Cold Regions Science and Technology 120 (2015) 227–236

Contents lists available at ScienceDirect

Cold Regions Science and Technology

journal homepage: www.elsevier.com/locate/coldregions

Meteorological variables to aid forecasting deep slab avalanches on persistent weak layers

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ARTICLE INFO

Article history:
Received 13 November 2014
Received in revised form 31 July 2015
Accepted 4 August 2015
Available online 18 August 2015

Keywords:
Deep slabs
Avalanche forecasting
Classification trees
Random forest
Persistent weak layers

ABSTRACT

Deep slab avalanches are particularly challenging to forecast. These avalanches are difficult to trigger, yet when they release they tend to propagate far and can result in large and destructive avalanches. We utilized a 44-year record of avalanche control and meteorological data from Bridger Bowl ski area in southwest Montana to test the usefulness of meteorological variables for predicting seasons and days with deep slab avalanches. We defined deep slab avalanches as those that failed on persistent weak layers deeper than 0.9 m, and that occurred after February 1st. Previous studies often used meteorological variables from days prior to avalanches, but we also considered meteorological variables over the early months of the season. We used classification trees and random forests for our analyses. Our results showed seasons with either dry or wet deep slabs on persistent weak layers typically had less precipitation from November through January than seasons without deep slabs on persistent weak layers. Days with deep slab avalanches on persistent weak layers often had warmer minimum 24-hour air temperatures, and more precipitation over the prior seven days, than days without deep slabs on persistent weak layers. Days with deep wet slab avalanches on persistent weak layers were typically preceded by three days of above freezing air temperatures. Seasonal and daily meteorological variables were found useful to aid forecasting dry and wet deep slab avalanches on persistent weak layers, and should be used in combination with continuous observation of the snowpack and avalanche activity.

1. Introduction

Forecasting deep slab avalanches on persistent weak layers becomes an increasingly challenging task as the winter snowpack deepens. Avalanches that fail on a particular weak layer often become less common the longer the weak layer is buried, but when they do occur they are typically larger and more destructive than other avalanches (Comey and McCollister, 2008; Tracz, 2012). In contrast to avalanches that fail on recently buried persistent weak layers and new snow instabilities, deep slab avalanches on persistent weak layers are seldom accompanied by strong evidence that suggests instability (LaChapelle and Atwater, 1961). After certain weak layers form (e.g., depth hoar), they endure frequent changes between weakening due to strong temperature gradients and strengthening due to weak temperature gradients or pressure from snow accumulating above the weak layer (Bradley and Bowles, 1967). Avalanches on recently buried weak layers are common during and after most storms, which lends strong evidence towards predicting their timing (e.g., Davis et al., 1999). Deep slab avalanches are commonly triggered during and shortly after storms, but it is difficult to differentiate between storms that will trigger a deep slab avalanche and storms that will not (e.g., Conlan et al., 2014). Various studies have explored the difference in meteorological conditions prior to days with deep slab avalanches compared to conditions prior to days without deep slab avalanches (e.g., Conlan et al., 2014; Jamieson et al., 2001). However, few have considered the meteorological conditions during weak layer formation over the early months of seasons with deep slab avalanches compared to those meteorological conditions during seasons without deep slab avalanches. We examined the meteorological conditions during weak layer formation in November, December, and January of each season, as well as the meteorological conditions over days prior to deep slab avalanches on persistent weak layers at Bridger Bowl ski area in southwest Montana.

In a study by Davis et al. (1999), meteorological conditions during weak layer formation were considered by including the starting snow depth of the year in models created to forecast avalanche days and size. They found starting snow depth of the year to be significant in explaining the daily sum of avalanche size and maximum avalanche size. Jamieson et al. (2001) compared meteorological conditions during persistent weak layer formation between two regions where the same weak layer developed, but only one region had extensive avalanche

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http://dx.doi.org/10.1016/j.coldregions.2015.08.007
0165-232X/

activity on this layer. They suggested that persistent weak layer formation can be predicted based on air temperature, snowfall, and precipitation measurements from a suitable weather station.

A variety of definitions have been used for deep slab avalanches in order to study meteorological variables associated with them. Jamieson et al. (2001) focused on avalanches that failed on a buried facet-crust weak layer throughout one season. They found that prior meteorological conditions associated with avalanches on this layer were cumulative precipitation up to 19 days and air temperature change over 4–5 days. Savage (2006) found a weak correlation between prior cumulative precipitation and deep slab avalanches, which were defined by average crown depths deeper than 1.2 m. However, all deep slab avalanches that he studied had wind transport on at least one of four prior days, and 55% of deep slab avalanches occurred when four out of five prior days had wind transport (Savage pers. comm., 2014). Furthermore, small explosive charges were more common triggers than larger explosive charges (Savage, 2006).

Schweizer et al. (2009) found large avalanches (i.e., those running past a given point on an avalanche path) on one path in Switzerland to be most strongly associated with substantial loading over 3–5 days prior to avalanche release and slight increases in air temperature over the prior 24 h. They noted that seasonally dependent variables associated with these avalanches were a weak snowpack base and a snow depth deeper than the terrain roughness. Tracz (2012) examined meteorological conditions prior to naturally triggered avalanches with crown depths greater than 0.8 m. He found prior precipitation up to 12 days, changes in air temperature up to six days, and hours of above freezing temperatures over a period up to 12 days to be associated with these avalanches. Similarly, Conlan et al. (2014) found hard-to-forecast avalanches, defined as avalanches that fail on a weak layer some time after the initial cycle of avalanches on that weak layer, to be associated with precipitation and warming air temperatures. They showed precipitation amounts prior to hard-to-forecast avalanches were not much greater than precipitation amounts that did not precede these avalanches, and warming also commonly accompanied most snowstorms in their region of study. This resulted in high false alarm rates when using these variables to predict hard-to-forecast avalanches (Conlan et al., 2014).

Our study included both dry and wet deep slab avalanches on persistent weak layers. In general, dry slab avalanches are the result of stress being added to the snowpack more quickly than increases in snowpack strength, while wet slab avalanches are the result of a decrease in strength of the snowpack that allows it to succumb to existing, and sometimes added, stresses (Tremper, 2008). The addition of free water to the snowpack is a primary contributing factor to the initiation of wet slabs (Baggi and Schweizer, 2009; Kattelmann, 1984; Peitzsch et al., 2012; Reardon and Lundy, 2004). Previous research has used measurements of SWE loss or snow settlement, and sustained warming, which suggest the introduction of water to the snowpack, to forecast wet slabs (Baggi and Schweizer, 2009; Peitzsch et al., 2012). Baggi and Schweizer (2009) effectively used the presence of capillary barriers (a significant difference in grain size between adjacent layers that may impede vertical water flow through the snowpack), increased load on a weakened snowpack, and days since the snowpack went isothermal to forecast wet slabs in Davos, Switzerland. Previous research has also described situations when added stress preceded wet slab avalanche initiation, in conjunction with a decrease in snowpack strength (e.g., Baggi and Schweizer, 2009; Marienthal et al., 2012). Reardon and Lundy (2004) described a snowpack structure for wet slab avalanches that included a weak basal layer. While non-basal weak layers have been observed as failure planes for wet slabs (e.g., Conway and Raymond, 1993), they are less frequently an issue in ski area settings due to the frequent disturbance of the snowpack (Kattelmann, 1984).

We used classification trees and random forests to find meteorological variables that were associated with deep slab avalanches on persistent weak layers late in the season. Classification trees are a popular statistical tool for avalanche forecasting and research (e.g., Baggi and Schweizer, 2009; Davis et al., 1999; Hendrikx et al., 2005, 2014). They typically have comparable correct classification rates (70–86% when cross-validated) to traditional statistical forecasting methods such as discriminant analysis and nearest neighbors (e.g., McClung and Tweedy, 1994). Although classification trees have had minimal improvement in operational forecasting accuracy, they have many benefits. They are useful for both prediction and explanation, and they are usually easier to interpret by end users than other statistical methods (Davis et al., 1999; Hendrikx et al., 2005).

Random forests are a bootstrapping method that iteratively grows a given number of classification trees while withholding random subsets of data, which are used to assess model performance and parameter importance (Breiman, 2001). Random forests have been used for avalanche research on spatial variability (Guy and Birkeland, 2013) and forecasting wet slab avalanches (Mitterer and Schweizer, 2013).

For this analysis we defined deep slab avalanches as those that failed on persistent weak layers deeper than 0.9 m, and that occurred between February 1st and the end of the operational season (early April). Avalanche records often did not specify the weak layer type for each event. So, in order to imply if avalanches slid on a persistent weak layer we used other characteristics that are commonly recorded with avalanches. We grew classification trees and random forests from two datasets to examine both seasonal and daily meteorological variables that preceded deep slab avalanches on persistent weak layers at Bridger Bowl ski area in Montana. We used variables that represent meteorological conditions during weak layer development to separate seasons with and seasons without deep slabs on persistent weak layers. In addition, we used meteorological variables up to seven days prior to deep slab avalanches on persistent weak layers to differentiate between days with and days without deep slabs on persistent weak layers.

2. Methods

2.1. Deep slab avalanches on persistent weak layers

We defined deep slab avalanches that failed on persistent weak layers from 44 seasons (1968–2013) of avalanche occurrence records at Bridger Bowl (the 1995–96 season was omitted due to missing data). Each season roughly spanned from November to April, with exact start and end dates varying. Ski patrollers at Bridger Bowl recorded all avalanches that were triggered by explosives as well as all in-bounds avalanches larger than or equal to relative size (R-size) two (Greene et al., 2010). Ski patrol often, but not always, recorded large and visible avalanches that occurred adjacent to the ski area due to natural or human triggers. Standards used to record observed avalanches previously followed guidelines of the West Wide Avalanche Network (WWAN), and recently evolved towards recording standards set forth by Greene et al. (2010). These standards did not typically require weak layer type and other weak layer properties to be recorded, so we used other avalanche characteristics to determine if an avalanche was a deep slab on a persistent weak layer.

Avalanche characteristics that we used in this study were recorded with most observations and include: date, type of trigger, avalanche type, R-size, crown depth, and bed surface (i.e., layers involved) (Greene et al., 2010). Deep slabs become more difficult to forecast the longer a persistent weak layer has been buried (e.g., Conlan et al., 2014), so we restricted our study to avalanches that occurred after February 1st. If an avalanche after February 1st was recorded with bed surface as "ground" (or layers involved as "all"), then we considered it to have been a deep slab on depth hoar (or basal facets), because this is a common persistent weak layer near the ground in the intermountain snow climate of Bridger Bowl (Mock and Birkeland, 2000).

Observers did not always record the bed surface as the ground for avalanches on deep persistent weak layers. Avalanches that failed in depth hoar might have failed on the upper boundary of the layer or above a thin melt–freeze crust, leaving a layer of snow on the ground, which would cause an observer to have recorded the bed surface as "old snow". Furthermore, observers would not have recorded the bed surface as the ground for avalanches that failed on persistent weak layers higher in the snowpack, which are still important to this study.

If an avalanche after February 1st was not recorded as sliding on the ground (i.e., a basal persistent weak layer), then we used bed surface, R-size, average crown depth, and avalanche type to determine if it was a deep slab on a persistent weak layer. We individually examined avalanches that were recorded with a bed surface of "old snow", an R-size greater than or equal to size 2, and an average crown depth greater than 0.9 m. We included these events as deep slabs on persistent weak layers if they were larger (size or depth) in comparison with other events during the same cycle, occurred without the addition of new snow, were substantially deeper than preceding days' storm totals, or had similar crown depths to avalanches that were recorded as sliding on the ground during the same or adjacent cycles. We required these events to have either an avalanche type of "hard slab" or "wet slab" or similar characteristics to avalanches recorded as sliding on the ground during the same or adjacent cycles. This process was not entirely objective, but it resulted in a thorough search of each season's avalanche and meteorological history in an attempt to ensure that deep storm snow slabs and wind slabs were not included.

We included soft slabs and wet loose avalanches if the bed surface was recorded as the ground. Therefore, the dataset included wet loose avalanches that failed on basal persistent weak layers in addition to all deep slab avalanches (i.e., wet slab, soft slab, and hard slab) that failed on persistent weak layers. The first author knew weak layer types of avalanches between the 2010–11 and 2012–13 seasons. During this time, only the 2011–12 season had deep slab avalanches on persistent weak layers after February 1st. We included events from this season that were known to have failed on depth hoar and facet layers that formed earlier in the season (e.g., Marienthal et al., 2012).

Statistical comparisons are typically more robust when they use a dataset with an almost equal number of events as non-events (Bois et al., 1975). While a benefit of classification trees is that they are insensitive to underlying distributions of data (Breiman et al., 1993), a dataset with an equal number of non-events during similar times as events is beneficial to avoid including variables during times that deep slabs can already be ruled out (e.g., early in the season or when the snowpack does not have a persistent weak layer). For seasonal trees, we used all seasons that did not have deep slabs on persistent weak layers as non-events. This gave us a dataset of 24 seasons with deep slabs on persistent weak layers and 20 seasons without deep slabs on persistent weak layers.

For the daily analysis we randomly selected days in each season, proportional to the number of days with deep slabs on persistent weak layers, that were after February 1st, before the date of the last deep slab, had avalanche control performed or recorded avalanche activity, and did not have a deep slab avalanche. We used this selection to compare days that did not have deep slabs, but did have a persistent weak layer present and potentially active, to an equal number of days (in each season) that did have deep slabs on persistent weak layers. We selected from days with avalanche control performed or observed avalanche activity because this indicates that there was some suspicion of instability. A total of eight days were omitted due to missing explanatory variables, so our analysis used a dataset of 71 days with, and 73 days without, deep slabs on persistent weak layers.

2.2. Meteorological variables

Bridger Bowl ski patrol recorded daily observations of snow depth, new snowfall amount, new snow water equivalent (SWE), and minimum and maximum air temperature over a 24-hour period. Ski patrol collected observations once per day (1600 h) at the Alpine weather station (2286 m). Avalanche starting zones at Bridger Bowl are primarily between 2400 m and 2677 m, so actual weather values were likely different between the weather station and starting zones. Relative meteorological trends were likely similar, however, between starting zones and the weather station. Therefore, the consistent weather observations from the Alpine station are a suitable approximation of what was happening to the snowpack in higher elevation starting zones.

Table 1
Observed daily meteorological variables used in this study.

Variable	Symbol	Description
Height of snow (cm)	HS	Height of snow on ground
24 hour snowfall (cm)	HN	Height of new snow in last 24 h
Daily SWE (mm w.e.)	SWE	Total snow water equivalent (SWE) in 24 h
Daily maximum air temperature (°C)	Tmax	Maximum air temperature over last 24 h
Daily minimum air temperature (°C)	Tmin	Minimum air temperature over last 24 h

We used daily weather observations to derive two types of meteorological variables that may be associated with deep slabs on persistent weak layers. Those were daily and seasonal meteorological variables. Similar to previous studies (e.g., Hendrikx et al., 2014; Peitzsch et al., 2012), we used observed daily values (Table 1), and derived multi-day totals, averages, and differences, as explanatory variables (Table 2). We created classification trees with these variables to discriminate between days with deep slabs on persistent weak layers and days without deep slabs on persistent weak layers. We used summaries of meteorological observations over the early months of the season (Table 3), when deep persistent weak layers form and develop, as explanatory variables in classification trees in order to discriminate between seasons with and seasons without deep slabs on persistent weak layers late in the season.

We used seasonal meteorological variables that represented meteorological conditions conducive to persistent weak layer development (Table 3). Monthly summaries of snow depth, daily snowfall, and daily precipitation (SWE) may indicate if snow existed on the ground early in the season, and if it was shallow enough to create a persistent weak layer, or deep enough to create a continuous weak layer or bed surface above local terrain features (rocks and vegetation that would disrupt weak layer continuity within, and between, localized starting zones) (e.g., Schweizer et al., 2009). Monthly summaries of snowfall and SWE also indicate if there was loading during the time of weak layer development, which may compact and strengthen weak layers due to the weight of the snow above (e.g., Bradley and Bowles, 1967). Loading could also induce avalanches that may indicate future instability, or destroy weak layers in certain areas.

We also included monthly averages of daily snowpack temperature gradients (Table 3). Persistent weak layers form due to a strong vapor pressure gradient in the snowpack, which is mainly driven by the temperature gradient through the snowpack (Akitaya, 1974). Constructive

Table 2
Derived daily meteorological variables used in this study.

Variable	Symbol	Summary Intervals, i
Total (sum) 24 hour snowfall (cm)	HNi	2,3,5, and 7 days
Total (sum) daily SWE (mm w.e.)	SWEi	2,3,5, and 7 days
Change in snow depth (cm)	HSi	2,3,5, and 7 days
Max. air temperature during time i (°C)	maxTi	2,3,5, and 7 days
Min. air temperature during time i (°C)	minTi	2,3,5, and 7 days
Average min. air temperature (°C)	Tminavi	2,3,5, and 7 days
Average max. air temperature (°C)	Tmaxavi	2,3,5, and 7 days
Degrees above zero min. air temperature (°C)	minAbovezi	1,2,3, and 5 days
Degrees above zero max. air temperature (°C)	maxAbovezi	1,2,3, and 5 days
Difference in minimum air temperature (°C)	TminDif2	T(avalanche day)-T (prior day)
Difference in maximum air temperature (°C)	TmaxDif2	T(avalanche day)-T (prior day)

Table 3
Derived seasonal meteorological variables used in this study. Summary intervals ND = November and December, NDJ = November, December, and January.

Variable	Symbol	Summaries	Summary Intervals
Height of snow (cm)	HS	Avg, max	Nov, Dec, Jan
Daily SWE (mm w.e.)	SWE	Total (sum)	Nov, Dec, Jan, ND, NDJ
24 hour snowfall (cm)	HN	Total (sum)	Nov, Dec, Jan, ND, NDJ
Daily temperature gradient (°C/10 cm)	tg	Avg	Nov, Dec, Jan, ND, NDJ
Days with TG > 10 °C/m & HS < 1 m	tgcnt	Proportion	Nov, Dec, Jan, ND, NDJ
Height of snow on Feb. 1st (cm)	Feb1HS	(Observed value)	Once/season

metamorphism is the physical process that forms persistent weak layers (Armstrong, 1985), and in practice, is associated with temperature gradients within the snowpack that exceed 10 °C/m (e.g., McClung and Schaerer, 2006; Mock and Birkeland, 2000). We derived the daily minimum temperature gradient through the snowpack by assuming the ground was at 0 °C, and dividing the daily minimum air temperature by snow depth. Previous studies have used similar calculations as an effective estimate of the snowpack temperature gradient (Mock and Birkeland, 2000).

A deeper snowpack attenuates the effect of air temperature on the snowpack temperature gradient (Gray and Male, 1981 p. 298). Therefore, we quantified the proportion of days in each month, or group of months, that had conditions conducive to persistent weak layer development by counting days with a calculated temperature gradient stronger than 10 °C/m and a snow depth less than one meter (Table 3). This variable potentially summarizes the relative amount of time that a weak layer (e.g., depth hoar) was subject to constructive metamorphism each season.

The height of snow on February 1st, the day we began considering deep slabs on persistent weak layers, was included because a shallow snow depth may be reflective of higher potential for persistent weak layer development prior to the date in which we began forecasting. This is the only seasonal meteorological variable that is an isolated observed value, not a summary of values over one or more months.

2.3. Classification trees

Classification trees split a dataset into smaller homogenous groups of observations by placing observations in a group based on whether its value for an explanatory variable is above or below a statistically defined threshold. Groups are successively split until a homogenous group is achieved, or until a specified stopping criterion is met (Breiman et al., 1993). Trees that meet these criteria are considered maximum or over-fit trees. Over-fit trees have been used for exploratory purposes because the structure of these trees may reflect existing relationships between physical processes (Davis et al., 1999). However, over-fit trees are often overly optimistic and not suited for prediction (James et al., 2013). A large tree can contain splits that have poor predictive power on independent samples, and lead to higher true misclassification rates than a smaller “best” sized tree (Breiman et al., 1993). Therefore, we applied a traditional cross-validation pruning rule to find the “best” sized tree, which would reflect more accurate measures of misclassification should the tree be used for prediction.

Previous studies have implemented classification trees for avalanche forecasting purposes using 10-fold cross-validation to find the “best” sized trees (e.g., Baggi and Schweizer, 2009; Hendrikx et al., 2005, 2014; Peitzsch et al., 2012). This method is described in detail in Breiman et al. (1993), and in regards to an avalanche dataset in Hendrikx et al. (2005). Previous work that used this method for avalanche forecasting produced trees with 71–86% overall correct classification (e.g., Baggi and Schweizer, 2009; Hendrikx et al., 2005, 2014).

We grew and pruned classification trees through recursive partitioning using the rpart package (Therneau et al., 2013) in R statistical software (R Core Team, 2013). The default for this package used the Gini index to create splits that reduce the probability of misclassification (Breiman et al., 1993). We grew over-fit trees using the default stopping criteria in R, which stopped creating splits when groups had less than 20 observations, or a minimum of seven observations (i.e., if a split would create a group with less than seven observations, then the split was not attempted). We implemented 10-fold cross-validation using the one standard error rule (Breiman et al., 1993) to determine the “best” sized trees.

We grew trees to split seasons into groups of seasons that had deep slabs on persistent weak layers and groups of seasons that did not. We also grew trees to split days into groups of days that had deep slabs on persistent weak layers and groups of days that did not. We described predictive model performance of the over-fit and cross-validated classification trees using measures explained by Wilks (1995) and Doswell et al. (1990). These measures have also been used with regards to avalanche forecasting by Schweizer et al. (2009) and Hendrikx et al. (2014). We used the unweighted average accuracy (RPC), true skill score (TSS), false alarm ratio (FAR), probability of detection (POD), probability of non-events (PON), and probability of non-detection (FSR i.e., false stable ratio). Ideal models have a low FAR and a high POD and PON, which would lead to a high RPC and TSS (Hendrikx et al., 2014). These measures are defined in Eqs. (1)–(6) as:

$$\text{Unweighted average accuracy}:\quad \mathrm{RPC} = 0.5\left(\frac{a}{a+c}+\frac{d}{b+d}\right) \tag{1}$$

$$\text{True skill score}:\quad \mathrm{TSS} = \frac{d}{b+d}-\frac{c}{a+c} \tag{2}$$

$$\text{False alarm ratio}:\quad \mathrm{FAR} = \frac{c}{c+d} \tag{3}$$

$$\text{Probability of detection}:\quad \mathrm{POD} = \frac{d}{b+d} \tag{4}$$

$$\text{Probability of non-events}:\quad \mathrm{PON} = \frac{a}{a+c} \tag{5}$$

$$\text{Probability of non-detection}:\quad \mathrm{FSR} = \frac{b}{b+d} \tag{6}$$

where the definitions for a–d are defined in a contingency table (Table 4).

Due to the small dataset, we used random forests to assess the stability of the classification trees' predictive power (Breiman, 2001). The random forest method iteratively grows 500 classification trees while successively withholding (with replacement) random variables and subsets of data. This method gives a more accurate (average) measure of predictive model performance at the expense of interpretability. We used the randomForest package in R statistical software to create random forests (Liaw and Wiener, 2002). The randomForest package determined Model performance for the random forest models using the estimated classification rates for the data that were withheld from fitting of each tree, which is referred to as the “out-of-bag” sample (Breiman, 2001). We assessed the importance of each variable using the mean decrease in accuracy (MDA), which was calculated in randomForest by individually permuting each variable in every tree in

Table 4
Contingency table showing definitions for measures used to calculate model performance (Eqs. (1)–(6)). “Av.” = avalanche days (or seasons) and “Non-av.” = non-avalanche days (or seasons).

		Observed	
		Non-av.	Av.
Predicted	Non-av.	a = correct non-events	b = misses
	Av.	c = false alarms	d = hits

Table 5
Summary of days with avalanches in the 24 seasons that had at least one avalanche failing on a deep persistent weak layer after February 1st. Seasons are defined by the year in which they started (e.g., 1968 was from November 1968–April 1969). Totals from each season are summarized by type: hard-slab (HS), soft-slab (SS), wet-loose (WL), and wet-slab (WS).

Season	# of days	Wet snow days	# of avalanches	Wet snow avalanches	HS	SS	WL	WS
1968	3	1	8	4	3	1	0	4
1971	2	1	3	1	2	0	0	1
1974	2	0	2	0	0	2	0	0
1975	5	4	49	48	0	1	10	38
1976	2	1	2	1	1	0	0	1
1977	1	1	4	4	0	0	4	0
1978	2	1	2	1	1	0	1	0
1979	3	0	3	0	3	0	0	0
1980	3	0	13	0	3	10	0	0
1981	1	0	1	0	0	1	0	0
1984	6	3	22	12	9	1	0	12
1985	3	1	6	2	4	0	0	2
1986	4	1	11	7	0	4	0	7
1987	1	1	1	1	0	0	0	1
1989	1	1	1	1	0	0	1	0
1991	1	1	2	2	0	0	2	0
1992	4	2	9	5	3	1	3	2
1993	1	0	1	0	1	0	0	0
2000	1	1	1	1	0	0	1	0
2002	9	1	13	2	3	8	2	0
2003	2	1	3	2	1	0	2	0
2006	4	0	10	0	1	9	0	0
2009	1	0	1	0	1	0	0	0
2011	14	4	29	17	10	2	0	17
Total	76	26	197	111	46	40	26	85

the forest during modeling. The MDA for a variable was the average difference (across all trees) in error rate, for classifying the out-of-bag data when that variable was permuted in a tree, divided by the standard deviation of the difference in error rate for all trees (Breiman, 2001).

3. Results

Deep slab avalanches failed on persistent weak layers after February 1st during 24 of the 44 seasons studied. There were a total of 197 events on 76 days in February, March, and April. Of these days, 50 had dry slab avalanches and 26 had wet snow avalanches. Five seasons had only wet snow avalanches, seven seasons had only dry slab avalanches, and the other twelve seasons had both wet and dry deep slab avalanches on persistent weak layers after February 1st (Table 5).

Total SWE in November, December, and January split seasons with avalanches on deep persistent weak layers from seasons without avalanches on deep persistent weak layers in the only split of the seasonal cross-validated tree (Fig. 1). Seasons that had greater than or equal to 308 mm w.e. of SWE from November through January did not have deep slabs on persistent weak layers during 92% (11 of 12) of those seasons. Seasons that had less than 308 mm w.e. of SWE from November through January had deep slabs on persistent weak layers during 72% (23 of 32) of those seasons. The over-fit tree further split the seasons with less SWE towards homogeneity based on the total SWE in December (Fig. 1, node 3) and the maximum snow depth in November (Fig. 1, node 4).

The minimum air temperature over the past 24 h was the primary split in the cross-validated classification tree that split days with and days without deep slabs on persistent weak layers (Fig. 2). The group of days that had minimum air temperatures less than −9.5 °C did not have deep slabs on persistent weak layers on 75% (48 of 64) of the days. The group of days that had minimum air temperatures greater than or equal to −9.5 °C had deep slabs on persistent weak layers on 66% (53 of 80) of the days. The latter group was further split based on the average maximum air temperature over the previous three days (Fig. 2, node 5). The group of days that had an average maximum air temperature over the previous three days greater than 7.2 °C had deep slabs on persistent weak layers on 95% of the days. Avalanches on these days were usually wet avalanches.

Days with a lower average maximum air temperature over three days were split based on the change in snow depth over the previous seven days (Fig. 2, node 6). Days with more than 10 cm of snow settlement over the previous seven days did not have any (0 of 9) deep slabs on persistent weak layers. Days with less settlement, or more precipitation, had deep slab avalanches on persistent weak layers on 66% (33 of 50) of the days. The over-fit tree further split this last group of days based on the height of snow and snow depth change over the previous three days (Fig. 2, nodes 8 & 9).

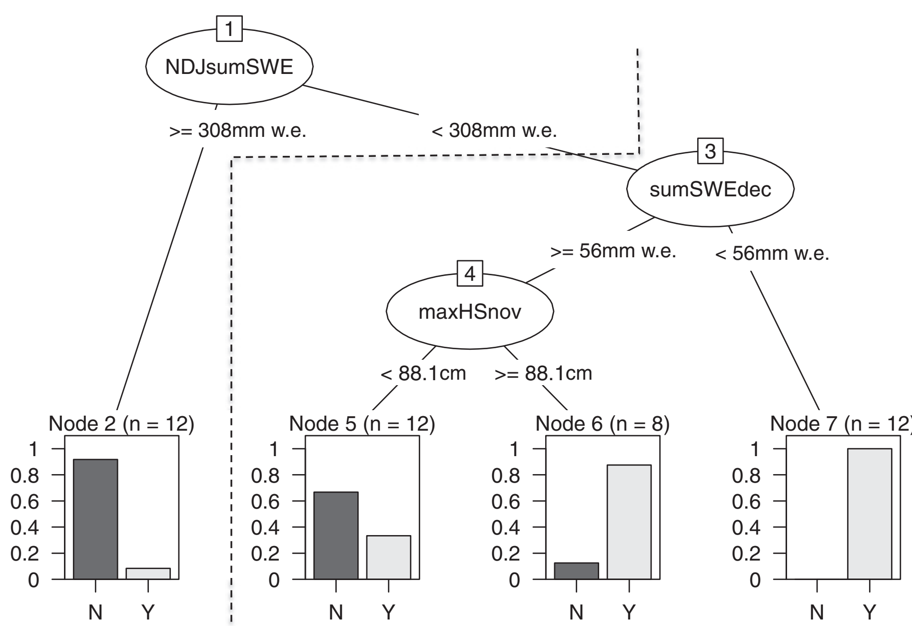

Fig. 1. Over-fit classification tree to split seasons with (Y) and seasons without (N) deep slabs on persistent weak layers. The cross-validated tree consists of split number one only, shown above the dotted line. The first split is the total SWE in November, December, and January (node 1). The second split is the total SWE in December (node 3), followed by the maximum height of snow in November (node 4). Variables are described in Tables 1, 2 & 3.

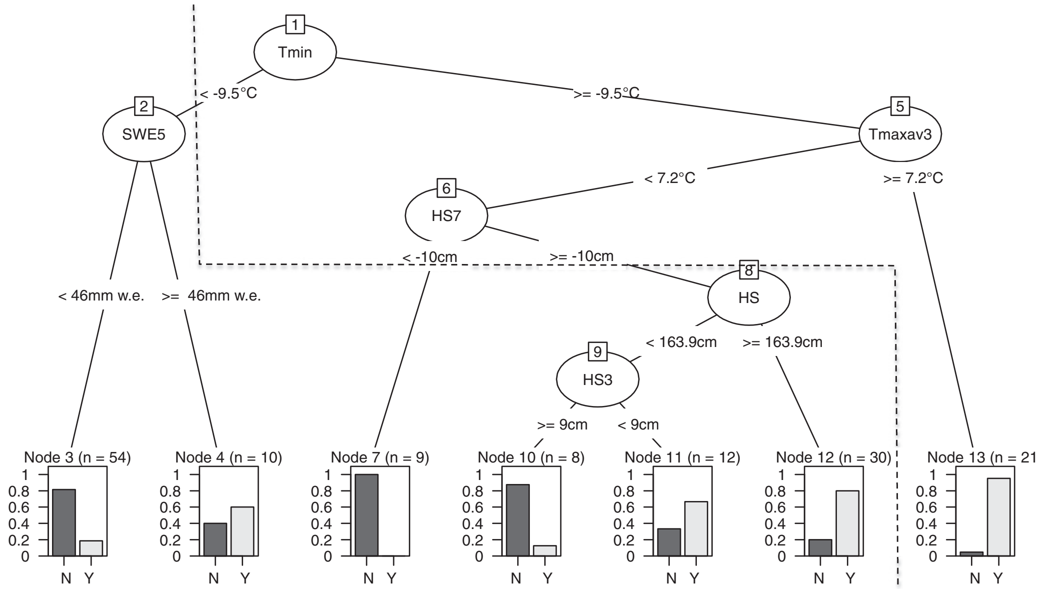

Fig. 2. Over-fit classification tree to split days with (Y) and days without (N) deep slabs on persistent weak layers. The cross-validated tree, made up of splits above the dotted line, has only splits at nodes one, five, and six. The splits are: minimum temperature (node 1), sum of SWE over five days (node 2), average maximum temperature over three days (node 5), change in snow depth over seven days (node 6), height of snow (node 8), and change in snow depth over three days (node 9). Variables are described in Tables 1, 2 & 3.

The cross-validated trees, which are most suitable for predictive purposes, had stronger model performance for both sets of data (Tables 6, 7) than the random forests (Tables 8, 9). The random forests ranked the most important variables based on the MDA. In the seasonal forest, total new snow in December was the most important variable followed by total SWE in December, total SWE over November, December and January, and total SWE in January. These were followed by the proportion of days in November and December with conditions conducive to constructive metamorphism, and then the proportion of days in November, December and January with these conditions. The seventh and eighth most important variables in the seasonal forest were maximum snow depth in November and maximum snow depth in December (Fig. 3).

The most important variable in the daily forest, based on the MDA, was minimum air temperature. This was accompanied in the top ten most important variables by average maximum air temperature over 7,5,3 and 2 days, minimum daily temperature gradient, total degrees above zero for the maximum air temperature over 2,3 and 5 days, and total degrees above zero over 5 days for the minimum air temperature (Fig. 3).

4. Discussion

4.1. Seasons with deep slabs on persistent weak layers

The classification trees for each dataset were useful for displaying the underlying structure of the data, and to show which variables were associated with deep slabs on persistent weak layers at Bridger Bowl. The first split in the tree for seasons with and seasons without deep slabs on persistent weak layers isolated seasons without deep slabs based on those seasons having greater total SWE in November, December, and January (Fig. 1). This variable indicates that seasons with more than 308 mm w.e. of SWE from November through January less frequently had deep slab avalanches than seasons with less precipitation during that time.

More precipitation early in the season implies higher snow depth and snow density, which would decrease the overall snowpack temperature gradient and limit conditions for weak layer development. Cold air temperatures are often needed in addition to a shallow snowpack to create a strong temperature gradient. However, the frequent occurrence of long clear nights in southwest Montana allows for substantial cooling of the snowpack due to emitted longwave radiation, even when air temperature is relatively warm. Therefore, a shallow snow depth alone may imply weak layer formation in this region. Furthermore, abundant precipitation early in the season helps stabilize late season deep slab instability even if a persistent weak layer does develop. Avalanches on persistent weak layers earlier in the season may destroy persistent weak layers, and pressure from the weight of snow accumulated above weak layers can strengthen weak layers in some situations (Bradley and Bowles, 1967).

The second split (Fig. 1, node 3) used total SWE in December to divide seasons with less than 308 mm w.e. of SWE in November, December, and January. All seasons that had less than 56 mm w.e. of SWE in December had deep slabs on persistent weak layers. Seasons

Table 6
Contingency tables for all classification trees. “Av.” = avalanche days (or seasons) and “Non-av.” = non-avalanche days (or seasons), “CV” = cross-validated.

			Observed			
			Seasons		Days	
			Non-av.	Av.	Non-av.	Av.
Predicted	Over-fit	Non-av.	19	5	60	11
		Av.	1	19	15	58
	CV	Non-av.	11	1	57	16
		Av.	9	23	18	53

Table 7
Measures of model performance for each classification tree (Eqs. (1)–(6)): unweighted average accuracy (RPC), true skill score (TSS), false alarm ratio (FAR), probability of detection (POD), probability of non-events (PON), and probability of non-detection (FSR). The first and third rows pertain to the over-fit trees for seasons and days, respectively, and the second and fourth rows are for the cross-validated (CV) trees.

	RPC	TSS	FAR	POD	PON	FSR
Seasons	0.87	0.74	0.05	0.79	0.95	0.21
CV	0.75	0.51	0.28	0.96	0.55	0.04
Days	0.82	0.64	0.21	0.84	0.80	0.16
CV	0.76	0.53	0.25	0.77	0.76	0.23

Table 8
Contingency table for random forests. "Av." = avalanche days (or seasons) and "Non-av." = non-avalanche days (or seasons).

		Observed			
		Seasons		Days	
		Non-av.	Av.	Non-av.	Av.
Predicted	Non-av.	13	7	49	7
	Av.	9	14	32	33

Table 9
Measures of model performance for random forest (Eqs. (1)–(6)): unweighted average accuracy (RPC), true skill score (TSS), false alarm ratio (FAR), probability of detection (POD), probability of non-events (PON), and probability of non-detection (FSR).

	RPC	TSS	FAR	POD	PON	FSR
Seasons	0.63	0.26	0.39	0.67	0.59	0.33
Days	0.59	0.18	0.49	0.58	0.60	0.42

with more SWE in December, despite overall less SWE from November through January, had deep slabs more often when the maximum November snow depth was deeper than 88.1 cm (Fig. 1). The inclusion of maximum November snow depth in the tree suggests that while a shallow snow depth early in the season is conducive to a weak snowpack, enough depth must be maintained in order for a weak layer, or bed surface, to form above local terrain features (e.g., Schweizer et al., 2009).

Total SWE in November, December, and January became the only split between seasons with and seasons without deep slabs after 10-fold cross-validation. The cross-validated tree provided a desirably low FSR (0.04) despite decreasing overall accuracy and skill (Table 7). The inclusion of values from November through January in this cumulative SWE total implies the importance of continuous observation of meteorological conditions across all months. When November, December, and January SWE totals are combined in a forecast for deep slabs on persistent weak layers late in the season, there is less uncertainty than when they are used individually. Stated more broadly, the effect of early season meteorological conditions on late season deep slab avalanche stability is dependent on the continuous interaction of various meteorological conditions throughout the entire early season. The bottom ranking of the February 1st height of snow, our only isolated seasonal observation, in the random forest (Fig. 3) is further support that observations from isolated, rather than continuous, periods of time have higher uncertainty in an avalanche forecast.

4.2. Days with deep slabs on persistent weak layers

Air temperatures over days prior to deep slabs on persistent weak layers were typically warmer than days without deep slabs on persistent weak layers (Fig. 2). There was also greater cumulative precipitation prior to days with deep slabs on persistent weak layers than prior to days without deep slabs on persistent weak layers. The groups of days that were split based on five-day total SWE or change in snow depth over seven days had deep slabs on persistent weak layers on 60–66% of the days that had greater precipitation (Fig. 2). Previous findings have also shown significance of cumulative loading and warming trends prior to deep slabs (Conlan et al., 2014; Jamieson et al., 2001; Schweizer et al., 2009; Tracz, 2012).

The final splits of the over-fit daily tree, which utilize height of snow and a positive change in snow depth over three days, do not provide as clear of an interpretation as the higher splits, but they support the importance of considering overall snow depth and cumulative load prior to deep slabs (Fig. 2). Days with a snow depth greater than 163.9 cm were mostly deep slab days (Fig. 2). This is somewhat of a surprise as a shallower snowpack can often indicate more instability. This highlights the importance of considering meteorological conditions continuously through months prior to periods of elevated likelihood of deep slab avalanches.

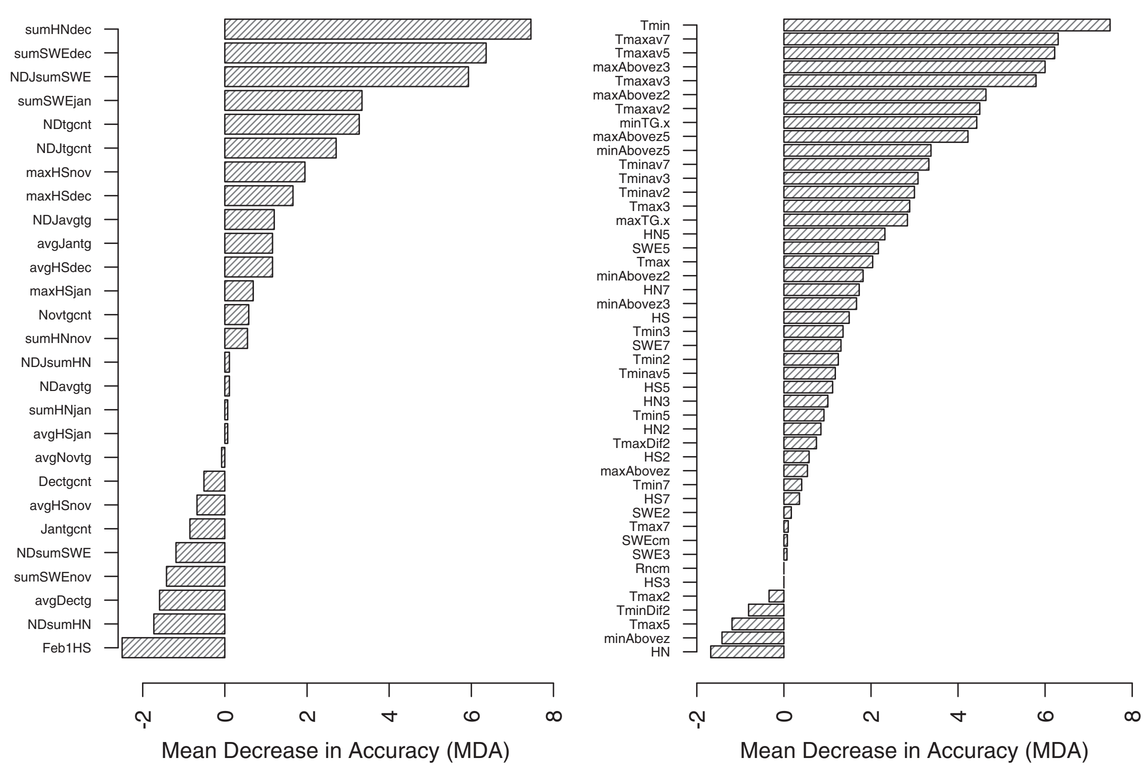

Fig. 3. Variable importance shown using the MDA for each variable in the random forests for seasonal variables (left) and daily variables (right). Variables are described in Tables 1, 2 & 3.

Days that had an average maximum air temperature over the prior three days greater than 7.2 °C were mostly days with deep wet avalanches (Fig. 2). Sustained above freezing air temperatures prior to wet slabs is common as it implies a variety of conditions that are conducive to wet slab initiation (e.g., Baggi and Schweizer, 2009; Peitzsch et al., 2012). While longer periods of sustained warming may be more conducive than shorter periods of sustained warming to the initiation of deep wet slabs (e.g., more time may be required before a refreeze for water to reach a deep weak layer), other variables must also be considered to assess deep wet slab potential, such as snowpack structure (e.g., Reardon and Lundy, 2004), and previous deep dry slab activity on persistent weak layers (e.g., Marienthal et al., 2012). Nonetheless, if the potential for deep slabs on persistent weak layers exists, then sustained above freezing air temperatures are evidence to suggest increasing hazard.

While the introduction of liquid water due to above freezing air temperatures is a relevant factor for wet slabs (Baggi and Schweizer, 2009; Peitzsch et al., 2012), above freezing and warm air temperatures also affect slab deformation rates in regards to dry slab avalanche initiation (McClung, 1996; Reuter and Schweizer, 2012; Wilson et al., 1999). Tracz (2012) found sustained above freezing air temperatures prior to dry deep slabs. In addition, previous research has suggested that warmer snow surface temperatures facilitate skier-triggering of dry slabs and increase overall slab instability (McClung, 1996; McClung and Schweizer, 1999; Reuter and Schweizer, 2012; Schweizer and Jamieson, 2010; Schweizer et al., 1995; Wilson et al., 1999). Despite empirical data of dry deep slabs during warming and warmer temperatures (e.g., Conlan et al., 2014; Schweizer et al., 2009), strong evidence to support an explainable causal effect for the coincidence of dry slab avalanches during warming is rare (e.g., Reuter and Schweizer, 2012; Schweizer and Jamieson, 2010).

4.3. Random forests

Variables that made up splits in the cross-validated classification trees also had high importance rankings in the random forests (Fig. 3). This supports the variables' utility as predictors for deep slabs on persistent weak layers as well as interpretations of their physical relationship to deep slabs. The cross-validated trees did not choose the variables representing the proportion of days with temperature gradient and snow depth conducive to weak layer development as splits. However, the high ranking of these variables in the random forests shows the importance of the upper threshold of early season snow depth (i.e., 1 m) on impeding weak layer development, while the importance of maximum November and December snow depth may represent a minimum early season snow depth requirement, as shown in the over-fit classification tree (Fig. 1).

Minimum 24-hour air temperature was the most important variable in the random forest for predicting days with deep slabs on persistent weak layers (Fig. 3), and it was the primary split for the daily classification trees (Fig. 2). Average maximum air temperature over three days was the only other variable among the ten most important in the random forest that was also used as a split in the classification trees (Fig. 2). However, the abundance of highly important variables that summarize maximum air temperatures over multiple days strengthens the importance of sustained warming and variables that reflect rate dependent processes when forecasting deep slabs (e.g., Tracz, 2012).

The random forest suggested an overall lack of importance of loading variables for forecasting days with deep slabs. Despite being ranked low, the most important loading variable in the random forest was total new snow over five days, directly followed by total SWE over five days (Fig. 3). This supports the higher importance of cumulative precipitation amounts compared to precipitation amounts over a shorter time. The difficulty in forecasting deep slabs based on loading from precipitation is apparent from the low rank of these variables, likely due to high false alarm rates when trying to forecast deep slabs based on a threshold amount of precipitation (e.g., Conlan et al., 2014).

4.4. Model performance

Although over-fit trees are not suitable for prediction, their measures of model performance were included to display the overall reduction in model performance after cross-validation (Table 7). Cross-validation resulted in a decrease in average accuracy (RPC) for both trees. The only improvements for the seasonal tree after cross-validation were an increased POD and decreased FSR. Despite these improvements, the overall skill (TSS) and accuracy (RPC) of this tree dropped due to an increased FAR and decreased PON. The best measure of overall performance may be the TSS, and it was low (0.53 and 0.51) for both trees. Hendrikx et al. (2014) achieved a TSS of 0.47 and an RPC of 0.73 on the dataset used to fit their tree. Schweizer et al. (2009) had RPCs ranging from 0.77–0.89 and TSS ranging from 0.29–0.54 for various datasets. Our cross-validated trees had similar levels of performance as trees previously applied for avalanche forecasting.

While our trees' achieved model performance was comparable to previous avalanche forecasting models, it should be noted that the sample size was relatively low for cross-validation and growing classification trees in general (Breiman et al., 1993). Despite the small sample size, cross-validation is typically conservative in small datasets that have many predictors, which promotes the value of the seasonal cross-validated tree's sole predictor (Fig. 1) and the three variables that made splits in the daily cross-validated tree (Fig. 2).

The overall predictive accuracy of the random forests, based on model performance measures, was poorer than for the cross-validated trees (Table 9). In addition, the random forests had a large increase in FAR and FSR, and decreased TSS. This shows the random forests' decreased ability to separate seasons (or days) with deep slabs from those without deep slabs as compared to the cross-validated trees. The random forests, however, are a depiction of the average predictive power of either dataset (Liaw and Wiener, 2002), and they further support the importance of the variables used as splits in the classification trees.

Guy and Birkeland (2013) found a wide range of success rates (62–80%) and TSS (0.17–0.38) when using random forests to classify potential avalanche trigger locations based on terrain parameters. Our model performance results are comparable despite being close to the lower end of those ranges. While the cross-validated trees provide better TSS and lower FAR and FSR, the random forests likely provide a more accurate estimate of the uncertainty in the dataset since their model performance is an average across all trees.

4.5. Limitations, uncertainty, and scope of study

The models' relatively low skill, inherent uncertainty in the data, and the scope of this study limit the sole use of these models, or their important variables, for predicting deep slab avalanches. The measures of model performance are too low to rely on for an avalanche forecast, but the models and their findings are still useful when combined with experience and knowledge of other forecasting tools and avalanche behavior. Our results provide interpretations of observed meteorological data, which often require greater evaluation to reduce their uncertainty. Interpretations of these data should be combined with two other previously described types of data: 1) snowpack structure data and 2) snow mechanical data that directly indicate instability due to an applied load (e.g., avalanche occurrence), which both have inherently lower (in decreasing order) uncertainty (LaChapelle, 1980; McClung, 2002). Direct observation of the snowpack and avalanche occurrences, and intimate knowledge of local to regional terrain and climate, are essential to understand in addition to model predictions and meteorological variables suggested to be of high importance by research and observation.

Our method of selecting days with deep slabs on persistent weak layers introduced further uncertainty to this study. The absence of documented weak layer types in avalanche observations greatly limited the selection of deep slabs on persistent weak layers. It is possible that we included deep slabs not on persistent weak layers, and excluded some deep slabs on persistent weak layers. We may have not included noteworthy events that occurred late in January due to only considering deep slabs after February 1st. We thoroughly reviewed avalanches that were selected as deep slabs on persistent weak layers to limit errors.

Our dataset of avalanches at Bridger Bowl included both dry and wet deep slab avalanches on persistent weak layers (Table 5). Combining these events should not have affected our results of which meteorological variables early in the season were associated with deep slabs on persistent weak layers later in the season. A similar snowpack structure, which forms due to early season meteorological variables, contributes to deep dry slabs and deep wet slabs on persistent weak layers (e.g., Marienthal et al., 2012; Reardon and Lundy, 2004). Furthermore, our classification tree that split days with deep slab avalanches from days without deep slabs split out deep wet slabs based on the average of the maximum air temperature over the previous three days. This displays the classification tree's ability to split different types of avalanches based on a variable that is reflective of a major difference in the release mechanism of each avalanche type.

The scope of the data and analysis further limit the findings of this study. These data were entirely observational (i.e., no random assignment to groups) and not selected from a larger population. Therefore, we make no statistical inference about the causal relationship between meteorological variables and deep slabs on persistent weak layers, and we make no statistical inferences about similar phenomena outside the study area and time period. We can make practical inferences, however, to future situations within the study area and in areas that have similar terrain and snow climates. Therefore, our findings are practically applicable to Bridger Bowl ski area and similar regions that experience a predominantly intermountain or continental snow climate with frequent persistent weak layers near the base of the snowpack.

A more holistic solution to forecasting deep slabs on persistent weak layers may require the inclusion of snowpack properties and avalanche occurrence on persistent weak layers throughout the season. While inclusion of other data may reduce uncertainty in models and forecasts, an approach that considers every situation as unique and acknowledges that many factors may not be accounted for is essential for an avalanche forecast. Furthermore, personal and operational goals affect the acceptable level of risk for a given avalanche forecast and will add bias that should be recognized in order to reduce uncertainty.

5. Conclusion

We used classification trees and random forests to model meteorological variables associated with deep slab avalanches on persistent weak layers after February 1st at Bridger Bowl. While our models did not show improvement in predictive performance over previous work, the variables used in the models provide valuable insight about which meteorological conditions may precede deep slab avalanches on persistent weak layers at Bridger Bowl.

In line with much previous work, our results showed greater cumulative precipitation and warmer air temperatures prior to days with deep slabs on persistent weak layers, and sustained above freezing air temperatures prior to days with deep wet slabs on persistent weak layers, as compared to days without deep slabs on persistent weak layers. The abundance of highly important variables that summarize warm air temperatures over days preceding deep slabs indicate the importance of temperature and rate dependent variables for forecasting dry and wet deep slabs. A lack of importance of variables, in the random forest, that indicate loading prior to days with deep slabs further exemplifies the difficulty in considering the amount of loading due to precipitation when forecasting deep slabs.

We gained additional information regarding potential for deep slab avalanches on persistent weak layers by considering meteorological variables from the beginning of the season. Seasonal meteorological conditions that indicated higher potential for late season deep slabs were an overall relatively dry early season combined with an early season snowpack that was shallow enough for weak layer formation, yet deep enough to form a spatially continuous weak layer or bed surface above local terrain features.

Our results from random forests further support the important splits that we found in classification trees. Maximum early season snow depth, early season precipitation, and minimum snow depth required for a sufficient weak layer to form, were highlighted in the random forest for seasons with deep slabs on persistent weak layers. Minimum 24-hour air temperature was ranked most important in the random forest, and it was the primary split in the classification tree, for days with deep slabs on persistent weak layers.

We found that summaries of observed meteorological variables through the season are useful to aid forecasting deep slab avalanches on persistent weak layers. The specific meteorological variables featured in this paper are limited to areas with similar terrain and climate as Bridger Bowl, and observed meteorological variables should be combined with continuous analysis of local snowpack observations and avalanche activity when forecasting deep slab avalanches on persistent weak layers.

Acknowledgments

The authors would like to acknowledge the American Avalanche Association Graduate Student Research Grant, Montana State University, and Bridger Bowl for financial support of this research. We also thank the Bridger Bowl ski patrol for collection and upkeep of weather and avalanche control records. Additional input and support that was crucial to this research came from Doug Richmond and Randy Elliot of Bridger Bowl, Scotty Savage and the Big Sky ski patrol, the Gallatin National Forest Avalanche Center, and the Snow and Avalanche Laboratory at Montana State University. We also thank Mark Greenwood and two anonymous reviewers for reviewing this manuscript. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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