.008	1.02	73.40%
DDAvgT(0,-1,-2), DDAvgT(0,-1)	0.128	0.99	0.013	1.01	71.10%
DDAvgT(0,-1,-2), DDAvgT(0,-1,-2,-3)	0.02	1.01	0.1	0.99	69.30%
DDAvgT(0,-1,-2), Day	0.008	1	0.042	1.05	69.50%
DDAvgT(0,-1,-2), MaxT(-2)	0.001	1.01	0.036	0.86	69.30%
DDAvgT(0,-1,-2), MinT(-2)	0.009	1.01	0.251	0.99	69.50%
DDAvgT(0,-1,-2), AvgT(-2)	0.001	1.01	0.029	0.92	71.00%
DDAvgT(0,-1,-2), HS(0)-HS(-1)	0.001	1.01	0.004	0.85	72.40%
DDAvgT(0,-1,-2), HS(0)-HS(-2)	0.002	1.01	0.001	0.89	75.30%
DDAvgT(0,-1,-2), HS(0)-HS(-3)	0.012	1	0.046	0.95	71.00%
DDAvgT(0,-1,-2), Stl(0,-1)	0.001	1.01	0.004	0.85	72.40%
DDAvgT(0,-1,-2), Stl(0,-1,-2)	0.002	1.01	0.004	0.91	73.60%
DDAvgT(0,-1,-2), Stl(0,-1,-2,-3)	0.003	1	0.044	0.95	71.30%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDAvgT(0,-1,-2,-3), MaxT(0)	0.75	1	0.004	1.08	73.60%
DDAvgT(0,-1,-2,-3), MaxT(-1)	0.321	1	0.523	1.04	65.40%
DDAvgT(0,-1,-2,-3), AvgMaxT(0,-1)	0.551	1	0.02	1.22	71.20%
DDAvgT(0,-1,-2,-3), AvgMaxT(0,-1-2)	0.834	1	0.174	1.06	66.90%
DDAvgT(0,-1,-2,-3), AvgMaxT(0,-1,-2,-3)	0.271	1.01	0.707	0.94	65.10%
DDAvgT(0,-1,-2,-3), MinT(0)	0.392	1	0.134	1.12	69.30%
DDAvgT(0,-1,-2,-3), MinT(-1)	0.406	1	0.437	1	65.20%
DDAvgT(0,-1,-2,-3), AvgMinT(0,-1)	0.995	1	0.069	1.01	67.80%
DDAvgT(0,-1,-2,-3), AvgMinT(0,-1,-2)	0.926	1	0.18	1.01	66.60%
DDAvgT(0,-1,-2,-3), AvgMinT(0,-1,-2,-3)	0.472	1	0.845	1	65.20%
DDAvgT(0,-1,-2,-3), AvgT(0)	0.365	1	0.002	1.02	73.40%
DDAvgT(0,-1,-2,-3), AvgT(-1)	0.772	1	0.305	1.01	65.50%
DDAvgT(0,-1,-2,-3), AvgAvgT(0,-1)	0.121	0.99	0.003	1.02	71.00%
DDAvgT(0,-1,-2,-3), AvgAvgT(0,-1,-2)	0.104	0.99	0.021	1.08	69.30%
DDAvgT(0,-1,-2,-3), AvgAvgT(0,-1,-2,-3)	0.818	0.98	0.77	1.11	64.90%
DDAvgT(0,-1,-2,-3), DDMaxT(0)	0.75	1	0.004	1.08	73.60%
DDAvgT(0,-1,-2,-3), DDMaxT(0,-1)	0.486	1	0.014	1.04	71.00%
DDAvgT(0,-1,-2,-3), DDMaxT(0,-1,-2)	0.863	1	0.191	1.03	66.70%
DDAvgT(0,-1,-2,-3), DDMaxT(0,-1,-2,-3)	0.288	1.01	0.738	0.99	64.90%
DDAvgT(0,-1,-2,-3), DDAvgT(0)	0.365	1	0.002	1.02	73.40%
DDAvgT(0,-1,-2,-3), DDAvgT(0,-1)	0.119	0.99	0.003	1.01	71.10%
DDAvgT(0,-1,-2,-3), DDAvgT(0,-1,-2)	0.1	0.99	0.02	1	69.30%
DDAvgT(0,-1,-2,-3), Day	0.028	1.01	0.037	1.05	68.30%
DDAvgT(0,-1,-2,-3), MaxT(-2)	0.007	1.01	0.091	0.88	66.80%
DDAvgT(0,-1,-2,-3), MinT(-2)	0.075	1.01	0.647	0.99	65.30%
DDAvgT(0,-1,-2,-3), AvgT(-2)	0.017	1.01	0.125	0.94	67.50%
DDAvgT(0,-1,-2,-3), HS(0)-HS(-1)	0.003	1.01	0.002	0.85	71.20%
DDAvgT(0,-1,-2,-3), HS(0)-HS(-2)	0.003	1.01	0	0.88	75.20%
DDAvgT(0,-1,-2,-3), HS(0)-HS(-3)	0.023	1.01	0.019	0.94	70.30%
DDAvgT(0,-1,-2,-3), Stl(0,-1)	0.003	1.01	0.002	0.85	71.20%
DDAvgT(0,-1,-2,-3), Stl(0,-1,-2)	0.004	1.01	0.002	0.9	73.60%
DDAvgT(0,-1,-2,-3), Stl(0,-1,-2,-3)	0.009	1.01	0.029	0.95	70.70%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HS(0)-HS(-1), HS(0)-HS(-2)	0.774	0.98	0.037	0.91	71.40%
HS(0)-HS(-1), HS(0)-HS(-3)	0.204	0.93	0.098	0.95	69.20%
HS(0)-HS(-1), Stl(0,-1)	na	na	na	na	na
HS(0)-HS(-1), Stl(0,-1,-2)	0.299	0.94	0.121	0.94	67.50%
HS(0)-HS(-1), Stl(0,-1,-2,-3)	0.08	0.9	0.34	0.97	66.30%
HS(0)-HS(-1), Day	0.018	0.89	0.039	1.05	67.30%
HS(0)-HS(-1), MaxT(0)	0.033	0.89	0.001	1.06	75.10%
HS(0)-HS(-1), MaxT(-1)	0.002	0.85	0.004	1.12	70.30%
HS(0)-HS(-1), MaxT(-2)	0.003	0.86	0.061	1.07	67.80%
HS(0)-HS(-1), AvgMaxT(0,-1)	0.007	0.86	0.001	1.17	73.90%
HS(0)-HS(-1), AvgMaxT(0,-1-2)	0.004	0.85	0.002	1.06	73.00%
HS(0)-HS(-1), AvgMaxT(0,-1,-2,-3)	0.003	0.85	0.006	1.14	71.60%
HS(0)-HS(-1), MinT(0)	0.013	0.88	0.008	1.16	70.90%
HS(0)-HS(-1), MinT(-1)	0.005	0.86	0.005	1.01	69.40%
HS(0)-HS(-1), MinT(-2)	0.003	0.86	0.025	1.01	66.10%
HS(0)-HS(-1), AvgMinT(0,-1)	0.008	0.87	0.002	1.01	71.60%
HS(0)-HS(-1), AvgMinT(0,-1,-2)	0.004	0.86	0.002	1.01	70.40%
HS(0)-HS(-1), AvgMinT(0,-1,-2,-3)	0.003	0.85	0.005	1.01	70.00%
HS(0)-HS(-1), AvgT(0)	0.037	0.89	0	1.01	75.00%
HS(0)-HS(-1), AvgT(-1)	0.003	0.85	0.002	1.02	71.00%
HS(0)-HS(-1), AvgT(-2)	0.003	0.85	0.027	1.04	68.20%
HS(0)-HS(-1), AvgAvgT(0,-1)	0.009	0.87	0	1.01	73.60%
HS(0)-HS(-1), AvgAvgT(0,-1,-2)	0.004	0.85	0.001	1.03	72.50%
HS(0)-HS(-1), AvgAvgT(0,-1,-2,-3)	0.002	0.85	0.003	1.03	71.50%
HS(0)-HS(-1), DDMaxT(0)	0.033	0.89	0.001	1.06	75.10%
HS(0)-HS(-1), DDMaxT(0,-1)	0.007	0.86	0.001	1.03	73.90%
HS(0)-HS(-1), DDMaxT(0,-1,-2)	0.004	0.85	0.002	1.03	73.30%
HS(0)-HS(-1), DDMaxT(0,-1,-2,-3)	0.003	0.85	0.006	1.03	71.40%
HS(0)-HS(-1), DDAvgT(0)	0.037	0.89	0	1.01	75.00%
HS(0)-HS(-1), DDAvgT(0,-1)	0.009	0.87	0	1	73.70%
HS(0)-HS(-1), DDAvgT(0,-1,-2)	0.004	0.85	0.001	1.01	72.40%
HS(0)-HS(-1), DDAvgT(0,-1,-2,-3)	0.002	0.85	0.003	1.01	71.20%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HS(0)-HS(-2), HS(0)-HS(-1)	0.037	0.91	0.774	0.98	71.40%
HS(0)-HS(-2), HS(0)-HS(-3)	0.066	0.92	0.482	0.98	72.80%
HS(0)-HS(-2), Stl(0,-1)	0.037	0.91	0.774	0.98	71.40%
HS(0)-HS(-2), Stl(0,-1,-2)	na	na	na	na	na
HS(0)-HS(-2), Stl(0,-1,-2,-3)	0.025	0.88	0.749	1.01	72.80%
HS(0)-HS(-2), Day	0.002	0.9	0.035	1.05	72.60%
HS(0)-HS(-2), MaxT(0)	0.005	0.9	0.001	1.07	77.30%
HS(0)-HS(-2), MaxT(-1)	0.001	0.89	0.01	1.1	74.70%
HS(0)-HS(-2), MaxT(-2)	0	0.88	0.031	1.08	73.70%
HS(0)-HS(-2), AvgMaxT(0,-1)	0.003	0.9	0.002	1.16	76.20%
HS(0)-HS(-2), AvgMaxT(0,-1-2)	0.001	0.89	0.002	1.06	75.80%
HS(0)-HS(-2), AvgMaxT(0,-1,-2,-3)	0	0.88	0.006	1.14	75.00%
HS(0)-HS(-2), MinT(0)	0.004	0.9	0.013	1.16	75.00%
HS(0)-HS(-2), MinT(-1)	0.001	0.89	0.007	1.01	73.50%
HS(0)-HS(-2), MinT(-2)	0	0.88	0.016	1.02	72.50%
HS(0)-HS(-2), AvgMinT(0,-1)	0.003	0.9	0.003	1.01	74.20%
HS(0)-HS(-2), AvgMinT(0,-1,-2)	0.001	0.89	0.003	1.01	74.20%
HS(0)-HS(-2), AvgMinT(0,-1,-2,-3)	0.001	0.88	0.005	1.01	74.40%
HS(0)-HS(-2), AvgT(0)	0.008	0.91	0	1.01	76.20%
HS(0)-HS(-2), AvgT(-1)	0.001	0.89	0.004	1.02	74.10%
HS(0)-HS(-2), AvgT(-2)	0	0.87	0.013	1.04	73.30%
HS(0)-HS(-2), AvgAvgT(0,-1)	0.003	0.9	0.001	1.01	75.20%
HS(0)-HS(-2), AvgAvgT(0,-1,-2)	0.001	0.89	0.002	1.03	75.30%
HS(0)-HS(-2), AvgAvgT(0,-1,-2,-3)	0	0.88	0.003	1.03	75.30%
HS(0)-HS(-2), DDMaxT(0)	0.005	0.9	0.001	1.07	77.30%
HS(0)-HS(-2), DDMaxT(0,-1)	0.003	0.9	0.001	1.03	75.90%
HS(0)-HS(-2), DDMaxT(0,-1,-2)	0.001	0.89	0.003	1.03	75.90%
HS(0)-HS(-2), DDMaxT(0,-1,-2,-3)	0	0.88	0.006	1.03	75.10%
HS(0)-HS(-2), DDAvgT(0)	0.008	0.91	0	1.01	76.20%
HS(0)-HS(-2), DDAvgT(0,-1)	0.003	0.9	0.001	1	75.20%
HS(0)-HS(-2), DDAvgT(0,-1,-2)	0.001	0.89	0.002	1.01	75.30%
HS(0)-HS(-2), DDAvgT(0,-1,-2,-3)	0	0.88	0.003	1.01	75.20%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HS(0)-HS(-3), HS(0)-HS(-1)	0.098	0.95	0.204	0.93	69.20%
HS(0)-HS(-3), HS(0)-HS(-2)	0.482	0.98	0.066	0.92	72.80%
HS(0)-HS(-3), Stl(0,-1)	0.098	0.95	0.204	0.93	69.20%
HS(0)-HS(-3), Stl(0,-1,-2)	0.172	0.96	0.172	0.95	70.90%
HS(0)-HS(-3), Stl(0,-1,-2,-3)	0.086	0.94	0.795	0.99	66.70%
HS(0)-HS(-3), Day	0.01	0.94	0.033	1.05	69.50%
HS(0)-HS(-3), MaxT(0)	0.12	0.96	0.002	1.06	74.20%
HS(0)-HS(-3), MaxT(-1)	0.031	0.94	0.054	1.08	68.60%
HS(0)-HS(-3), MaxT(-2)	0.008	0.93	0.255	1.04	68.60%
HS(0)-HS(-3), AvgMaxT(0,-1)	0.09	0.95	0.008	1.14	72.00%
HS(0)-HS(-3), AvgMaxT(0,-1-2)	0.047	0.95	0.021	1.04	70.30%
HS(0)-HS(-3), AvgMaxT(0,-1,-2,-3)	0.02	0.94	0.043	1.1	69.30%
HS(0)-HS(-3), MinT(0)	0.031	0.94	0.02	1.15	72.30%
HS(0)-HS(-3), MinT(-1)	0.031	0.94	0.038	1.01	69.30%
HS(0)-HS(-3), MinT(-2)	0.007	0.93	0.083	1.01	68.30%
HS(0)-HS(-3), AvgMinT(0,-1)	0.051	0.95	0.01	1.01	71.60%
HS(0)-HS(-3), AvgMinT(0,-1,-2)	0.029	0.94	0.014	1.01	70.50%
HS(0)-HS(-3), AvgMinT(0,-1,-2,-3)	0.014	0.94	0.021	1.01	70.10%
HS(0)-HS(-3), AvgT(0)	0.127	0.96	0.001	1.01	74.40%
HS(0)-HS(-3), AvgT(-1)	0.04	0.95	0.029	1.01	69.30%
HS(0)-HS(-3), AvgT(-2)	0.008	0.93	0.125	1.02	68.40%
HS(0)-HS(-3), AvgAvgT(0,-1)	0.105	0.95	0.004	1.01	72.10%
HS(0)-HS(-3), AvgAvgT(0,-1,-2)	0.045	0.95	0.012	1.02	71.00%
HS(0)-HS(-3), AvgAvgT(0,-1,-2,-3)	0.019	0.94	0.022	1.02	70.10%
HS(0)-HS(-3), DDMaxT(0)	0.12	0.96	0.002	1.06	74.20%
HS(0)-HS(-3), DDMaxT(0,-1)	0.098	0.95	0.006	1.02	71.90%
HS(0)-HS(-3), DDMaxT(0,-1,-2)	0.046	0.95	0.022	1.02	70.20%
HS(0)-HS(-3), DDMaxT(0,-1,-2,-3)	0.02	0.94	0.042	1.02	69.20%
HS(0)-HS(-3), DDAvgT(0)	0.127	0.96	0.001	1.01	74.40%
HS(0)-HS(-3), DDAvgT(0,-1)	0.105	0.95	0.003	1	72.20%
HS(0)-HS(-3), DDAvgT(0,-1,-2)	0.046	0.95	0.012	1	71.00%
HS(0)-HS(-3), DDAvgT(0,-1,-2,-3)	0.019	0.94	0.023	1.01	70.30%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
Stl(0,-1), HS(0)-HS(-1)	na	na	na	na	na
Stl(0,-1), HS(0)-HS(-2)	0.774	0.98	0.037	0.91	71.40%
Stl(0,-1), HS(0)-HS(-3)	0.204	0.93	0.098	0.95	69.20%
Stl(0,-1), Stl(0,-1,-2)	0.299	0.94	0.121	0.94	67.50%
Stl(0,-1), Stl(0,-1,-2,-3)	0.08	0.9	0.34	0.97	66.30%
Stl(0,-1), Day	0.018	0.89	0.039	1.05	67.30%
Stl(0,-1), MaxT(0)	0.033	0.89	0.001	1.06	75.10%
Stl(0,-1), MaxT(-1)	0.002	0.85	0.004	1.12	70.30%
Stl(0,-1), MaxT(-2)	0.003	0.86	0.061	1.07	67.80%
Stl(0,-1), AvgMaxT(0,-1)	0.007	0.86	0.001	1.17	73.90%
Stl(0,-1), AvgMaxT(0,-1-2)	0.004	0.85	0.002	1.06	73.00%
Stl(0,-1), AvgMaxT(0,-1,-2,-3)	0.003	0.85	0.006	1.14	71.60%
Stl(0,-1), MinT(0)	0.013	0.88	0.008	1.16	70.90%
Stl(0,-1), MinT(-1)	0.005	0.86	0.005	1.01	69.40%
Stl(0,-1), MinT(-2)	0.003	0.86	0.025	1.01	66.10%
Stl(0,-1), AvgMinT(0,-1)	0.008	0.87	0.002	1.01	71.60%
Stl(0,-1), AvgMinT(0,-1,-2)	0.004	0.86	0.002	1.01	70.40%
Stl(0,-1), AvgMinT(0,-1,-2,-3)	0.003	0.85	0.005	1.01	70.00%
Stl(0,-1), AvgT(0)	0.037	0.89	0	1.01	75.00%
Stl(0,-1), AvgT(-1)	0.003	0.85	0.002	1.02	71.00%
Stl(0,-1), AvgT(-2)	0.003	0.85	0.027	1.04	68.20%
Stl(0,-1), AvgAvgT(0,-1)	0.009	0.87	0	1.01	73.60%
Stl(0,-1), AvgAvgT(0,-1,-2)	0.004	0.85	0.001	1.03	72.50%
Stl(0,-1), AvgAvgT(0,-1,-2,-3)	0.002	0.85	0.003	1.03	71.50%
Stl(0,-1), DDMaxT(0)	0.033	0.89	0.001	1.06	75.10%
Stl(0,-1), DDMaxT(0,-1)	0.007	0.86	0.001	1.03	73.90%
Stl(0,-1), DDMaxT(0,-1,-2)	0.004	0.85	0.002	1.03	73.30%
Stl(0,-1), DDMaxT(0,-1,-2,-3)	0.003	0.85	0.006	1.03	71.40%
Stl(0,-1), DDAvgT(0)	0.037	0.89	0	1.01	75.00%
Stl(0,-1), DDAvgT(0,-1)	0.009	0.87	0	1	73.70%
Stl(0,-1), DDAvgT(0,-1,-2)	0.004	0.85	0.001	1.01	72.40%
Stl(0,-1), DDAvgT(0,-1,-2,-3)	0.002	0.85	0.003	1.01	71.20%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
Stl(0,-1,-2), HS(0)-HS(-1)	0.121	0.94	0.299	0.94	67.50%
Stl(0,-1,-2), HS(0)-HS(-2)	na	na	na	na	na
Stl(0,-1,-2), HS(0)-HS(-3)	0.172	0.95	0.172	0.96	70.90%
Stl(0,-1,-2), Stl(0,-1)	0.121	0.94	0.299	0.94	67.50%
Stl(0,-1,-2), Stl(0,-1,-2,-3)	0.078	0.91	0.871	1.01	70.70%
Stl(0,-1,-2), Day	0.004	0.91	0.018	1.06	70.90%
Stl(0,-1,-2), MaxT(0)	0.015	0.92	0	1.07	76.40%
Stl(0,-1,-2), MaxT(-1)	0.004	0.91	0.01	1.1	72.70%
Stl(0,-1,-2), MaxT(-2)	0.002	0.9	0.054	1.07	71.70%
Stl(0,-1,-2), AvgMaxT(0,-1)	0.01	0.92	0.001	1.17	74.60%
Stl(0,-1,-2), AvgMaxT(0,-1-2)	0.005	0.91	0.003	1.06	73.60%
Stl(0,-1,-2), AvgMaxT(0,-1,-2,-3)	0.003	0.9	0.008	1.14	73.10%
Stl(0,-1,-2), MinT(0)	0.01	0.92	0.008	1.17	73.80%
Stl(0,-1,-2), MinT(-1)	0.004	0.91	0.006	1.01	71.50%
Stl(0,-1,-2), MinT(-2)	0.002	0.91	0.03	1.01	70.70%
Stl(0,-1,-2), AvgMinT(0,-1)	0.008	0.92	0.002	1.01	72.80%
Stl(0,-1,-2), AvgMinT(0,-1,-2)	0.005	0.91	0.003	1.01	72.40%
Stl(0,-1,-2), AvgMinT(0,-1,-2,-3)	0.003	0.9	0.006	1.01	72.40%
Stl(0,-1,-2), AvgT(0)	0.018	0.92	0	1.01	75.80%
Stl(0,-1,-2), AvgT(-1)	0.004	0.91	0.004	1.02	72.60%
Stl(0,-1,-2), AvgT(-2)	0.002	0.9	0.026	1.04	71.30%
Stl(0,-1,-2), AvgAvgT(0,-1)	0.01	0.92	0	1.01	74.20%
Stl(0,-1,-2), AvgAvgT(0,-1,-2)	0.004	0.91	0.002	1.03	73.50%
Stl(0,-1,-2), AvgAvgT(0,-1,-2,-3)	0.002	0.9	0.004	1.03	73.50%
Stl(0,-1,-2), DDMaxT(0)	0.015	0.92	0	1.07	76.40%
Stl(0,-1,-2), DDMaxT(0,-1)	0.01	0.92	0.001	1.03	74.60%
Stl(0,-1,-2), DDMaxT(0,-1,-2)	0.005	0.91	0.003	1.02	73.70%
Stl(0,-1,-2), DDMaxT(0,-1,-2,-3)	0.003	0.9	0.008	1.03	73.20%
Stl(0,-1,-2), DDAvgT(0)	0.018	0.92	0	1.01	75.80%
Stl(0,-1,-2), DDAvgT(0,-1)	0.01	0.92	0	1	74.20%
Stl(0,-1,-2), DDAvgT(0,-1,-2)	0.004	0.91	0.002	1.01	73.60%
Stl(0,-1,-2), DDAvgT(0,-1,-2,-3)	0.002	0.9	0.004	1.01	73.60%

Old Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
Stl(0,-1,-2,-3), HS(0)-HS(-1)	0.34	0.97	0.08	0.9	66.30%
Stl(0,-1,-2,-3), HS(0)-HS(-2)	0.749	1.01	0.025	0.88	72.80%
Stl(0,-1,-2,-3), HS(0)-HS(-3)	0.795	0.99	0.086	0.94	66.70%
Stl(0,-1,-2,-3), Stl(0,-1)	0.34	0.97	0.08	0.9	66.30%
Stl(0,-1,-2,-3), Stl(0,-1,-2)	0.871	1.01	0.078	0.91	70.70%
Stl(0,-1,-2,-3), Day	0.034	0.95	0.02	1.05	67.80%
Stl(0,-1,-2,-3), MaxT(0)	0.102	0.96	0	1.07	74.60%
Stl(0,-1,-2,-3), MaxT(-1)	0.044	0.95	0.013	1.1	69.10%
Stl(0,-1,-2,-3), MaxT(-2)	0.026	0.95	0.124	1.05	67.70%
Stl(0,-1,-2,-3), AvgMaxT(0,-1)	0.068	0.96	0.001	1.17	72.90%
Stl(0,-1,-2,-3), AvgMaxT(0,-1-2)	0.048	0.95	0.004	1.05	70.80%
Stl(0,-1,-2,-3), AvgMaxT(0,-1,-2,-3)	0.031	0.95	0.015	1.12	70.20%
Stl(0,-1,-2,-3), MinT(0)	0.058	0.96	0.008	1.17	71.90%
Stl(0,-1,-2,-3), MinT(-1)	0.043	0.95	0.008	1.01	69.00%
Stl(0,-1,-2,-3), MinT(-2)	0.032	0.95	0.059	1.01	67.20%
Stl(0,-1,-2,-3), AvgMinT(0,-1)	0.054	0.95	0.002	1.01	71.50%
Stl(0,-1,-2,-3), AvgMinT(0,-1,-2)	0.044	0.95	0.004	1.01	70.00%
Stl(0,-1,-2,-3), AvgMinT(0,-1,-2,-3)	0.031	0.95	0.011	1.01	70.10%
Stl(0,-1,-2,-3), AvgT(0)	0.113	0.96	0	1.01	73.90%
Stl(0,-1,-2,-3), AvgT(-1)	0.043	0.95	0.005	1.02	69.60%
Stl(0,-1,-2,-3), AvgT(-2)	0.026	0.95	0.063	1.03	67.60%
Stl(0,-1,-2,-3), AvgAvgT(0,-1)	0.069	0.96	0.001	1.01	72.60%
Stl(0,-1,-2,-3), AvgAvgT(0,-1,-2)	0.044	0.95	0.003	1.02	71.30%
Stl(0,-1,-2,-3), AvgAvgT(0,-1,-2,-3)	0.029	0.95	0.008	1.02	70.50%
Stl(0,-1,-2,-3), DDMaxT(0)	0.102	0.96	0	1.07	74.60%
Stl(0,-1,-2,-3), DDMaxT(0,-1)	0.96	0.91	0.001	1.03	72.80%
Stl(0,-1,-2,-3), DDMaxT(0,-1,-2)	0.047	0.95	0.005	1.02	71.10%
Stl(0,-1,-2,-3), DDMaxT(0,-1,-2,-3)	0.031	0.95	0.015	1.03	70.20%
Stl(0,-1,-2,-3), DDAvgT(0)	0.113	0.96	0	1.01	73.90%
Stl(0,-1,-2,-3), DDAvgT(0,-1)	0.069	0.96	0.001	1	72.70%
Stl(0,-1,-2,-3), DDAvgT(0,-1,-2)	0.044	0.95	0.003	1	71.30%
Stl(0,-1,-2,-3), DDAvgT(0,-1,-2,-3)	0.029	0.91	0.009	1	70.70%

"NEW SNOW BINOMIAL LOGISTIC REGRESSION RESULTS"

The following charts provide the new snow binomial logistic regression results. Each significant new snow variable was entered into the binomial logistic regression equation individually and in groups of two and the resulting p-values, odds ratios and percent concordant pairs are tabulated in the charts.

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	Variable P-Value	Variable Odds Ratio	Percent Concordant Pairs
MinT(0)	0.03	1.11	60.70%
AvgMinT(0,-1)	0.115	1.01	56.30%
AvgT(0)	0.059	1.01	60.40%
DDAvgT(0)	0.059	1.01	60.40%
MaxT(0)-MaxT(-2)	0.154	1.05	54.70%
MinT(0)-MinT(-1)	0.187	1.06	54.00%
MinT(0)-MinT(-2)	0.114	1.06	56.40%
MinT(0)-MinT(-3)	0.059	1.04	56.70%
AvgT(0)-AvgT(-1)	0.133	1.08	55.40%
AvgT(0)-AvgT(-2)	0.095	1.06	56.90%
AvgT(0)-AvgT(-3)	0.134	1.05	55.20%
MaxT(-1)-MinT(0)	0.049	0.78	56.40%
HN(0,-1,-2)	0.118	1.01	59.70%
HN(0,-1,-2,-3)	0.063	1.01	60.60%
Stl(0,-1)	0.199	0.96	54.60%
Stl(0,-1,-2)	0.191	0.97	54.20%
Stl(0,-1-2,-3)	0.052	0.97	55.40%
HNW(0,-1)	0.022	1.35	60.50%
HNW(0,-1,-2)	0.01	1.33	67.80%
HNW(0,-1,-2,-3)	0.002	1.34	68.30%
HND(0,-1)	0.01	1.01	63.20%
HND(0,-1,-2,-3)	0.024	1.01	62.60%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MinT(0), AvgMinT(0,-1)	0.064	1.18	0.406	0.99	62.20%
MinT(0), AvgT(0)	0.223	1.13	0.816	1	61.30%
MinT(0), DDAvgT(0)	0.223	1.13	0.816	1	61.30%
MinT(0), MinT(0)-MinT(-2)	0.095	1.09	0.644	1.02	61.80%
MinT(0), MinT(0)-MinT(-3)	0.144	1.08	0.456	1.02	62.00%
MinT(0), AvgT(0)-AvgT(-3)	0.087	1.09	0.661	1.02	62.30%
MinT(0), EMaxT(0)-MaxT(-2)	0.059	1.09	0.417	1.03	63.10%
MinT(0), MinT(0)-MinT(-1)	0.063	1.1	0.657	1.02	61.90%
MinT(0), AvgT(0)-AvgT(-1)	0.066	1.09	0.417	1.04	62.60%
MinT(0), AvgT(0)-AvgT(-2)	0.094	1.09	0.458	1.03	63.00%
MinT(0), MaxT(-1)-MinT(0)	0.103	1.08	0.233	0.85	61.60%
MinT(0), HN(0,-1,-2)	0.009	1.14	0.022	1.02	67.00%
MinT(0), HN(0,-1,-2,-3)	0.007	1.14	0.009	1.02	68.80%
MinT(0), Stl(0,-1)	0.022	1.11	0.141	0.95	66.50%
MinT(0), Stl(0,-1,-2)	0.021	1.11	0.14	0.97	66.60%
MinT(0), Stl(0,-1-2,-3)	0.021	1.12	0.039	0.97	65.80%
MinT(0), HNW(0,-1)	0.023	1.11	0.016	1.38	67.30%
MinT(0), HNW(0,-1,-2)	0.016	1.13	0.004	1.39	70.40%
MinT(0), HNW(0,-1,-2,-3)	0.013	1.13	0.001	1.4	72.10%
MinT(0), HND(0,-1)	0.141	1.07	0.067	1.01	67.30%
MinT(0), HND(0,-1,-2,-3)	0.097	1.08	0.121	1.01	66.30%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgMinT(0,-1), MinT(0)	0.406	0.99	0.064	1.18	62.20%
AvgMinT(0,-1), AvgT(0)	0.964	1	0.262	1.01	60.10%
AvgMinT(0,-1), DDAvgT(0)	0.964	1	0.262	1.01	60.10%
AvgMinT(0,-1), EMaxT(0)-MaxT(-2)	0.159	1.01	0.218	1.04	60.80%
AvgMinT(0,-1), MinT(0)-MinT(-1)	0.088	1.01	0.14	1.07	61.70%
AvgMinT(0,-1), MinT(0)-MinT(-2)	0.204	1.01	0.206	1.05	61.70%
AvgMinT(0,-1), MinT(0)-MinT(-3)	0.356	1	0.167	1.03	60.10%
AvgMinT(0,-1), AvgT(0)-AvgT(-1)	0.084	1.01	0.097	1.09	62.10%
AvgMinT(0,-1), AvgT(0)-AvgT(-2)	0.199	1.01	0.162	1.06	61.50%
AvgMinT(0,-1), AvgT(0)-AvgT(-3)	0.262	1	0.311	1.04	59.20%
AvgMinT(0,-1), MaxT(-1)-MinT(0)	0.143	1.01	0.061	0.78	60.80%
AvgMinT(0,-1), HN(0,-1,-2)	0.041	1.01	0.037	1.02	62.80%
AvgMinT(0,-1), HN(0,-1,-2,-3)	0.027	1.01	0.013	1.02	64.10%
AvgMinT(0,-1), Stl(0,-1)	0.077	1.01	0.128	0.95	62.20%
AvgMinT(0,-1), Stl(0,-1,-2)	0.067	1.01	0.125	0.97	62.00%
AvgMinT(0,-1), Stl(0,-1-2,-3)	0.063	1.01	0.034	0.97	61.20%
AvgMinT(0,-1), HNW(0,-1)	0.133	1.01	0.027	1.34	63.50%
AvgMinT(0,-1), HNW(0,-1,-2)	0.081	1.01	0.007	1.36	67.50%
AvgMinT(0,-1), HNW(0,-1,-2,-3)	0.058	1.01	0.001	1.38	68.80%
AvgMinT(0,-1), HND(0,-1)	0.515	1	0.039	1.01	65.40%
AvgMinT(0,-1), HND(0,-1,-2,-3)	0.383	1	0.086	1.01	64.40%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgT(0), MinT(0)	0.816	1	0.223	1.13	61.30%
AvgT(0), AvgMinT(0,-1)	0.262	1.01	0.964	1	60.10%
AvgT(0), DDAvgT(0)	na	na	na	na	
AvgT(0), MinT(0)-MinT(-3)	0.246	1.01	0.262	1.02	61.00%
AvgT(0), AvgT(0)-AvgT(-2)	0.212	1.01	0.384	1.04	60.90%
AvgT(0), AvgT(0)-AvgT(-3)	0.195	1.01	0.559	1.02	61.20%
AvgT(0), EMaxT(0)-MaxT(-2)	0.16	1.01	0.51	1.02	60.10%
AvgT(0), MinT(0)-MinT(-1)	0.106	1.01	0.419	1.04	61.90%
AvgT(0), MinT(0)-MinT(-2)	0.175	1.01	0.395	1.03	61.50%
AvgT(0), AvgT(0)-AvgT(-1)	0.136	1.01	0.367	1.05	61.00%
AvgT(0), MaxT(-1)-MinT(0)	0.096	1.01	0.087	0.8	62.40%
AvgT(0), HN(0,-1,-2)	0.011	1.02	0.015	1.02	67.30%
AvgT(0), HN(0,-1,-2,-3)	0.008	1.02	0.007	1.02	68.60%
AvgT(0), Stl(0,-1)	0.038	1.01	0.132	0.95	67.30%
AvgT(0), Stl(0,-1,-2)	0.035	1.01	0.132	0.97	65.70%
AvgT(0), Stl(0,-1-2,-3)	0.036	1.01	0.037	0.97	64.40%
AvgT(0), HNW(0,-1)	0.019	1.02	0.011	1.41	67.90%
AvgT(0), HNW(0,-1,-2)	0.01	1.02	0.002	1.43	71.60%
AvgT(0), HNW(0,-1,-2,-3)	0.006	1.02	0	1.45	73.00%
AvgT(0), HND(0,-1)	0.194	1.01	0.071	1.01	67.30%
AvgT(0), HND(0,-1,-2,-3)	0.126	1.01	0.126	1.01	66.60%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
DDAvgT(0), MinT(0)	0.816	1	0.223	1.13	61.30%
DDAvgT(0), AvgMinT(0,-1)	0.262	1.01	0.964	1	60.10%
DDAvgT(0), AvgT(0)	na	na	na	na	
DDAvgT(0), MinT(0)-MinT(-3)	0.246	1.01	0.262	1.02	61.00%
DDAvgT(0), AvgT(0)-AvgT(-2)	0.212	1.01	0.384	1.04	60.90%
DDAvgT(0), AvgT(0)-AvgT(-3)	0.195	1.01	0.559	1.02	61.20%
DDAvgT(0), MaxT(0)-MaxT(-2)	0.16	1.01	0.51	1.02	60.10%
DDAvgT(0), MinT(0)-MinT(-1)	0.106	1.01	0.419	1.04	61.90%
DDAvgT(0) ,MinT(0)-MinT(-2)	0.175	1.01	0.395	1.03	61.50%
DDAvgT(0), AvgT(0)-AvgT(-1)	0.136	1.01	0.367	1.05	61.00%
DDAvgT(0), MaxT(-1)-MinT(0)	0.096	1.01	0.087	0.8	62.40%
DDAvgT(0), HN(0,-1,-2)	0.011	1.02	0.015	1.02	67.30%
DDAvgT(0), HN(0,-1,-2,-3)	0.008	1.02	0.007	1.02	68.60%
DDAvgT(0), Stl(0,-1)	0.038	1.01	0.132	0.95	67.30%
DDAvgT(0), Stl(0,-1,-2)	0.035	1.01	0.132	0.97	65.70%
DDAvgT(0), Stl(0,-1,-2,-3)	0.036	1.01	0.037	0.97	64.40%
DDAvgT(0), HNW(0,-1)	0.019	1.02	0.011	1.41	67.90%
DDAvgT(0), HNW(0,-1,-2)	0.01	1.02	0.002	1.43	71.60%
DDAvgT(0), HNW(0,-1,-2,-3)	0.006	1.02	0	1.45	73.00%
DDAvgT(0), HND(0,-1)	0.194	1.01	0.071	1.01	67.30%
DDAvgT(0), HND(0,-1,-2,-3)	0.126	1.01	0.126	1.01	66.60%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MaxT(0)-MaxT(-2), MinT(0)-MinT(-2)	0.575	1.02	0.392	1.04	57.80%
MaxT(0)-MaxT(-2), MinT(0)-MinT(-3)	0.595	1.02	0.183	1.03	58.00%
MaxT(0)-MaxT(-2), AvgT(0)-AvgT(-1)	0.463	1.03	0.413	1.05	56.70%
MaxT(0)-MaxT(-2), AvgT(0)-AvgT(-2)	0.835	0.98	0.377	1.08	57.50%
MaxT(0)-MaxT(-2), AvgT(0)-AvgT(-3)	0.574	1.03	0.477	1.03	55.80%
MaxT(0)-MaxT(-2), MinT(0)	0.417	1.03	0.059	1.09	63.10%
MaxT(0)-MaxT(-2), AvgMinT(0,-1)	0.218	1.04	0.159	1.01	60.80%
MaxT(0)-MaxT(-2), AvgT(0)	0.51	1.02	0.16	1.01	60.10%
MaxT(0)-MaxT(-2), DDAvgT(0)	0.51	1.02	0.16	1.01	60.10%
MaxT(0)-MaxT(-2), MinT(0)-MinT(-1)	0.276	1.04	0.366	1.04	57.60%
MaxT(0)-MaxT(-2), MaxT(-1)-MinT(0)	0.406	1.03	0.12	0.81	58.40%
MaxT(0)-MaxT(-2), HN(0,-1,-2)	0.091	1.06	0.061	1.02	60.00%
MaxT(0)-MaxT(-2), HN(0,-1,-2,-3)	0.146	1.05	0.059	1.01	60.70%
MaxT(0)-MaxT(-2), Stl(0,-1)	0.161	1.05	0.188	0.96	59.30%
MaxT(0)-MaxT(-2), Stl(0,-1,-2)	0.19	1.04	0.247	0.97	57.50%
MaxT(0)-MaxT(-2), Stl(0,-1,-2,-3)	0.251	1.04	0.084	0.97	57.30%
MaxT(0)-MaxT(-2), HNW(0,-1)	0.046	1.07	0.006	1.45	68.30%
MaxT(0)-MaxT(-2), HNW(0,-1,-2)	0.042	1.07	0.003	1.41	69.50%
MaxT(0)-MaxT(-2), HNW(0,-1,-2,-3)	0.087	1.06	0.002	1.36	69.40%
MaxT(0)-MaxT(-2), HND(0,-1)	0.115	1.06	0.008	1.01	66.70%
MaxT(0)-MaxT(-2), HND(0,-1,-2,-3)	0.105	1.06	0.017	1.01	67.20%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MinT(0)-MinT(-1), MinT(0)-MinT(-2)	0.687	1.02	0.325	1.04	56.80%
MinT(0)-MinT(-1), AvgT(0)-AvgT(-1)	0.957	1	0.457	1.07	56.40%
MinT(0)-MinT(-1), AvgT(0)-AvgT(-2)	0.608	1.03	0.239	1.05	57.10%
MinT(0)-MinT(-1), MaxT(-1)-MinT(0)	0.995	1	0.151	0.78	56.60%
MinT(0)-MinT(-1), MinT(0)	0.657	1.02	0.063	1.1	61.90%
MinT(0)-MinT(-1), AvgMinT(0,-1)	0.14	1.07	0.088	1.01	61.70%
MinT(0)-MinT(-1), AvgT(0)	0.419	1.04	0.106	1.01	61.90%
MinT(0)-MinT(-1), DDAvgT(0)	0.419	1.04	0.106	1.01	61.90%
MinT(0)-MinT(-1), MaxT(0)-MaxT(-2)	0.366	1.04	0.276	1.04	57.60%
MinT(0)-MinT(-1), MinT(0)-MinT(-3)	0.509	1.03	0.125	1.03	58.40%
MinT(0)-MinT(-1), AvgT(0)-AvgT(-3)	0.388	1.04	0.243	1.04	56.50%
MinT(0)-MinT(-1), HN(0,-1,-2)	0.172	1.06	0.109	1.01	59.80%
MinT(0)-MinT(-1), HN(0,-1,-2,-3)	0.196	1.06	0.07	1.01	61.60%
MinT(0)-MinT(-1), Stl(0,-1)	0.213	1.06	0.268	0.97	59.60%
MinT(0)-MinT(-1), Stl(0,-1,-2)	0.238	1.05	0.272	0.98	59.20%
MinT(0)-MinT(-1), Stl(0,-1,-2,-3)	0.267	1.05	0.077	0.97	59.20%
MinT(0)-MinT(-1), HNW(0,-1)	0.081	1.08	0.009	1.42	64.40%
MinT(0)-MinT(-1), HNW(0,-1,-2)	0.118	1.07	0.006	1.36	67.70%
MinT(0)-MinT(-1), HNW(0,-1,-2,-3)	0.156	1.07	0.002	1.35	69.40%
MinT(0)-MinT(-1), HND(0,-1)	0.159	1.07	0.008	1.01	66.90%
MinT(0)-MinT(-1), HND(0,-1,-2,-3)	0.147	1.07	0.017	1.01	66.00%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MinT(0)-MinT(-2), MaxT(0)-MaxT(-2)	0.392	1.04	0.575	1.02	57.80%
MinT(0)-MinT(-2), MinT(0)-MinT(-1)	0.325	1.04	0.687	1.02	56.80%
MinT(0)-MinT(-2), MinT(0)-MinT(-3)	0.696	1.02	0.279	1.03	57.70%
MinT(0)-MinT(-2), AvgT(0)-AvgT(-1)	0.404	1.04	0.531	1.04	56.60%
MinT(0)-MinT(-2), AvgT(0)-AvgT(-2)	0.874	1.01	0.557	1.05	57.40%
MinT(0)-MinT(-2), AvgT(0)-AvgT(-3)	0.419	1.04	0.537	1.03	57.20%
MinT(0)-MinT(-2), MaxT(-1)-MinT(0)	0.614	1.02	0.214	0.82	57.40%
MinT(0)-MinT(-2), MinT(0)	0.644	1.02	0.095	1.09	61.80%
MinT(0)-MinT(-2), AvgMinT(0,-1)	0.206	1.05	0.204	1.01	61.70%
MinT(0)-MinT(-2), AvgT(0)	0.395	1.03	0.175	1.01	61.50%
MinT(0)-MinT(-2), DDAvgT(0)	0.395	1.03	0.175	1.01	61.50%
MinT(0)-MinT(-2), HN(0,-1,-2)	0.072	1.06	0.068	1.02	61.00%
MinT(0)-MinT(-2), HN(0,-1,-2,-3)	0.099	1.06	0.055	1.01	61.60%
MinT(0)-MinT(-2), Stl(0,-1)	0.125	1.06	0.21	0.96	60.30%
MinT(0)-MinT(-2), Stl(0,-1,-2)	0.147	1.05	0.261	0.98	59.70%
MinT(0)-MinT(-2), Stl(0,-1,-2,-3)	0.185	1.05	0.083	0.97	60.10%
MinT(0)-MinT(-2), HNW(0,-1)	0.048	1.07	0.008	1.43	65.50%
MinT(0)-MinT(-2), HNW(0,-1,-2)	0.04	1.08	0.003	1.41	67.90%
MinT(0)-MinT(-2), HNW(0,-1,-2,-3)	0.072	1.07	0.001	1.37	68.80%
MinT(0)-MinT(-2), HND(0,-1)	0.146	1.05	0.011	1.01	66.90%
MinT(0)-MinT(-2), HND(0,-1,-2,-3)	0.102	1.06	0.018	1.01	66.90%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MinT(0)-MinT(-3), MinT(0)	0.456	1.02	0.144	1.08	62.00%
MinT(0)-MinT(-3), AvgT(0)	0.262	1.02	0.246	1.01	61.00%
MinT(0)-MinT(-3), DDAvgT(0)	0.262	1.02	0.246	1.01	61.00%
MinT(0)-MinT(-3), MaxT(0)-MaxT(-2)	0.183	1.03	0.595	1.02	58.00%
MinT(0)-MinT(-3), MinT(0)-MinT(-2)	0.279	1.03	0.696	1.02	57.70%
MinT(0)-MinT(-3), AvgT(0)-AvgT(-2)	0.308	1.03	0.573	1.03	58.40%
MinT(0)-MinT(-3), AvgT(0)-AvgT(-3)	0.229	1.06	0.62	0.96	57.40%
MinT(0)-MinT(-3), AvgMinT(0,-1)	0.167	1.03	0.356	1	60.10%
MinT(0)-MinT(-3), MinT(0)-MinT(-1)	0.125	1.03	0.509	1.03	58.40%
MinT(0)-MinT(-3), AvgT(0)-AvgT(-1)	0.149	1.03	0.393	1.05	58.10%
MinT(0)-MinT(-3), MaxT(-1)-MinT(0)	0.238	1.03	0.191	0.83	59.20%
MinT(0)-MinT(-3), HN(0,-1,-2)	0.023	1.05	0.038	1.02	62.40%
MinT(0)-MinT(-3), HN(0,-1,-2,-3)	0.025	1.04	0.024	1.02	62.70%
MinT(0)-MinT(-3), Stl(0,-1)	0.056	1.04	0.193	0.96	60.90%
MinT(0)-MinT(-3), Stl(0,-1,-2)	0.061	1.04	0.222	0.97	60.20%
MinT(0)-MinT(-3), Stl(0,-1,-2,-3)	0.087	1.03	0.085	0.97	59.80%
MinT(0)-MinT(-3), HNW(0,-1)	0.029	1.04	0.01	1.41	66.20%
MinT(0)-MinT(-3), HNW(0,-1,-2)	0.013	1.05	0.002	1.44	69.90%
MinT(0)-MinT(-3), HNW(0,-1,-2,-3)	0.011	1.05	0	1.43	71.10%
MinT(0)-MinT(-3), HND(0,-1)	0.114	1.03	0.016	1.01	67.60%
MinT(0)-MinT(-3), HND(0,-1,-2,-3)	0.081	1.03	0.028	1.01	67.80%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgT(0)-AvgT(-1), MaxT(0)-MaxT(-2)	0.413	1.05	0.463	1.03	56.70%
AvgT(0)-AvgT(-1), MinT(0)-MinT(-1)	0.457	1.07	0.957	1	56.40%
AvgT(0)-AvgT(-1), MinT(0)-MinT(-2)	0.531	1.04	0.404	1.04	56.60%
AvgT(0)-AvgT(-1), AvgT(0)-AvgT(-2)	0.614	1.03	0.348	1.05	57.30%
AvgT(0)-AvgT(-1), MaxT(-1)-MinT(0)	0.963	1	0.217	0.77	56.40%
AvgT(0)-AvgT(-1), MinT(0)	0.417	1.04	0.066	1.09	62.60%
AvgT(0)-AvgT(-1), AvgMinT(0,-1)	0.097	1.09	0.084	1.01	62.10%
AvgT(0)-AvgT(-1), AvgT(0)	0.367	1.05	0.136	1.01	61.00%
AvgT(0)-AvgT(-1), DDAvgT(0)	0.367	1.05	0.136	1.01	61.00%
AvgT(0)-AvgT(-1), MinT(0)-MinT(-3)	0.393	1.05	0.149	1.03	58.10%
AvgT(0)-AvgT(-1), AvgT(0)-AvgT(-3)	0.348	1.05	0.332	1.04	56.60%
AvgT(0)-AvgT(-1), HN(0,-1,-2)	0.12	1.08	0.104	1.01	59.60%
AvgT(0)-AvgT(-1), HN(0,-1,-2,-3)	0.15	1.08	0.076	1.01	60.50%
AvgT(0)-AvgT(-1), Stl(0,-1)	0.152	1.08	0.268	0.97	59.20%
AvgT(0)-AvgT(-1), Stl(0,-1,-2)	0.179	1.07	0.299	0.98	58.60%
AvgT(0)-AvgT(-1), Stl(0,-1,-2,-3)	0.224	1.06	0.09	0.97	58.80%
AvgT(0)-AvgT(-1), HNW(0,-1)	0.034	1.12	0.005	1.47	65.70%
AvgT(0)-AvgT(-1), HNW(0,-1,-2)	0.068	1.1	0.005	1.37	66.80%
AvgT(0)-AvgT(-1), HNW(0,-1,-2,-3)	0.097	1.09	0.002	1.36	68.50%
AvgT(0)-AvgT(-1), HND(0,-1)	0.081	1.1	0.006	1.01	66.20%
AvgT(0)-AvgT(-1), HND(0,-1,-2,-3)	0.08	1.1	0.014	1.01	66.30%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgT(0)-AvgT(-2), AvgT(0)	0.384	1.04	0.212	1.01	60.90%
AvgT(0)-AvgT(-2), DDAvgT(0)	0.384	1.04	0.212	1.01	60.90%
AvgT(0)-AvgT(-2), MaxT(0)-MaxT(-2)	0.377	1.08	0.835	0.98	57.50%
AvgT(0)-AvgT(-2), MinT(0)-MinT(-1)	0.239	1.05	0.608	1.03	57.10%
AvgT(0)-AvgT(-2), MinT(0)-MinT(-2)	0.557	1.05	0.874	1.01	57.40%
AvgT(0)-AvgT(-2), MinT(0)-MinT(-3)	0.573	1.03	0.308	1.03	58.40%
AvgT(0)-AvgT(-2), AvgT(0)-AvgT(-1)	0.348	1.05	0.614	1.03	1.03
AvgT(0)-AvgT(-2), AvgT(0)-AvgT(-3)	0.395	1.05	0.695	1.02	57.00%
AvgT(0)-AvgT(-2), MaxT(-1)-MinT(0)	0.432	1.03	0.208	0.83	58.40%
AvgT(0)-AvgT(-2),MinT(0)	0.458	1.03	0.094	1.09	63.00%
AvgT(0)-AvgT(-2), AvgMinT(0,-1)	0.162	1.06	0.199	1.01	61.50%
AvgT(0)-AvgT(-2), HN(0,-1,-2)	0.052	1.08	0.054	1.02	61.10%
AvgT(0)-AvgT(-2), HN(0,-1,-2,-3)	0.085	1.07	0.056	1.01	61.10%
AvgT(0)-AvgT(-2), Stl(0,-1)	0.103	1.06	0.203	0.96	60.50%
AvgT(0)-AvgT(-2), Stl(0,-1,-2)	0.123	1.06	0.272	0.98	59.40%
AvgT(0)-AvgT(-2), Stl(0,-1,-2,-3)	0.169	1.05	0.093	0.97	59.80%
AvgT(0)-AvgT(-2), HNW(0,-1)	0.027	1.09	0.005	1.46	67.10%
AvgT(0)-AvgT(-2), HNW(0,-1,-2)	0.023	1.1	0.002	1.43	69.20%
AvgT(0)-AvgT(-2), HNW(0,-1,-2,-3)	0.051	1.08	0.001	1.37	70.00%
AvgT(0)-AvgT(-2), HND(0,-1)	0.092	1.07	0.009	1.01	67.50%
AvgT(0)-AvgT(-2), HND(0,-1,-2,-3)	0.07	1.07	0.016	1.01	68.30%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
AvgT(0)-AvgT(-3), MinT(0)	0.661	1.02	0.087	1.09	62.30%
AvgT(0)-AvgT(-3), AvgT(0)	0.559	1.02	0.195	1.01	61.20%
AvgT(0)-AvgT(-3), DDAvgT(0)	0.559	1.02	0.195	1.01	61.20%
AvgT(0)-AvgT(-3), MaxT(0)-MaxT(-2)	0.477	1.03	0.574	1.03	55.80%
AvgT(0)-AvgT(-3), MinT(0)-MinT(-2)	0.537	1.03	0.419	1.04	57.20%
AvgT(0)-AvgT(-3), MinT(0)-MinT(-3)	0.62	0.96	0.229	1.06	57.40%
AvgT(0)-AvgT(-3), AvgT(0)-AvgT(-2)	0.695	1.02	0.395	1.05	57.00%
AvgT(0)-AvgT(-3), AvgMinT(0,-1)	0.311	1.04	0.262	1	59.20%
AvgT(0)-AvgT(-3), MinT(0)-MinT(-1)	0.243	1.04	0.388	1.04	56.50%
AvgT(0)-AvgT(-3), AvgT(0)-AvgT(-1)	0.332	1.04	0.348	1.05	56.60%
AvgT(0)-AvgT(-3), MaxT(-1)-MinT(0)	0.363	1.03	0.121	0.81	58.40%
AvgT(0)-AvgT(-3), HN(0,-1,-2)	0.047	1.07	0.035	1.02	61.00%
AvgT(0)-AvgT(-3), HN(0,-1,-2,-3)	0.058	1.07	0.025	1.02	61.70%
AvgT(0)-AvgT(-3), Stl(0,-1)	0.122	1.05	0.182	0.96	59.80%
AvgT(0)-AvgT(-3), Stl(0,-1,-2)	0.14	1.05	0.219	0.97	58.30%
AvgT(0)-AvgT(-3), Stl(0,-1,-2,-3)	0.198	1.04	0.082	0.97	57.80%
AvgT(0)-AvgT(-3), HNW(0,-1)	0.05	1.07	0.008	1.43	66.90%
AvgT(0)-AvgT(-3), HNW(0,-1,-2)	0.024	1.09	0.002	1.45	70.10%
AvgT(0)-AvgT(-3), HNW(0,-1,-2,-3)	0.022	1.09	0	1.44	70.80%
AvgT(0)-AvgT(-3), HND(0,-1)	0.191	1.05	0.013	1.01	67.30%
AvgT(0)-AvgT(-3), HND(0,-1,-2,-3)	0.149	1.05	0.025	1.01	67.50%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
MaxT(-1)-MinT(0), MinT(0)-MinT(-1)	0.151	0.78	0.995	1	56.60%
MaxT(-1)-MinT(0), MinT(0)-MinT(-2)	0.214	0.82	0.614	1.02	57.40%
MaxT(-1)-MinT(0), AvgT(0)-AvgT(-1)	0.217	0.77	0.963	1	56.40%
MaxT(-1)-MinT(0), AvgT(0)-AvgT(-2)	0.208	0.83	0.432	1.03	58.40%
MaxT(-1)-MinT(0), MinT(0)	0.233	0.85	0.103	1.08	61.60%
MaxT(-1)-MinT(0), AvgMinT(0,-1)	0.061	0.78	0.143	1.01	60.80%
MaxT(-1)-MinT(0), AvgT(0)	0.087	0.8	0.096	1.01	62.40%
MaxT(-1)-MinT(0), DDAvgT(0)	0.087	0.8	0.096	1.01	62.40%
MaxT(-1)-MinT(0), MaxT(0)-MaxT(-2)	0.12	0.81	0.406	1.03	58.40%
MaxT(-1)-MinT(0), MinT(0)-MinT(-3)	0.191	0.83	0.238	1.03	59.20%
MaxT(-1)-MinT(0), AvgT(0)-AvgT(-3)	0.121	0.81	0.363	1.03	58.40%
MaxT(-1)-MinT(0), HN(0,-1,-2)	0.066	0.79	0.165	1.01	58.70%
MaxT(-1)-MinT(0), HN(0,-1,-2,-3)	0.081	0.8	0.118	1.01	59.60%
MaxT(-1)-MinT(0), Stl(0,-1)	0.066	0.79	0.317	0.97	58.80%
MaxT(-1)-MinT(0), Stl(0,-1,-2)	0.078	0.79	0.359	0.98	58.80%
MaxT(-1)-MinT(0), Stl(0,-1,-2,-3)	0.103	0.81	0.116	0.98	59.90%
MaxT(-1)-MinT(0), HNW(0,-1)	0.04	0.76	0.01	1.4	65.80%
MaxT(-1)-MinT(0), HNW(0,-1,-2)	0.081	0.79	0.011	1.33	66.60%
MaxT(-1)-MinT(0), HNW(0,-1,-2,-3)	0.118	0.81	0.004	1.32	67.90%
MaxT(-1)-MinT(0), HND(0,-1)	0.04	0.75	0.004	1.01	67.00%
MaxT(-1)-MinT(0), HND(0,-1,-2,-3)	0.042	0.76	0.011	1.01	66.70%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HN(0,-1,-2), HN(0,-1,-2,-3)	0.85	1	0.284	1.02	60.20%
HN(0,-1,-2), Stl(0,-1,-2)	0.374	1.01	0.657	0.99	59.40%
HN(0,-1,-2), HNW(0,-1)	0.947	1	0.144	1.33	61.60%
HN(0,-1,-2), HNW(0,-1,-2)	0.32	0.98	0.037	1.64	68.00%
HN(0,-1,-2), HNW(0,-1,-2,-3)	0.35	0.99	0.007	1.48	68.90%
HN(0,-1,-2), MinT(0)	0.022	1	0.009	1.03	67.00%
HN(0,-1,-2), AvgMinT(0,-1)	0.037	1.02	0.041	1.01	62.80%
HN(0,-1,-2), AvgT(0)	0.015	1.02	0.011	1.02	67.30%
HN(0,-1,-2), DDAvgT(0)	0.015	1.02	0.011	1.02	67.30%
HN(0,-1,-2), MaxT(0)-MaxT(-2)	0.061	1.02	0.091	1.06	60.00%
HN(0,-1,-2), MinT(0)-MinT(-1)	0.109	1.01	0.172	1.06	59.80%
HN(0,-1,-2), MinT(0)-MinT(-2)	0.068	1.02	0.072	1.06	61.00%
HN(0,-1,-2), MinT(0)-MinT(-3)	0.038	1.02	0.023	1.05	62.40%
HN(0,-1,-2), AvgT(0)-AvgT(-1)	0.104	1.01	0.12	1.08	59.60%
HN(0,-1,-2), AvgT(0)-AvgT(-2)	0.054	1.02	0.052	1.08	61.10%
HN(0,-1,-2), AvgT(0)-AvgT(-3)	0.035	1.02	0.047	1.07	61.00%
HN(0,-1,-2), MaxT(-1)-MinT(0)	0.165	1.01	0.066	0.79	58.70%
HN(0,-1,-2), Stl(0,-1)	0.323	1.01	0.612	0.98	60.60%
HN(0,-1,-2), Stl(0,-1,-2,-3)	0.548	1.01	0.21	0.98	58.70%
HN(0,-1,-2), HND(0,-1)	0.022	1.02	0.003	1.01	68.80%
HN(0,-1,-2), HND(0,-1,-2,-3)	0.039	1.02	0.01	1.01	67.60%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HN(0,-1,-2,-3), HN(0,-1,-2)	0.284	1.02	0.85	1	60.20%
HN(0,-1,-2,-3), Stl(0,-1)	0.182	1.01	0.711	0.99	60.20%
HN(0,-1,-2,-3), Stl(0,-1,-2)	0.209	1.01	0.838	0.99	60.80%
HN(0,-1,-2,-3), Stl(0,-1,-2,-3)	0.431	1.01	0.33	0.98	60.00%
HN(0,-1,-2,-3), HNW(0,-1)	0.45	1.01	0.187	1.24	64.80%
HN(0,-1,-2,-3), HNW(0,-1,-2)	0.98	1	0.128	1.32	67.80%
HN(0,-1,-2,-3), HNW(0,-1,-2,-3)	0.25	0.98	0.014	1.64	68.70%
HN(0,-1,-2,-3), MinT(0)	0.009	1.02	0.007	1.14	68.80%
HN(0,-1,-2,-3), AvgMinT(0,-1)	0.013	1.02	0.027	1.01	64.10%
HN(0,-1,-2,-3), AvgT(0)	0.007	1.02	0.008	1.02	68.60%
HN(0,-1,-2,-3), DDAvgT(0)	0.007	1.02	0.008	1.02	68.60%
HN(0,-1,-2,-3), MaxT(0)-MaxT(-2)	0.059	1.01	0.146	1.05	60.70%
HN(0,-1,-2,-3), MinT(0)-MinT(-1)	0.07	1.01	0.196	1.06	61.60%
HN(0,-1,-2,-3), MinT(0)-MinT(-2)	0.055	1.01	0.099	1.06	61.60%
HN(0,-1,-2,-3), MinT(0)-MinT(-3)	0.024	1.02	0.025	1.04	62.70%
HN(0,-1,-2,-3), AvgT(0)-AvgT(-1)	0.076	1.01	0.15	1.08	60.50%
HN(0,-1,-2,-3), AvgT(0)-AvgT(-2)	0.056	1.01	0.085	1.07	61.10%
HN(0,-1,-2,-3), AvgT(0)-AvgT(-3)	0.025	1.02	0.058	1.07	61.70%
HN(0,-1,-2,-3), MaxT(-1)-MinT(0)	0.118	1.01	0.081	0.8	59.60%
HN(0,-1,-2,-3), HND(0,-1)	0.008	1.02	0.002	1.01	68.90%
HN(0,-1,-2,-3), HND(0,-1,-2,-3)	0.012	1.02	0.006	1.01	67.50%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
Stl(0,-1), HN(0,-1,-2,-3)	0.711	0.99	0.182	1.01	60.20%
Stl(0,-1), Stl(0,-1,-2)	0.696	0.98	0.603	0.98	57.70%
Stl(0,-1), Stl(0,-1,-2,-3)	0.922	1	0.153	0.97	56.40%
Stl(0,-1), MinT(0)	0.141	0.95	0.022	1.11	66.50%
Stl(0,-1), AvgMinT(0,-1)	0.128	0.95	0.077	1.01	62.20%
Stl(0,-1), AvgT(0)	0.132	0.95	0.038	1.01	67.30%
Stl(0,-1), DDAvgT(0)	0.132	0.95	0.038	1.01	67.30%
Stl(0,-1), MaxT(0)-MaxT(-2)	0.188	0.96	0.161	1.05	59.30%
Stl(0,-1), MinT(0)-MinT(-1)	0.268	0.97	0.213	1.06	59.60%
Stl(0,-1), MinT(0)-MinT(-2)	0.21	0.96	0.125	1.06	60.30%
Stl(0,-1), MinT(0)-MinT(-3)	0.193	0.96	0.056	1.04	60.90%
Stl(0,-1), AvgT(0)-AvgT(-1)	0.268	0.97	0.152	1.08	59.20%
Stl(0,-1), AvgT(0)-AvgT(-2)	0.203	0.96	0.103	1.06	60.50%
Stl(0,-1), AvgT(0)-AvgT(-3)	0.182	0.96	0.122	1.05	59.80%
Stl(0,-1), MaxT(-1)-MinT(0)	0.317	0.97	0.066	0.79	58.80%
Stl(0,-1), HN(0,-1,-2)	0.612	0.98	0.323	1.01	60.60%
Stl(0,-1), HNW(0,-1)	0.596	0.98	0.07	1.3	62.80%
Stl(0,-1), HNW(0,-1,-2)	0.741	0.99	0.032	1.31	68.40%
Stl(0,-1), HNW(0,-1,-2,-3)	0.889	1	0.008	1.33	68.50%
Stl(0,-1), HND(0,-1)	0.076	0.94	0.005	1.01	67.10%
Stl(0,-1), HND(0,-1,-2,-3)	0.08	0.95	0.012	1.01	65.90%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
Stl(0,-1,-2), HN(0,-1,-2)	0.657	0.99	0.374	1.01	59.40%
Stl(0,-1,-2), HN(0,-1,-2,-3)	0.838	0.99	0.209	1.01	60.80%
Stl(0,-1,-2), Stl(0,-1)	0.603	0.98	0.696	0.98	57.70%
Stl(0,-1,-2), Stl(0,-1,-2,-3)	0.583	1.02	0.132	0.96	54.60%
Stl(0,-1,-2), MinT(0)	0.14	0.97	0.021	1.11	66.60%
Stl(0,-1,-2), AvgMinT(0,-1)	0.125	0.97	0.067	1.01	62.00%
Stl(0,-1,-2), AvgT(0)	0.132	0.97	0.035	1.01	65.70%
Stl(0,-1,-2), DDAvgT(0)	0.132	0.97	0.035	1.01	65.70%
Stl(0,-1,-2), MaxT(0)-MaxT(-2)	0.247	0.97	0.19	1.04	57.50%
Stl(0,-1,-2), MinT(0)-MinT(-1)	0.272	0.98	0.238	1.05	59.20%
Stl(0,-1,-2), MinT(0)-MinT(-2)	0.261	0.98	0.147	1.05	59.70%
Stl(0,-1,-2), MinT(0)-MinT(-3)	0.222	0.97	0.061	1.04	60.20%
Stl(0,-1,-2), AvgT(0)-AvgT(-1)	0.299	0.98	0.179	0.97	58.60%
Stl(0,-1,-2), AvgT(0)-AvgT(-2)	0.272	0.98	0.123	1.06	59.40%
Stl(0,-1,-2), AvgT(0)-AvgT(-3)	0.219	0.97	0.14	1.05	58.30%
Stl(0,-1,-2), MaxT(-1)-MinT(0)	0.359	0.98	0.078	0.79	58.80%
Stl(0,-1,-2), HNW(0,-1)	0.496	0.98	0.069	1.29	65.00%
Stl(0,-1,-2), HNW(0,-1,-2)	0.778	0.99	0.041	1.3	68.40%
Stl(0,-1,-2), HNW(0,-1,-2,-3)	0.99	1	0.01	1.33	67.90%
Stl(0,-1,-2), HND(0,-1)	0.068	0.96	0.004	1.01	67.50%
Stl(0,-1,-2), HND(0,-1,-2,-3)	0.063	0.96	0.01	1.01	66.90%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
Stl(0,-1,-2,-3), HN(0,-1,-2,-3)	0.33	0.98	0.431	1.01	60.00%
Stl(0,-1,-2,-3), Stl(0,-1)	0.153	0.97	0.922	1	56.40%
Stl(0,-1,-2,-3), Stl(0,-1,-2)	0.132	0.96	0.583	1.02	54.60%
Stl(0,-1,-2,-3), MinT(0)	0.039	0.97	0.021	1.12	65.80%
Stl(0,-1,-2,-3), AvgMinT(0,-1)	0.034	0.97	0.063	1.01	61.20%
Stl(0,-1,-2,-3), AvgT(0)	0.037	0.97	0.036	1.01	64.40%
Stl(0,-1,-2,-3), DDAvgT(0)	0.037	0.97	0.036	1.01	64.40%
Stl(0,-1,-2,-3), MaxT(0)-MaxT(-2)	0.084	0.97	0.251	1.04	57.30%
Stl(0,-1,-2,-3), MinT(0)-MinT(-1)	0.077	0.97	0.267	1.05	59.20%
Stl(0,-1,-2,-3), MinT(0)-MinT(-2)	0.083	0.97	0.185	1.05	60.10%
Stl(0,-1,-2,-3), MinT(0)-MinT(-3)	0.085	0.97	0.087	1.03	59.80%
Stl(0,-1,-2,-3), AvgT(0)-AvgT(-1)	0.09	0.97	0.224	1.06	58.80%
Stl(0,-1,-2,-3), AvgT(0)-AvgT(-2)	0.093	0.97	0.169	1.05	59.80%
Stl(0,-1,-2,-3), AvgT(0)-AvgT(-3)	0.082	0.97	0.198	1.04	57.80%
Stl(0,-1,-2,-3), MaxT(-1)-MinT(0)	0.116	0.98	0.103	0.81	59.90%
Stl(0,-1,-2,-3), HN(0,-1,-2)	0.21	0.98	0.548	1.01	58.70%
Stl(0,-1,-2,-3), HNW(0,-1)	0.12	0.98	0.072	1.27	63.80%
Stl(0,-1,-2,-3), HNW(0,-1,-2)	0.269	0.98	0.065	1.26	67.00%
Stl(0,-1,-2,-3), HNW(0,-1,-2,-3)	0.479	0.99	0.024	1.28	68.20%
Stl(0,-1,-2,-3), HND(0,-1)	0.012	0.96	0.003	1.01	67.20%
Stl(0,-1,-2,-3), HND(0,-1,-2,-3)	0.013	0.96	0.008	1.01	66.80%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HNW(0,-1), HN(0,-1,-2)	0.144	1.33	0.947	1	61.60%
HNW(0,-1), HN(0,-1,-2,-3)	0.187	1.24	0.45	1.01	64.80%
HNW(0,-1), HNW(0,-1,-2)	0.781	1.06	0.193	1.28	68.10%
HNW(0,-1), HNW(0,-1,-2,-3)	0.862	1.03	0.034	1.32	68.50%
HNW(0,-1), MinT(0)	0.016	1.38	0.023	1.11	67.30%
HNW(0,-1), AvgMinT(0,-1)	0.027	1.34	0.133	1.01	63.50%
HNW(0,-1), AvgT(0)	0.011	1.41	0.019	1.02	67.90%
HNW(0,-1), DDAvgT(0)	0.011	1.41	0.019	1.02	67.90%
HNW(0,-1), MaxT(0)-MaxT(-2)	0.006	1.45	0.046	1.07	68.30%
HNW(0,-1), MinT(0)-MinT(-1)	0.009	1.42	0.081	1.08	64.40%
HNW(0,-1), MinT(0)-MinT(-2)	0.008	1.43	0.048	1.07	65.50%
HNW(0,-1), MinT(0)-MinT(-3)	0.01	1.41	0.029	1.04	66.20%
HNW(0,-1), AvgT(0)-AvgT(-1)	0.005	1.47	0.034	1.12	65.70%
HNW(0,-1), AvgT(0)-AvgT(-2)	0.005	1.46	0.027	1.09	67.10%
HNW(0,-1), AvgT(0)-AvgT(-3)	0.008	1.43	0.05	1.07	66.90%
HNW(0,-1), MaxT(-1)-MinT(0)	0.01	1.4	0.04	0.76	65.80%
HNW(0,-1), Stl(0,-1)	0.07	1.3	0.596	0.98	62.80%
HNW(0,-1), Stl(0,-1,-2)	0.069	1.29	0.496	0.98	65.00%
HNW(0,-1), Stl(0,-1,-2,-3)	0.072	1.27	0.12	0.98	63.80%
HNW(0,-1), HND(0,-1)	0.11	1.26	0.031	1.01	64.00%
HNW(0,-1), HND(0,-1,-2,-3)	0.082	1.27	0.062	1.01	64.10%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HNW(0,-1,-2), HN(0,-1,-2)	0.037	1.64	0.32	0.98	68.00%
HNW(0,-1,-2), HN(0,-1,-2,-3)	0.128	1.32	0.98	1	67.80%
HNW(0,-1,-2), HNW(0,-1)	0.193	1.28	0.781	1.06	68.10%
HNW(0,-1,-2), HNW(0,-1,-2,-3)	0.913	0.98	0.082	1.36	68.00%
HNW(0,-1,-2), MinT(0)	0.004	1.39	0.016	1.13	70.40%
HNW(0,-1,-2), AvgMinT(0,-1)	0.007	1.36	0.081	1.01	67.50%
HNW(0,-1,-2), AvgT(0)	0.002	1.43	0.01	1.02	71.60%
HNW(0,-1,-2), DDAvgT(0)	0.002	1.43	0.01	1.02	71.60%
HNW(0,-1,-2), MaxT(0)-MaxT(-2)	0.003	1.41	0.042	1.07	69.50%
HNW(0,-1,-2), MinT(0)-MinT(-1)	0.006	1.36	0.118	1.07	67.70%
HNW(0,-1,-2), MinT(0)-MinT(-2)	0.003	1.41	0.04	1.08	67.90%
HNW(0,-1,-2), MinT(0)-MinT(-3)	0.002	1.44	0.013	1.05	69.90%
HNW(0,-1,-2), AvgT(0)-AvgT(-1)	0.005	1.37	0.068	1.1	66.80%
HNW(0,-1,-2), AvgT(0)-AvgT(-2)	0.002	1.43	0.023	1.1	69.20%
HNW(0,-1,-2), AvgT(0)-AvgT(-3)	0.002	1.45	0.024	1.09	70.10%
HNW(0,-1,-2), MaxT(-1)-MinT(0)	0.011	1.33	0.081	0.79	66.60%
HNW(0,-1,-2), Stl(0,-1)	0.032	1.31	0.741	0.99	68.40%
HNW(0,-1,-2), Stl(0,-1,-2)	0.041	1.3	0.778	0.99	68.40%
HNW(0,-1,-2), Stl(0,-1,-2,-3)	0.065	1.26	0.269	0.98	67.00%
HNW(0,-1,-2), HND(0,-1)	0.03	1.29	0.022	1.01	67.90%
HNW(0,-1,-2), HND(0,-1,-2,-3)	0.037	1.28	0.062	1.01	67.80%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HNW(0,-1,-2,-3), HN(0,-1,-2)	0.007	1.48	0.35	0.99	68.90%
HNW(0,-1,-2,-3), HN(0,-1,-2,-3)	0.014	1.64	0.25	0.98	68.70%
HNW(0,-1,-2,-3), HNW(0,-1)	0.034	1.32	0.862	1.03	68.50%
HNW(0,-1,-2,-3), HNW(0,-1,-2)	0.082	1.36	0.913	0.98	68.00%
HNW(0,-1,-2,-3), MinT(0)	0.001	1.4	0.013	1.13	72.10%
HNW(0,-1,-2,-3), AvgMinT(0,-1)	0.001	1.38	0.058	1.01	68.80%
HNW(0,-1,-2,-3), AvgT(0)	0	1.45	0.006	1.02	73.00%
HNW(0,-1,-2,-3), DDAvgT(0)	0	1.45	0.006	1.02	73.00%
HNW(0,-1,-2,-3), MaxT(0)-MaxT(-2)	0.002	1.36	0.087	1.06	69.40%
HNW(0,-1,-2,-3), MinT(0)-MinT(-1)	0.002	1.35	0.156	1.07	69.40%
HNW(0,-1,-2,-3), MinT(0)-MinT(-2)	0.001	1.37	0.072	1.07	68.80%
HNW(0,-1,-2,-3), MinT(0)-MinT(-3)	0	1.43	0.011	1.05	71.10%
HNW(0,-1,-2,-3), AvgT(0)-AvgT(-1)	0.002	1.36	0.097	1.09	68.50%
HNW(0,-1,-2,-3), AvgT(0)-AvgT(-2)	0.001	1.37	0.051	1.08	70.00%
HNW(0,-1,-2,-3), AvgT(0)-AvgT(-3)	0	1.44	0.022	1.09	70.80%
HNW(0,-1,-2,-3), MaxT(-1)-MinT(0)	0.004	1.32	0.118	0.81	67.90%
HNW(0,-1,-2,-3), Stl(0,-1)	0.008	1.33	0.889	1	68.50%
HNW(0,-1,-2,-3), Stl(0,-1,-2)	0.01	1.33	0.99	1	67.90%
HNW(0,-1,-2,-3), Stl(0,-1,-2,-3)	0.024	1.28	0.479	0.99	68.20%
HNW(0,-1,-2,-3), HND(0,-1)	0.006	1.32	0.02	1.01	69.50%
HNW(0,-1,-2,-3), HND(0,-1,-2,-3)	0.009	1.3	0.064	1.01	68.40%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HND(0,-1), HND(0,-1,-2,-3)	0.199	1.01	0.974	1	63.60%
HND(0,-1), MinT(0)	0.067	1.01	0.141	1.07	67.30%
HND(0,-1), AvgMinT(0,-1)	0.039	1.01	0.515	1	65.40%
HND(0,-1), AvgT(0)	0.071	1.01	0.194	1.01	67.30%
HND(0,-1), DDAvgT(0)	0.071	1.01	0.194	1.01	67.30%
HND(0,-1), MaxT(0)-MaxT(-2)	0.008	1.01	0.115	1.06	66.70%
HND(0,-1), MinT(0)-MinT(-1)	0.008	1.01	0.159	1.07	66.90%
HND(0,-1), MinT(0)-MinT(-2)	0.011	1.01	0.146	1.05	66.90%
HND(0,-1), MinT(0)-MinT(-3)	0.016	1.01	0.114	1.03	67.60%
HND(0,-1), AvgT(0)-AvgT(-1)	0.006	1.01	0.081	1.1	66.20%
HND(0,-1), AvgT(0)-AvgT(-2)	0.009	1.01	0.092	1.07	67.50%
HND(0,-1), AvgT(0)-AvgT(-3)	0.013	1.01	0.191	1.05	67.30%
HND(0,-1), MaxT(-1)-MinT(0)	0.004	1.01	0.04	0.75	67.00%
HND(0,-1), HN(0,-1,-2)	0.003	1.01	0.022	1.02	68.80%
HND(0,-1), HN(0,-1,-2,-3)	0.002	1.01	0.008	1.02	68.90%
HND(0,-1), Stl(0,-1)	0.005	1.01	0.076	0.94	67.10%
HND(0,-1), Stl(0,-1,-2)	0.004	1.01	0.068	0.96	67.50%
HND(0,-1), Stl(0,-1,-2,-3)	0.003	1.01	0.012	0.96	67.20%
HND(0,-1), HNW(0,-1)	0.031	1.01	0.11	1.26	64.00%
HND(0,-1), HNW(0,-1,-2)	0.022	1.01	0.03	1.29	67.90%
HND(0,-1), HNW(0,-1,-2,-3)	0.02	1.01	0.006	1.32	69.50%

New Snow Binomial Logistic Regression Results

Predictor Variables in Binomial Logistic Regression Model	1st Variable P-Value	1st Variable Odds Ratio	2nd Variable P-Value	2nd Variable Odds Ratio	Percent Concordant Pairs
HND(0,-1,-2,-3), HND(0,-1)	0.974	1	0.199	1.01	63.60%
HND(0,-1,-2,-3), MinT(0)	0.121	1.01	0.097	1.08	66.30%
HND(0,-1,-2,-3), AvgMinT(0,-1)	0.086	1.01	0.383	1	64.40%
HND(0,-1,-2,-3), AvgT(0)	0.126	1.01	0.126	1.01	66.60%
HND(0,-1,-2,-3), DDAvgT(0)	0.126	1.01	0.126	1.01	66.60%
HND(0,-1,-2,-3), MaxT(0)-MaxT(-2)	0.017	1.01	0.105	1.06	67.20%
HND(0,-1,-2,-3), MinT(0)-MinT(-1)	0.017	1.01	0.147	1.07	66.00%
HND(0,-1,-2,-3), MinT(0)-MinT(-2)	0.018	1.01	0.102	1.06	66.90%
HND(0,-1,-2,-3), MinT(0)-MinT(-3)	0.028	1.01	0.081	1.03	67.80%
HND(0,-1,-2,-3), AvgT(0)-AvgT(-1)	0.014	1.01	0.08	1.1	66.30%
HND(0,-1,-2,-3), AvgT(0)-AvgT(-2)	0.016	1.01	0.07	1.07	68.30%
HND(0,-1,-2,-3), AvgT(0)-AvgT(-3)	0.025	1.01	0.149	1.05	67.50%
HND(0,-1,-2,-3), MaxT(-1)-MinT(0)	0.011	1.01	0.042	0.76	66.70%
HND(0,-1,-2,-3), HN(0,-1,-2)	0.01	1.01	0.039	1.02	67.60%
HND(0,-1,-2,-3), HN(0,-1,-2,-3)	0.006	1.01	0.012	1.02	67.50%
HND(0,-1,-2,-3), Stl(0,-1)	0.012	1.01	0.08	0.95	65.90%
HND(0,-1,-2,-3), Stl(0,-1,-2)	0.01	1.01	0.063	0.96	66.90%
HND(0,-1,-2,-3), Stl(0,-1,-2,-3)	0.008	1.01	0.013	0.96	66.80%
HND(0,-1,-2,-3), HNW(0,-1)	0.062	1.01	0.082	1.27	64.10%
HND(0,-1,-2,-3), HNW(0,-1,-2)	0.062	1.01	0.037	1.28	67.80%
HND(0,-1,-2,-3), HNW(0,-1,-2,-3)	0.064	1.01	0.009	1.3	68.40%

"OLD SNOW MODEL SELECTION RESULTS"

The following charts provide the old snow model selection results. The five best old snow predictor variables are used to create the following models from which the top three and final old snow wet avalanche probability models were chosen.

Old Snow Model Selection Results

	Training Dataset			Testing Dataset		
Model Variables	**Day of Year**			**Day of Year**		
P-value	0.021			0.233		
Odds Ratio	1.05			1.06		
% Con, Dis, Tie	62.70%	34.60%	2.70%	62.10%	34.60%	3.30%
	Training Dataset			**Testing Dataset**		
Model Variables	**MaxT(0)**			**MaxT(0)**		
P-value	0			0.131		
Odds Ratio	1.07			1.05		
% Con, Dis, Tie	72.60%	24.60%	2.80%	69.20%	28.50%	2.30%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**			**MinT(0)**		
P-value	0.007			0.076		
Odds Ratio	1.18			1.18		
% Con, Dis, Tie	67.60%	28.10%	4.40%	70.30%	24.90%	4.90%
	Training Dataset			**Testing Dataset**		
Model Variables	**AvgT(0)**			**AvgT(0)**		
P-value	0			0.079		
Odds Ratio	1.01			1.01		
% Con, Dis, Tie	73.30%	25.40%	1.30%	73.30%	25.10%	1.50%
	Training Dataset			**Testing Dataset**		
Model Variables	**HS(0)-HS(-2)**			**HS(0)-HS(-2)**		
P-value	0.001			0.288		
Odds Ratio	0.9			0.95		
% Con, Dis, Tie	68.10%	21.10%	10.80%	68.20%	20.00%	11.80%
	Training Dataset			**Testing Dataset**		
Model Variables	**MaxT(0)**	**HS(0)-HS(-2)**		**MaxT(0)**	**HS(0)-HS(-2)**	
P-value	0.001	0.005		0.107	0.207	
Odds Ratio	1.07	0.9		1.06	0.93	
% Con, Dis, Tie	77.30%	21.80%	0.80%	73.80%	25.40%	0.80%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**Day**		**MinT(0)**	**Day**	
P-value	0.016	0.038		0.126	0.499	
Odds Ratio	1.16	1.05		1.16	1.03	
% Con, Dis, Tie	71.20%	28.10%	0.70%	71.50%	26.90%	1.50%

Old Snow Model Selection Results

	Training Dataset			Testing Dataset		
Model Variables	**MinT(0)**	**Day**	**HS(0)-HS(-2)**	**MinT(0)**	**Day**	**HS(0)-HS(-2)**
P-value	0.031	0.067	0.007	0.115	0.623	0.374
Odds Ratio	1.14	1.05	0.9	1.15	1.02	0.94
% Con, Dis, Tie	75.00%	24.20%	0.80%	74.60%	24.60%	0.80%

	Training Dataset			Testing Dataset		
Model Variables	**MinT(0)**	**HS(0)-HS(-2)**		**MinT(0)**	**HS(0)-HS(-2)**	
P-value	0.013	0.004		0.08	0.3	
Odds Ratio	1.16	0.9		1.17	0.94	
% Con, Dis, Tie	75.00%	24.00%	1.00%	72.80%	24.10%	3.10%

	Training Dataset			Testing Dataset		
Model Variables	**AvgT(0)**	**HS(0)-HS(-2)**		**AvgT(0)**	**HS(0)-HS(-2)**	
P-value	0	0.008		0.075	0.267	
Odds Ratio	1.01	0.91		1.01	0.93	
% Con, Dis, Tie	76.20%	22.90%	1.00%	74.60%	24.40%	1.00%

"NEW SNOW MODEL SELECTION RESULTS"

The following charts provide the new snow model selection results. The ten best new snow predictor variables are used to create the following models from which the top three and final new snow wet avalanche probability models were chosen.

New Snow Model Selection Results

	Training Dataset			Testing Dataset		
Model Variables	**MinT(0)**			**MinT(0)**		
P-value	0.03			0.028		
Odds Ratio	1.11			1.2		
% Con, Dis, Tie	60.70%	34.20%	5.10%	66.90%	28.80%	4.30%
	Training Dataset			**Testing Dataset**		
Model Variables	**MaxT(-1)-MinT(0)**			**MaxT(-1)-MinT(0)**		
P-value	0.049			0.009		
Odds Ratio	0.78			0.56		
% Con, Dis, Tie	56.40%	39.40%	4.20%	75.20%	22.10%	2.70%
	Training Dataset			**Testing Dataset**		
Model Variables	**HN(0,-1,-2)**			**HN(0,-1,-2)**		
P-value	0.118			0.446		
Odds Ratio	1.01			1.01		
% Con, Dis, Tie	59.70%	31.90%	8.40%	57.80%	36.20%	6.00%
	Training Dataset			**Testing Dataset**		
Model Variables	**HN(0,-1,-2,-3)**			**HN(0,-1,-2,-3)**		
P-value	0.063			0.261		
Odds Ratio	1.01			1.02		
% Con, Dis, Tie	60.60%	33.10%	6.30%	62.60%	33.90%	3.60%

New Snow Model Selection Results

	Training Dataset			Testing Dataset		
Model Variables	**Stl(0,-1,-2,-3)**			**Stl(0,-1,-2,-3)**		
P-value	0.052			0.034		
Odds Ratio	0.97			0.95		
% Con, Dis, Tie	55.40%	38.30%	6.30%	64.70%	29.80%	5.50%
	Training Dataset			**Testing Dataset**		
Model Variables	**HNW(0,-1)**			**HNW(0,-1)**		
P-value	0.022			0.681		
Odds Ratio	1.35			1.13		
% Con, Dis, Tie	60.50%	32.40%	7.10%	49.60%	37.90%	12.60%
	Training Dataset			**Testing Dataset**		
Model Variables	**HNW(0,-1,-2)**			**HNW(0,-1,-2)**		
P-value	0.01			0.416		
Odds Ratio	1.33			1.22		
% Con, Dis, Tie	67.80%	27.80%	4.40%	56.90%	37.90%	5.20%
	Training Dataset			**Testing Dataset**		
Model Variables	**HNW(0,-1,-2,-3)**			**HNW(0,-1,-2,-3)**		
P-value	0.002			0.182		
Odds Ratio	1.34			1.32		
% Con, Dis, Tie	68.30%	28.00%	3.70%	62.60%	34.00%	3.30%
	Training Dataset			**Testing Dataset**		
Model Variables	**HND(0,-1)**			**HND(0,-1)**		
P-value	0.01			0.428		
Odds Ratio	1.01			1		
% Con, Dis, Tie	63.20%	32.80%	4.00%	50.30%	44.50%	5.20%

New Snow Model Selection Results

	Training Dataset			Testing Dataset		
Model Variables	**HND(0,-1,-2,-3)**			**HND(0,-1,-2,-3)**		
P-value	0.024			0.514		
Odds Ratio	1.01			1		
% Con, Dis, Tie	62.60%	33.80%	3.60%	50.40%	43.90%	5.70%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**HN(0,-1,-2)**		**MinT(0)**	**HN(0,-1,-2)**	
P-value	0.009	0.022		0.01	0.109	
Odds Ratio	1.14	1.02		1.26	1.03	
% Con, Dis, Tie	67.00%	30.80%	2.20%	70.60%	28.10%	1.20%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**HN(0,-1,-2)**	**Stl(0,-1,-2,-3)**	**MinT(0)**	**HN(0,-1,-2)**	**Stl(0,-1,-2,-3)**
P-value	0.012	0.191	0.377	1.29	1.01	0.92
Odds Ratio	1.14	1.01	0.98	1.08	0.96	0.86
% Con, Dis, Tie	67.50%	30.40%	2.10%	79.90%	19.50%	0.60%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**HN(0,-1,-2,-3)**		**MinT(0)**	**HN(0,-1,-2,-3)**	
P-value	0.007	0.009		0.09	0.036	
Odds Ratio	1.14	1.02		1.3	1.04	
% Con, Dis, Tie	68.80%	29.30%	1.80%	75.10%	24.20%	0.70%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**Stl(0,-1,-2,-3)**		**MinT(0)**	**Stl(0,-1,-2,-3)**	
P-value	0.021	0.039		0.005	0.006	
Odds Ratio	1.12	0.97		1.28	0.92	
% Con, Dis, Tie	65.80%	32.00%	2.20%	80.10%	19.30%	0.60%

New Snow Model Selection Results

	Training Dataset			Testing Dataset		
Model Variables	**MinT(0)**	**HNW(0,-1)**		**MinT(0)**	**HNW(0,-1)**	
P-value	0.023	0.016		0.026	0.518	
Odds Ratio	1.11	1.38		1.2	1.23	
% Con, Dis, Tie	67.30%	30.70%	2.00%	68.50%	30.50%	1.00%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**HNW(0,-1)**	**MaxT(-1)-MinT(0)**	**MinT(0)**	**HNW(0,-1)**	**MaxT(-1)-MinT(0)**
P-value	0.087	0.011	0.214	0.372	0.411	0.085
Odds Ratio	1.09	1.4	0.83	1.09	1.31	0.63
% Con, Dis, Tie	68.30%	30.00%	1.70%	72.70%	26.10%	1.20%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**HNW(0,-1,-2)**		**MinT(0)**	**HNW(0,-1,-2)**	
P-value	0.016	0.004		0.023	0.273	
Odds Ratio	1.13	1.39		1.21	1.34	
% Con, Dis, Tie	70.40%	27.80%	1.80%	68.60%	30.20%	1.20%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**HNW(0,-1,-2,-3)**		**MinT(0)**	**HNW(0,-1,-2,-3)**	
P-value	0.013	0.001		0.016	0.078	
Odds Ratio	1.13	1.4		1.24	1.51	
% Con, Dis, Tie	72.10%	26.40%	1.50%	71.90%	27.30%	0.70%
	Training Dataset			**Testing Dataset**		
Model Variables	**MinT(0)**	**HNW(0,-1,-2,-3)**	**MaxT(-1)-MinT(0)**	**MinT(0)**	**HNW(0,-1,-2,-3)**	**MaxT(-1)-MinT(0)**
P-value	0.033	0.001	0.574	0.214	0.197	0.215
Odds Ratio	1.12	1.39	0.92	1.14	1.38	0.71
% Con, Dis, Tie	72.10%	26.60%	1.40%	74.40%	24.80%	0.80%

New Snow Model Selection Results

	Training Dataset			Testing Dataset		
Model Variables	**MaxT(-1)-MinT(0)**	**HNW(0,-1)**		**MaxT(-1)-MinT(0)**	**HNW(0,-1)**	
P-value	0.04	0.01		0.008	0.403	
Odds Ratio	0.76	1.4		0.55	1.31	
% Con, Dis, Tie	65.80%	31.40%	2.80%	74.00%	25.40%	0.60%
	Training Dataset			**Testing Dataset**		
Model Variables	**MaxT(-1)-MinT(0)**	**HNW(0,-1)**	**MinT(0)**	**MaxT(-1)-MinT(0)**	**HNW(0,-1)**	**MinT(0)**
P-value	0.214	0.011	0.087	0.085	0.411	0.372
Odds Ratio	0.83	1.4	1.09	0.63	1.31	1.09
% Con, Dis, Tie	68.30%	30.00%	1.70%	72.70%	26.10%	1.20%
	Training Dataset			**Testing Dataset**		
Model Variables	**MaxT(-1)-MinT(0)**	**HNW(0,-1)**	**MinT(0)-MinT(-3)**	**MaxT(-1)-MinT(0)**	**HNW(0,-1)**	**MinT(0)-MinT(-3)**
P-value	0.2	0.007	0.143	0.045	0.468	0.159
Odds Ratio	0.83	1.43	1.03	0.61	1.28	1.05
% Con, Dis, Tie	68.80%	29.40%	1.80%	74.80%	24.50%	0.70%

APPENDIX C:

WET AVALANCHE MODELS AND HELP PAGE

"WET AVALANCHE PREDICTION MODEL CALCULATIONS"

The following steps can be followed to create the old snow and new snow wet avalanche models in Microsoft Excel or similar program. Always compare the old snow model results with Figure 11 and Figures 19 through 22 in the main text. Always compare the new snow model results with Figures 29 through 33 in the main text. Refer to the "Help" document in this Appendix for model result interpretation

Use Figure 34 as a template for your Excel spreadsheet. Referring to Figure 34, the following equations should be entered in the red (or gray) cells that fall under "DO NOT TYPE IN THIS COLUMN"

New Snow Model:

1. In the red (or gray) cell after the line "Enter today's recorded, or expected minimum temperature (degrees Fahrenheit):" enter the following equation

    =(click on cell that you will enter Fahrenheit degrees - 32)/1.8

    Example: =(H18-32)/1.8

    If you have done this correctly 32°F will automatically be converted to "0.0°C." 0.0°C will appear in the red (or gray cell).

2. In the red (or gray) cell after the line "Enter today's recorded, or expected snow water equivalent (inches):" enter the following equation

    =(click on cell that you will enter SWE in inches)*2.54

    Example: =H20*2.54

    If you have done this correctly 2 inches of SWE will automatically be converted to 5.1cm of SWE. "5.1"cm will appear in the red (or gray) cell.

3. In the red (or gray) cell after the line "Enter yesterday's recorded snow water equivalent (inches):" enter the following equation.

    =(click on cell that you will enter SWE in inches)*2.54

    Example: =H20*2.54

    If you have done this correctly 0.5 inches of SWE will automatically be converted to 1.3cm of SWE. "1.3"cm will appear in the red (or gray) cell.

4. In the red (or gray) cell after the line "Enter the day before yesterday's recorded snow water equivalent (inches):" enter the following equation.

   =(click on cell that you will enter SWE in inches)*2.54

   Example: =H20*2.54

   If you have done this correctly 0.1 inches of SWE will automatically be converted to 0.3cm of SWE. "0.3"cm will appear in the red (or gray) cell.

5. In the red (or gray) cell after the line "Enter the snow water equivalent measured two days before yesterday (inches):" enter the following equation.

   =(click on cell that you will enter SWE in inches)*2.54

   Example: =H20*2.54

   If you have done this correctly 0.3 inches of SWE will automatically be converted to 0.8cm of SWE. "0.8"cm will appear in the red (or gray) cell.

6. The red (or gray) cell directly below the last snow water equivalent value will sum the four snow water equivalent entries.

   =Sum(click on all four red (or gray) SWE cells)

   Example: =SUM(I20:I23)

   If you have done this correctly your cumulative SWE value should equal 2.3cm. "2.3"cm will appear in the red (or gray) cell.

7. The last red cell contains the new snow model equation. Type the following equation into the red (or gray) cell.

=(EXP((0.14572*click on red minimum temp red cell)+(0.3371*click on red cumulative SWE cell))/(1+(EXP((0.14572*click on red minimum temp cell)+(0.3371*click on red cumulative SWE cell)))))

Example:
=(EXP((0.14572*I18)+(0.3371*I24))/(1+(EXP((0.14572*I18)+(0.3371*I24)))))

If you have done this correctly your wet avalanche probability is 92%.

Old Snow Model:

1. In the red (or gray) cell after the line "Enter today's recorded, or expected minimum temperature (degrees Fahrenheit):" enter the following equation.

   =(click on cell that you will enter Fahrenheit degrees - 32)/1.8

   Example: =(H18-32)/1.8

   If you have done this correctly 27°F will automatically be converted to –2.8°C in the red (or gray cell). "–2.8"°C will appear in the red (or gray) cell.

2. In the red (or gray) cell after the line "Enter today's recorded total snow depth (inches):" enter the following equation.

   =(click on cell that you will enter total snow depth in inches)*2.54

   Example: =H20*2.54

   If you have done this correctly 59 inches of total snow depth will automatically be converted to 149.9 cm of total snow depth. "149.9"cm will appear in the red (or gray) cell.

3. In the red (or gray) cell after the line "Enter day before yesterday's recorded total snow depth (inches):" enter the following equation.

   =(click on cell that you will enter total snow depth in inches)*2.54

   Example: =H20*2.54

   If you have done this correctly 61 inches of total snow depth will automatically be converted to 154.9cm of total snow depth. "154.9"cm will appear in the red (or gray) cell.

4. The red (or gray) cell directly below the last total snow depth value calculates the difference between the two snow depth measurements above. Enter the following equation.

=(click on first total snow depth red cell)-(click on second total snow depth red cell)

   Example: =I37-I38

   If you have done this correctly two day change in total snow depth should equal –5.1cm. "-5.1"cm will appear in the red (or gray) cell.

5. The last red cell contain the old snow model equation

=(EXP((0.14811*click on minimum temp red cell) + (-0.09047*click on change in total snow depth red cell))/(1+(EXP((0.14811*click on minimum temp red cell)+ (-0.09047*click on change in total snow depth red cell)))))

Example:
=(EXP((0.14811*I35)+(-0.09047*I39))/(1+(EXP((0.14811*I35)+(-0.09047*I39)))))

If you have done this correctly your wet avalanche probability is 51%.

“BRIDGER BOWL WET AVALANCHE MODELS HELP PAGE”

**It is recommended that you read “March Wet Avalanche Prediction at Bridger Bowl Ski Area, Montana” (Romig, 2004) for information regarding how these models were developed, how to interpret the variables, and the intended purpose for these models.

What are the equations for the new and old snow prediction models?

New Snow Equation:
$(Exp((0.14572*MinT_0)+(0.33710*HNW_{0,-1,-2,-3})) \div (1+((0.14572* MinT_0)+(0.33710* HNW_{0,-1,-2,-3}))))$

Where $MinT_0$ = today’s recorded or expected minimum temperature (°C)
$HNW_{0,-1,-2,-3}$ = the cumulative snow water equivalent (SWE) from today, yesterday, one day before yesterday and two days before yesterday (cm).

Old Snow Equation:
$(EXP((0.14811* MinT_0)+(-0.09047*HS_0-HS_{-2})) \div (1+(EXP((0.14811* MinT_0)+(-0.09047* HS_0-HS_{-2})))))$

Where $MinT_0$ = today’s recorded or expected minimum temperature
$HS_0 - HS_{-2}$ = the difference between today’s recorded total snowpack depth and the day before yesterday’s total snowpack depth (cm)

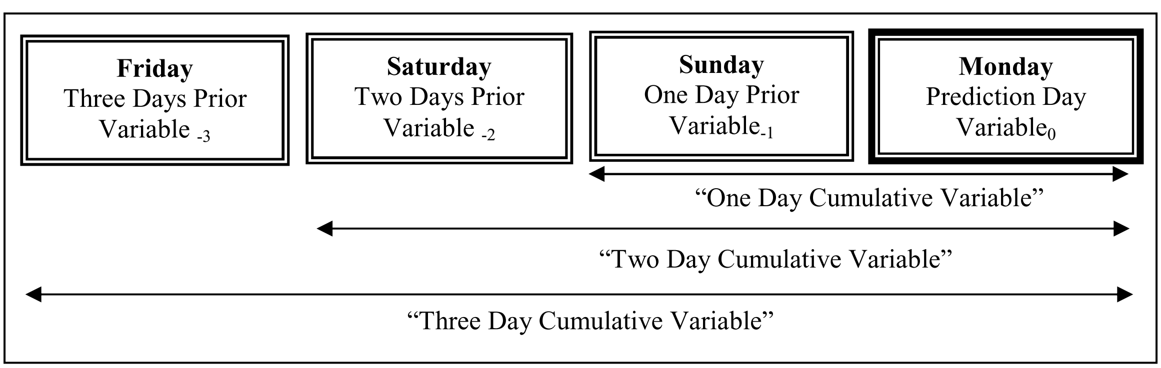
How do I convert from Fahrenheit to Celsius and inches to centimeters?

Fahrenheit to Celsius: Subtract 32 from Fahrenheit temperature and divide by 1.8 to get Celsius temperature.

Inches to Centimeters: Multiply inches by 2.54 to get centimeters.

What do the variable subscripts mean (i.e. $MinT_0$, $HNW_{0,-1,-2,-3}$)?

This study defines the variables within each dataset in terms of ‘prediction day’ (0), ‘one day prior’ (-1), ‘two days prior’ (-2), and ‘three days prior’ (-3). ‘Prediction day’ always refers to the day the model is predicting for, usually the current day, and is the day that the ‘one day prior’, ‘two days prior’ and ‘three days prior’ variables lead up to. A ‘prediction day’ may or may not have recorded wet avalanches. ‘One day prior’ always refers to the day that is one day prior to the ‘prediction day’; ‘two days prior’ always refers to the day that is two days prior to the 'prediction day'; and 'three days prior' always refers to the day that is three days prior to the 'prediction day'. The figure below serves as an example for the time-lag concept. Suppose that today, the day wet avalanche probability is being predicted for, is Monday. Any variable with an observation taken on this day is given a '0' subscript. Sunday is considered one day prior to the prediction day and any observation taken on this day is given a '-1' subscript. Saturday is two days prior to the prediction day and observations taken on this day are given subscript of '-2'. Friday is three days prior to the prediction day and observations taken on this day are given a '-3' subscript. Variables with only one subscript, such as $MinT_0$, are single day measurements. Variables with more than one subscript are cumulative day measurements, and the subscript numbers refer to which days are included in the cumulative measurement. For example, $HNW_{0,-1,-2,-3}$ is the cumulative new snow water equivalent that is calculated by adding the SWE for the prediction day (0), one day prior (-1), two days prior (-2) and three days prior (-3) to the prediction day.

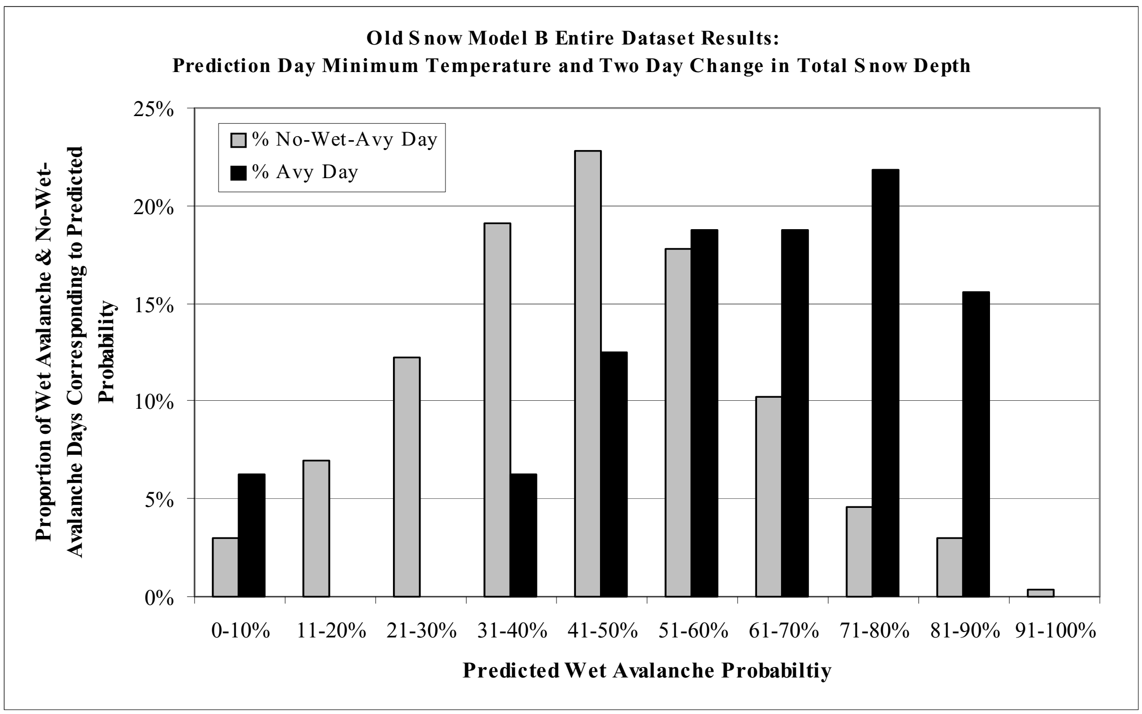


How do I interpret the model results? And what are the other graphs for?

When you enter the correct information into the New Snow and Old Snow Prediction Models, the models will calculate today's probability for wet avalanche conditions. The New Snow Model is has a 72% overall success rate and the Old Snow Model has a 75% overall success rate. This means that the New Snow Model calculated accurate wet avalanche probabilities for 72% of the new snow dataset, and the Old Snow Model calculated accurate wet avalanche probabilities for 75% of the old snow dataset. In order to gain more confidence in the probability the model is predicting, it is strongly recommended that you compare the model's prediction and the data collected from the Alpine weather station to the five graphs old snow and new snow graphs described below.

Old Snow Prediction Model Graphs

The "Old Snow Model: $MinT_0$, HS_0-HS_{-2} 1968-2001 Results" graph below describes the proportion of wet avalanche days and days with no wet avalanches that correspond to the Old Snow Model's predicted probability ranges. For example, about 3% of all the days with no wet avalanches recorded in March from 1968-2001 and about 6 % of all recorded wet avalanche days recorded in March from 1968-2001 were given a wet avalanche probability between 0-10%. All but one recorded wet avalanches in the past 32 years have occurred when the model predicts a 31-80% probability for wet avalanche conditions. The old snow model has a 75% overall success rate, that is, 75% of all the days in the old snow dataset were given accurate probabilities based on the model’s decision rule. The old snow models decision rule is positioned at 57%, the point that best divides the distributions of the observed wet avalanche days and no-wet-avalanche days (Fig 19). According to this decision rule, any day given a predicted wet avalanche probability of 57% or greater *should* be a wet avalanche day and any day given a predicted wet avalanche probability less than 57% *should* be a day without wet avalanches.



Old Snow Model: $MinT_0$, HS_0-HS_{-2} 1968-2001 Results

In order to correctly interpret a probability calculated by the model, the following must be considered: how often does the model give observed wet avalanche days a probability of 57% or greater, and how often does the model give observed days with no wet avalanches a probability less than 57%? There were 90 old snow days that were given a wet avalanche probability of 57% or greater (See “Old Snow Model Accuracy”

Table). According to the model's decision rule, all 90 days should be wet avalanche days. Only 18 of the 90 days (20%) were observed wet avalanche days. The remaining 72 days (80%) were actually observed days with no wet avalanches that were given an inaccurate probability by the model. There were 245 old snow days that were given a probability less than 57% by the model. According to the model's decision rule, all 245 days should be days with no wet avalanches. Out of the 245 days, 231 days (94%) were days with no wet avalanches. The remaining 14 days (6%) were inaccurately predicted observed wet avalanche days.

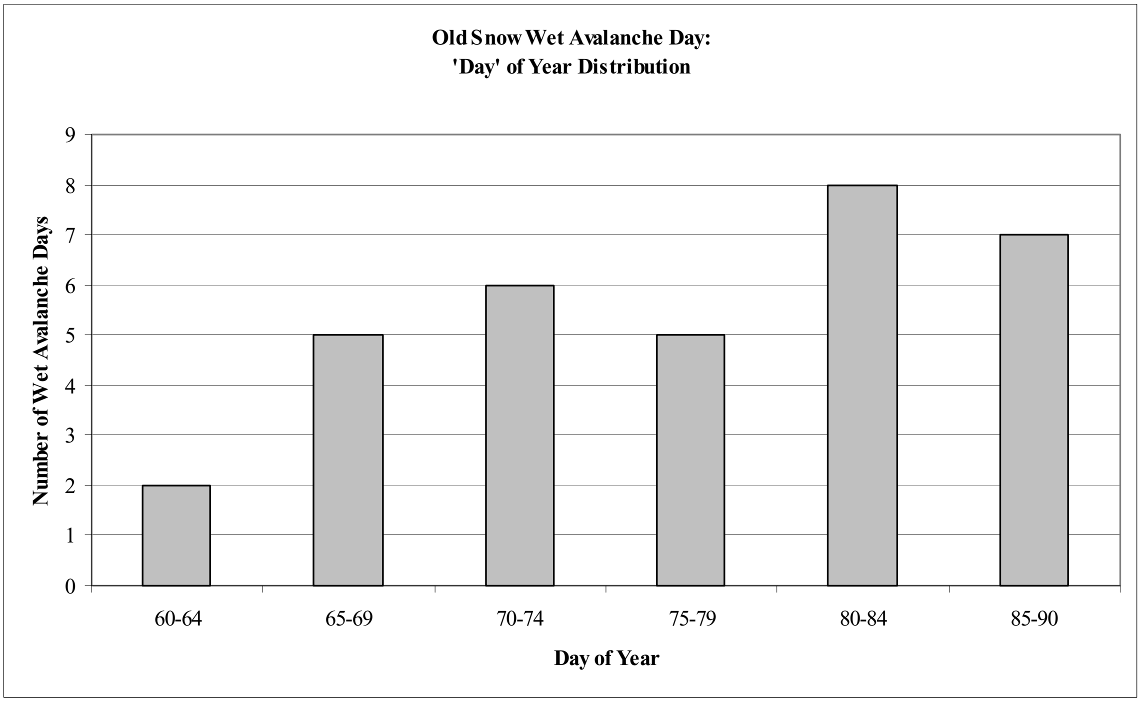
Old Snow Model Accuracy

	Observed Old Snow Wet Avalanche Days	**Observed Old Snow No-Wet-Avalanche Days**	
Old Snow Model Predicted Wet Avalanche Day (Probability $\geq$ 57%)	18 days (correctly predicted)	72 days (incorrectly predicted)	Total: 90 days
Old Snow Model Predicted No-Wet-Avalanche Day (Probabiltiy < 57%)	14 days (incorrectly predicted)	231 days (correctly predicted)	Total: 245 days
	Total: 32* days	Total: 303* days	

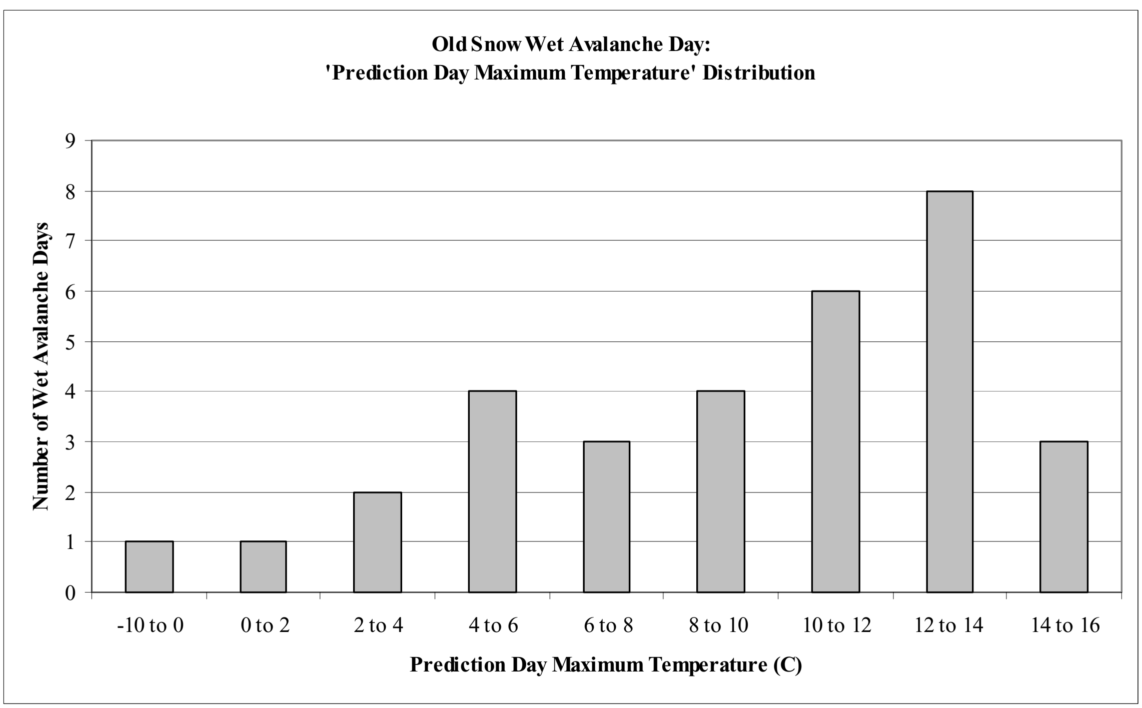
*One wet avalanche day and 6 no-wet-avalanche days were missing data.

What this means for the model user is when the old snow model calculates a wet avalanche probability between 0-56%, 9 out of 10 days will not have wet avalanches. When the model calculates a wet avalanche probability between 57-100%, only 2 out of 10 days will have wet avalanche conditions. To gain more confidence in the model's predicted probability, the user can compare the prediction day's meteorological and snowpack conditions with historical wet avalanche data to determine whether current conditions are similar to wet avalanche conditions in the past.

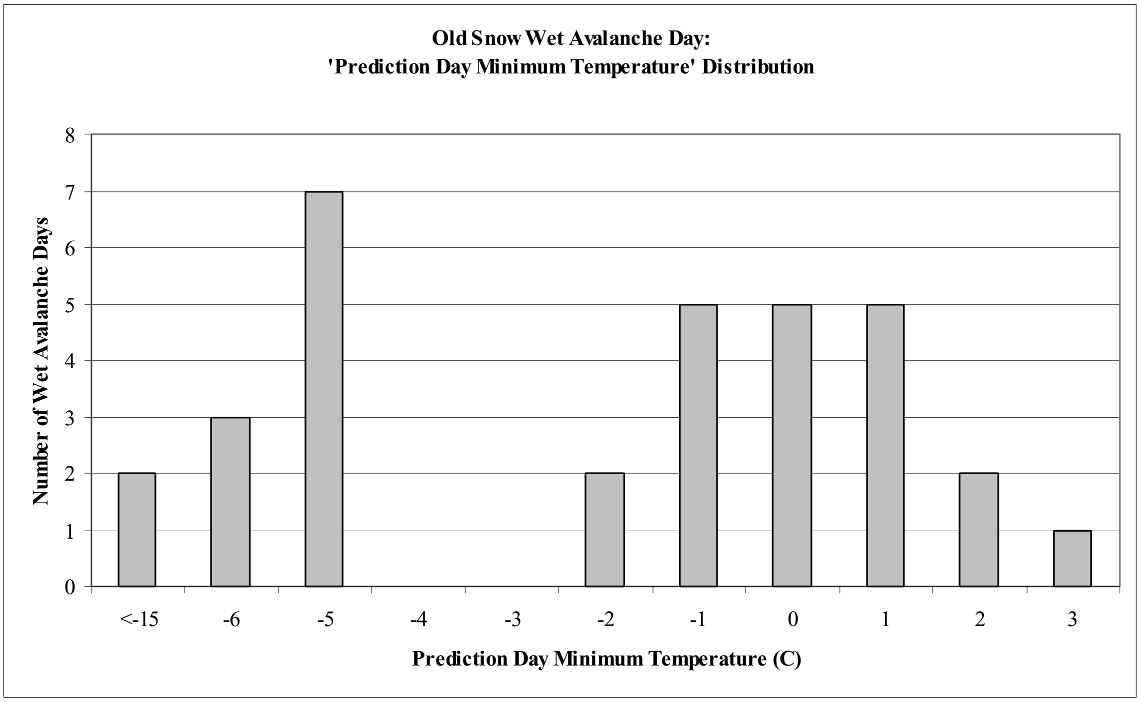
Each variable in the four graphs below were found to be good predictors for old snow wet avalanche conditions. The graphs show you the maximum, minimum and most common day of year, temperatures, and change in total snowpack that have been recorded on wet avalanche days between 1968-2001. For example, look at the "Old Snow: Day of Year Distribution" graph, wet avalanche activity appears to be at its minimum during the first five days of March (day 60-64). Wet avalanche activity generally increases from day 65 through day 84 and begins to taper off during the last 6 days of March. The "Old Snow: $MaxT_0$ Distribution" graph shows you the event day maximum temperature range for all the wet avalanche days that were recorded between 1968-2001. The "Old Snow: $MinT_0$ Distribution" graph shows the event day minimum temperature for all of the recorded wet avalanches between 1968-2001. The "Old Snow: HS_0-HS_{-2} Distribution" graph shows the range in the difference in total snowpack depth between the prediction day and two days prior to the prediction day for all of the wet avalanches recorded between 1968-2001.



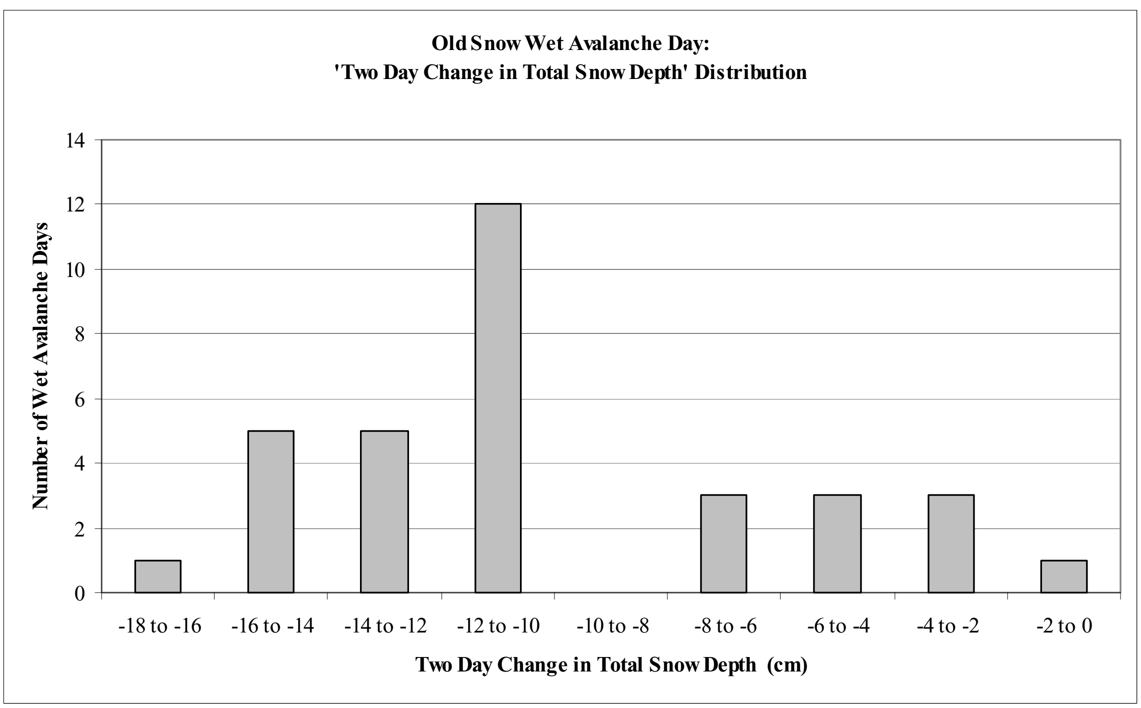
Old Snow Wet Avalanche Days: Day of Year Distribution



Old Snow Wet Avalanche Days: $MaxT_0$ Distribution



Old Snow Wet Avalanche Days: $MinT_0$ Distribution

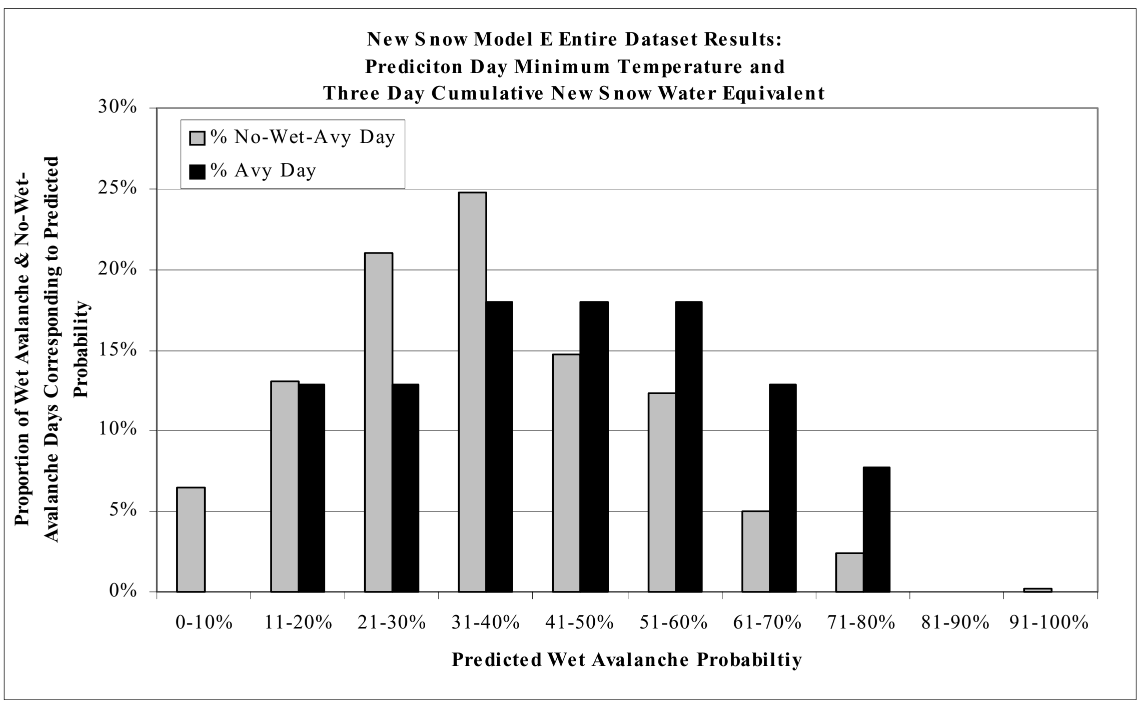


Old Snow Wet Avalanche Days: HS_0-HS_{-2} Distribution

Suppose today's minimum temperature is -7°C and the total snowpack depth has decreased by 3cm between today and two days before today. Given this information, the Old Snow Model calculates a 32% probability for wet avalanche conditions today. Based on the Old Snow Model's decision rule, we know that 9 out of 10 times will be a day with no wet avalanches whenever the model gives a probability lower than 57%, but there is still a 1 in 10 chance that the prediction day could be a wet avalanche day. Look at the four predictor variable graphs above to find more support for the model's prediction. The "Old Snow: $MinT_0$ Distribution" graph shows that there has never been a wet avalanche recorded on a day with a minimum temperature of -7°C. The "Old Snow: HS_0-HS_{-2} Distribution" graph shows that only 3 wet avalanche days have occurred between 1968-2001 when the snowpack has settled 3cm over the two days prior to the event day. Given the fairly low probability predicted by the model, and the rather low wet avalanche day occurrence on similar days in the past, the likelihood of wet avalanche conditions is relatively low, although still possible. It may be a good idea to look at a couple of the other predictor variable graphs such as the "Old Snow: Day or Year Distribution" graph and the "Old Snow: $MaxT_0$ Distribution" graph. Is it the second, third or fourth full week in March? If so, the past data show that wet avalanche occurrence increases at this time. How warm do you expect it to be today? In the past, wet avalanche occurrence increases steadily once maximum temperatures reach 6°C or greater. Information from these predictor variable graphs can give you more support for your wet avalanche safety decisions.

New Snow Prediction Model Graphs

The "New Snow Model: $MinT_0$, $HNW_{0,-1,-2,-3}$ 1968-2001 Results" graph describes the proportion of wet avalanche days and days with no wet avalanches that correspond to the New Snow Model's predicted probability ranges. For example, about 21% of all the days with no wet avalanches and about 13% of all wet avalanche days recorded in March between 1968-2001were given a wet avalanche probability between 0-10% by the New Snow Model. The New Snow Model gave all the wet avalanches that occurred between 1968-2001 a wet avalanche probability of 11-80%.



New Snow Model: $MinT_0$, $HNW_{0,-1,-2,-3}$ 1968-2001 Results

The new snow model has a 72% overall success rate, in other words, 72% of all the days in the new snow dataset were given accurate probabilities based on the model's decision rule. The new snow model's decision rule is positioned at 45%, the point that best divides the distributions of the observed wet avalanche days and days with no wet avalanches. According to the new snow model's decision rule, any day that is given a wet avalanche probability of 45% or greater *should* be a wet avalanche day and any day given a predicted wet avalanche probability less than 45% *should* be a day without wet avalanches. The same questions asked of the old snow model must be taken into consideration with the new snow model in order to correctly interpret its predicted probabilities: how often does the model give observed wet avalanche days a probability of 45% or greater, and how often does the model give observed days with no wet avalanches a probability less than 45%? There were a total of 195 new snow days that were given a wet avalanche probability of 45% or greater ("New Snow Model Accuracy" Table). According to the new snow model's decision rule, all 195 days should be wet avalanche days. Only 18 days (9%) were observed wet avalanche days. The remaining 177 days (91%) were observed days with no wet avalanches that were inaccurately given a probability greater than 45%. There were 477 days in the new snow dataset that were given a wet avalanche probability less than 45%. According to the new snow model's decision rule, all 477 days should be days with no wet avalanches. Of the 477 days, 456 days (96%) were observed days with no wet avalanches. The remaining 21 days (4%) were observed wet avalanche days that were given inaccurate probabilities by the model.

New Snow Model Accuracy

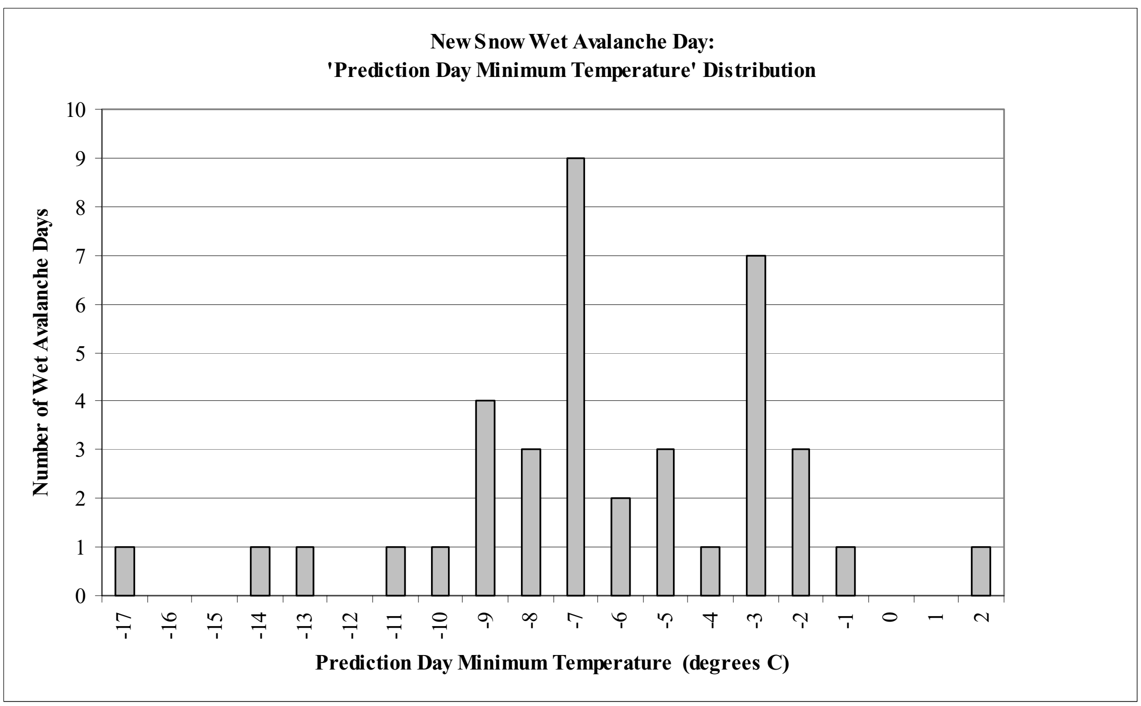
	Observed New Snow Wet Avalanche Days	Observed New Snow No-Wet-Avalanche Days	
Old Snow Model Predicted Wet Avalanche Day (Probability ≥ 57%)	18 days (correctly predicted)	177 days (incorrectly predicted)	Total: 195 days
Old Snow Model Predicted No-Wet-Avalanche Day (Probabiltiy < 57%)	21 days (incorrectly predicted)	456 days (correctly predicted)	Total: 477 days
	Total: 39 days	Total: 633* days	

*71 no-wet-avalanche days were missing data.

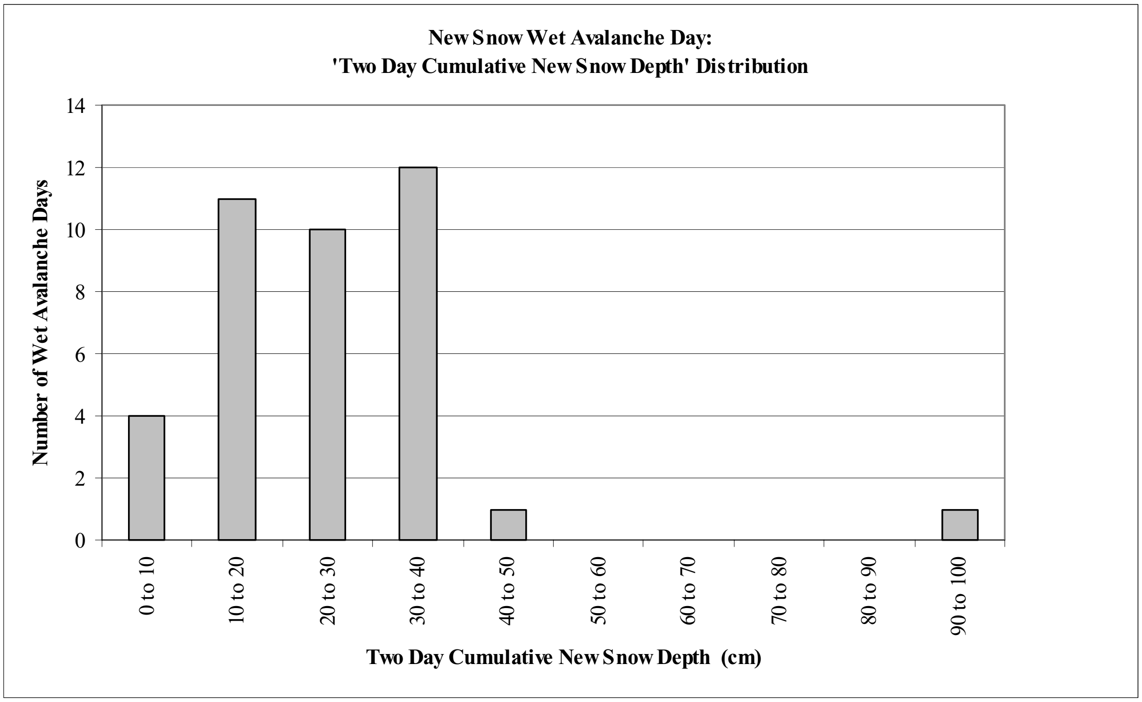
Interpretation of the new snow model's predicted wet avalanche probability is similar to the interpretation described for the old snow model. Based on 32 years of wet avalanche data, when the new snow model calculates a wet avalanche probability between 0-44%, 9 out of 10 days will not have wet avalanches. When the new snow model calculates a wet avalanche probability between 45-100%, only 1 out of 10 days will be a wet avalanche day. As with the old snow model, the user can compare the prediction day's meteorological and snowpack conditions with historical wet avalanche data to determine whether current conditions are similar to wet avalanche conditions in the past.

Each variable in the four graphs below were found to be good predictors for new snow wet avalanche conditions. The graphs show you the maximum, minimum and most common temperature, SWE and new snow depths that have been recorded on wet avalanche days between 1968-2001. For example look at the "New Snow: MinT_0

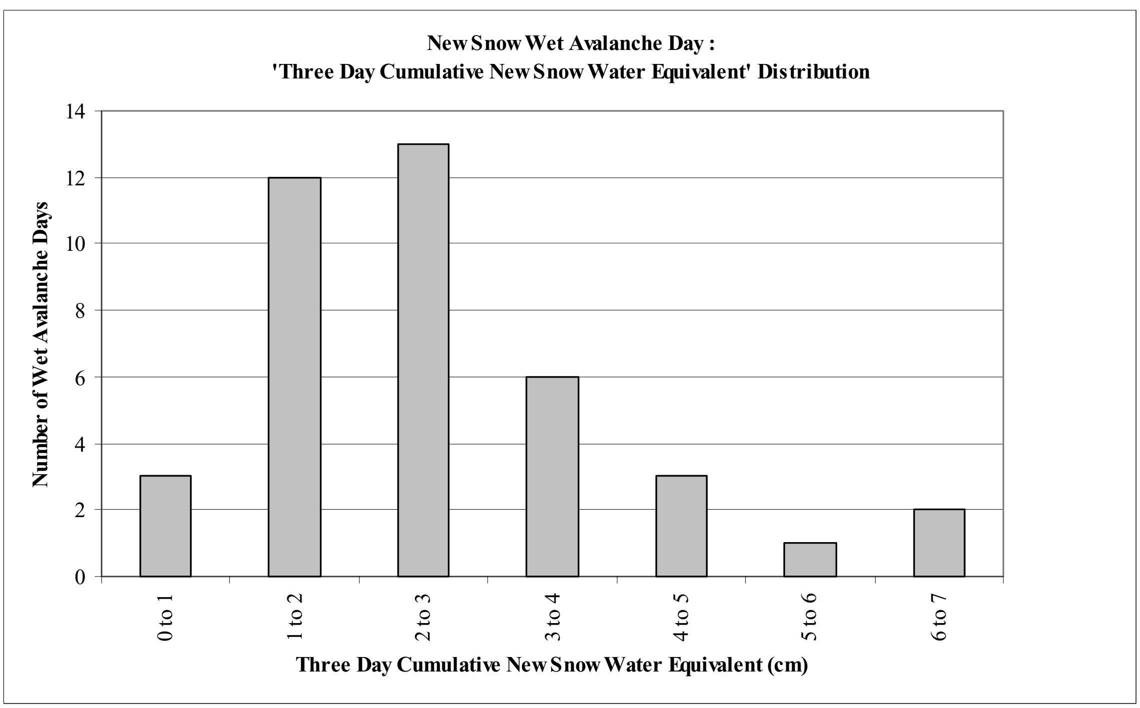
Distribution" graph, only 1 day between 1969-2001 had recorded wet avalanches when the minimum temperature was -17°C and 9 days had recorded wet avalanches when the minimum temperature was -7°C. The "New Snow: $HN_{0,-1,-2}$ Distribution" graph shows the cumulative two day new snow depth range for all of the recorded wet avalanches between 1968-2001. The "New Snow: $HNW_{0,-1,-2,-3}$ Distribution" graph shows you the cumulative three day SWE range for all the wet avalanche days that were recorded between 1968-2001. The "New Snow: $MaxT_{-1}$-$MinT_0$ Distribution" graph shows the overnight temperature range prior to the prediction day distribution for all of the wet avalanches recorded between 1968-2001.



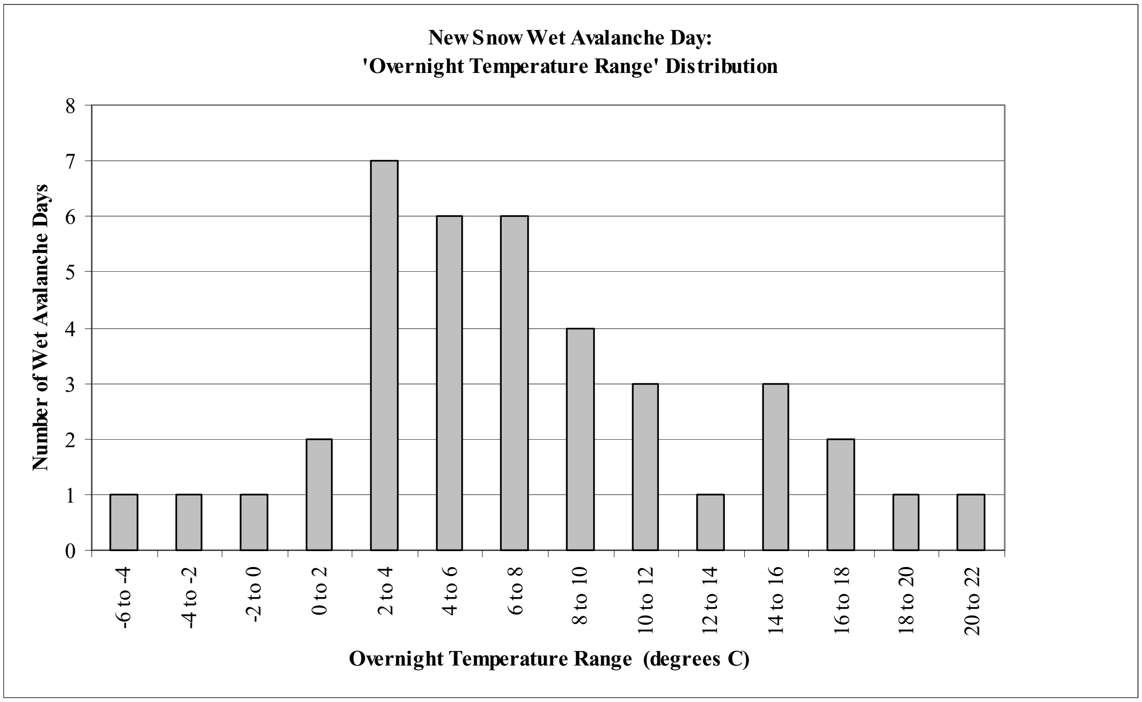
New Snow Wet Avalanche Day: $MinT_0$ Distribution



New Snow Wet Avalanche Day: $HN_{0,-1,-2}$ Distribution



New Snow Wet Avalanche Day: $HNW_{0,-1,-2,-3}$ Distribution



New Snow Wet Avalanche Day: $MaxT_{-1}$-$MinT_0$ Distribution

Suppose today's minimum temperature is -5°C and the cumulative three day SWE is 1.0cm. The New Snow Model calculates a 40% probability for wet avalanche conditions to develop today. Given the New Snow Model's decision rule, 9 out of days 10 days will not have wet avalanches when the model predicts a probability less than 45%, but there is still a 1 in 10 chance that the prediction day could be a wet avalanche day. The "New Snow Model: $MinT_0$, $HNW_{0,-1,-2,-3}$ 1968-2001 Results" graph shows that more days with no wet avalanches than wet avalanche days have occurred in the past when the model gives a probability within the 31-40% range. Now look at the "New Snow: $MinT_0$ Distribution" graph and the "New Snow: Day $HNW_{0,-1,-2,-3}$ Distribution" graph. Several wet avalanche days have been recorded in the past when the minimum temperature was -5°C. A cumulative three day SWE total of 1.0cm is within the 1 to 2cm range, which is one of the most frequent producers of wet avalanche days in the past. Given that 1 out of 10 days are wet avalanche days when the model gives a probability less than 45%, and how many wet avalanche days have occurred in the past with the same minimum temperature and SWE values, there is a chance that wet avalanche conditions could develop today. If you needed more information to back up your decision, you could compare your cumulative two day new snow totals and last night's temperature range with the wet avalanche day occurrences in the "New Snow: $HN_{0,-1,-2}$ Distribution" graph and the "New Snow: $MaxT_{-1}$-$MinT_0$ Distribution" graph.