METEOROLOGICAL VARIABLES ASSOCIATED WITH DEEP SLAB AVALANCHES ON PERSISTENT WEAK LAYERS

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ABSTRACT: Deep slab avalanches are a particularly challenging avalanche forecasting problem. These avalanches are typically difficult to trigger, yet when they release they tend to propagate far and can result in large and destructive avalanches. For this work we define deep slab avalanches as those that fail on persistent weak layers deeper than 0.9m (3 feet), and that occur after February 1st. 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 with deep slab avalanches. While previous studies often exclusively use data from the days preceding deep slab cycles, we include meteorological metrics over the early months of the season when persistent weak layers form. We used classification trees for our analyses. Our results showed that seasons with avalanches on deep persistent weak layers typically had drier early months, and often had maximum snow depth greater than 88cm in November, which provided ideal conditions for persistent weak layer development. This paper provides insights for ski patrollers, guides, and avalanche forecasters who seek to understand the seasonal conditions that are conducive to deep slab avalanches on persistent weak layers later in the season.

KEYWORDS: Deep slabs, avalanche forecasting, classification trees

1. INTRODUCTION

Forecasting deep slab avalanches on persistent weak layers becomes an increasingly challenging task as the winter snowpack deepens. Avalanches failing on a particular weak layer become less common the longer the weak layer is buried, but when avalanches do occur they are typically larger and more destructive than other avalanches (Comey and McCollister, 2008; Tracz, 2012). In contrast to recently buried persistent weak layers and new snow instabilities, deep slab avalanches are seldom accompanied by obvious evidence to suggest their impending collapse (LaChapelle and Atwater, 1961). After weak layers form they endure a balancing act between weakening due to strong temperature gradients and strengthening due to the addition of overburden pressure from snow loading (Bradley and Bowles, 1967). Deep slab avalanches are commonly triggered during and after storms, but differentiating between storms that will trigger a deep slab avalanche and storms that will not is difficult (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., Jamieson et al., 2001; Conlan et al., 2014), but few have considered the meteorological conditions during weak layer formation over the early months of seasons with deep slab avalanches compared to meteorological conditions during seasons without deep slab avalanches. In this paper we examine the meteorological conditions during the time of weak layer formation each season by summarizing meteorological observations from the months of November, December, and January.

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 that had the same weak layer develop, but only one region had extensive avalanche activity on this layer. They suggest that

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persistent weak layer formation can be predicted based on temperature, snowfall, and precipitation measurements from a suitable weather station.

Researchers have used a variety of definitions for deep slab avalanches. Jamieson et al. (2001) focused on avalanches that failed on a facet-crust weak layer throughout a season. Savage (2006) and Comey and McCollister (2008) defined deep slabs as avalanches with average crown depths deeper than 1.2m (4 feet). Schweizer et al. (2009) found large avalanches (i.e., running past a given point within the avalanche path) on one path in Switzerland to be associated with 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 0.8m. He also defined deep slab avalanches as those with average crown depths greater than the 80th percentile of average crown depths in a given region. Conlan et al. (2014) examined “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. We define deep slab avalanches as those that fail on persistent weak layers deeper than 0.9m (3 feet), and that occur after February 1st.

We use classification trees to find meteorological variables that are associated with deep slab avalanches on persistent weak layers late in the season. Classification trees are a popular statistical tool for avalanche forecasting (e.g., Davis, 1999; Hendrikx et al., 2005; Hendrikx et al., 2014), and they typically have comparable correct classification rates (70-86% when created for predictive purposes) to traditional statistical forecasting methods such as discriminant analysis and nearest neighbors (e.g., McClung and Tweedy, 1994). Classification trees split a dataset into increasingly homogenous groups of observations, in this case either events or non-events, based on a threshold value of explanatory variables. Although little improvement in operational forecasting accuracy has been gained by using classification trees, they have many benefits. They are useful for both prediction and explanation, can work with smaller datasets, and are usually more clear and easier to interpret by end users than other statistical methods (Davis et al., 1999; Hendrikx et al., 2005).

Classification trees were created to examine seasonal meteorological conditions that precede deep slab avalanches on persistent weak layers. A dataset of variables derived to summarize meteorological conditions during weak layer development were used to separate seasons with and seasons without deep slabs on persistent weak layers.

2. METHODS

Avalanches that failed on deep persistent weak layers late in the season were identified from a 44-year historical record of avalanche occurrences at Bridger Bowl ski area in southwest Montana. Meteorological variables that may be associated with seasons that have deep slab avalanches on persistent weak layers were defined from daily meteorological observations. We used classification trees as a statistical method to explore which meteorological variables may be useful for discriminating between seasons with and seasons without deep slab avalanches on persistent weak layers.

2.1 Classification trees

Classification trees essentially 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 certain 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.

Classification trees have previously been implemented for avalanche forecasting purposes using 10-fold cross validation to find the “best” sized trees (e.g., Hendrikx et al., 2005; Baggi and Schweizer 2009; Hendrikx et al., 2014). 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 has used this method for avalanche forecasting has produced trees with 71-86% overall correct classification (e.g., Hendrikx et al., 2005; Baggi and Schweizer, 2009; Hendrikx et al., 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). All trees were grown using the Gini index to create splits that reduce the probability of misclassification (Breiman et al., 1993). Over-fit trees were grown using a criteria to stop splitting 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 tree.

Trees were grown to split seasons into groups of seasons that had deep slabs on persistent weak layers and groups of seasons that did not. Predictive model performance of the over-fit and cross-validated classification trees was described using measures explained by Wilks (1995) and Doswell et al. (1990), and have also been used with regards to avalanche forecasting by Schweizer et al. (2009) and Hendrikx et al. (2014). We use 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 as:

$$\mathrm{RPC}=0.5\left(\frac{a}{a+c}+\frac{d}{b+d}\right) \tag{1}$$

$$\mathrm{TSS}=\frac{d}{b+d}-\frac{c}{a+c} \tag{2}$$

$$\mathrm{FAR}=\frac{c}{c+d} \tag{3}$$

$$\mathrm{POD}=\frac{d}{b+d} \tag{4}$$

$$\mathrm{PON}=\frac{a}{a+c} \tag{5}$$

$$\mathrm{FSR}=\frac{b}{b+d} \tag{6}$$

where the definitions for a-d are defined in a contingency table (Tbl. 1).

Tbl. 1: Contingency table showing definitions for measures of model performance.

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

2.2 Deep slab avalanches on persistent weak layers

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

Avalanche characteristics that are recorded with most observations, and that were used in this study include: Date, type of trigger, avalanche type, R-size, crown depth, and layers involved (i.e., bed surface) (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 was recorded with bed surface as "ground" (or layers involved as "all"), then it was considered to have failed on depth hoar (or basal facets) since this is a common weak layer near the ground in the intermountain snow climate of Bridger Bowl (Mock and Birkeland, 2000). Avalanches on deep persistent weak layers are not always recorded with the bed surface as the ground. Avalanches that fail in depth hoar might fail 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 record the bed surface as "old snow". Furthermore, persistent weak layers that form higher in the snowpack would not be recorded with a bed surface of the ground and are still significant to this study.

If an avalanche after February 1st was not recorded as sliding on a basal persistent weak layer (i.e., bed surface of the ground), then R-size, avalanche type, bed surface, and average crown depth were used to determine if it was a deep slab on a persistent weak layer. 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 0.9m were examined individually to see if they likely failed on a deep persistent weak layer. These events were included as deep slabs on persistent weak layers if they were larger in comparison with other events during the same cycle, occurred without the addition of new snow, were significantly 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. These events were required 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 was in order to ensure that deep storm slabs were not included.

Soft slabs and wet loose avalanches were included if the bed surface was recorded as the ground. Therefore, wet loose avalanches that failed on depth hoar are included in addition to all slab avalanches (i.e., wet slab, soft slab, and hard slab) that failed on depth hoar. Avalanches between the 2010-11 and 2012-13 season had weak layer types known to the senior author. During this time, only the 2011-12 season had deep slab avalanches on persistent weak layers after February 1st. Events from this season are included that were known to have failed on depth hoar and facet layers that formed earlier in the season (Marienthal et al., 2012).

Deep slab avalanches failed on persistent weak layers after February 1st during 24 of the 44 seasons studied. Five seasons had only wet snow avalanches, seven seasons had only dry slab avalanches, and the other twelve seasons had both wet and dry snow avalanches that failed on deep persistent weak layers after February 1st.

It is typically desirable to have an almost equal number of events as non-events for statistical comparisons (Bois, 1975). While a benefit of classification trees is that they are insensitive to underlying distributions of data (Breiman et al., 1993), having an equal number of non-events during similar times as events is beneficial to control for temporal variations in confounding site specific factors (e.g., climate and snowpack). For these 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.

2.3 Meteorological variables

Bridger Bowl ski patrol records snow depth, new snowfall, new snow water equivalent (SWE), and minimum and maximum temperature over a 24-hour period. Observations are recorded once per day (1600 hrs) at the Alpine weather station (2286m). Avalanche starting zones are primarily between 2400m and 2677m, so absolute weather values are likely to be different between the weather station and starting zones. Meteorological trends are likely similar, however, between starting zones and the weather station. Therefore, weather observations from the Alpine station still provide a suitable proxy about what is happening to the snowpack in higher elevation starting zones. Daily weather observations were used to derive summaries of meteorological observations over the early months of the season, when deep persistent weak layers form and develop (Tbl. 2). These were used as explanatory variables in classification trees that discriminate between seasons with and seasons without deep slabs on persistent weak layers late in the season.

Seasonal meteorological variables used are representative of meteorological conditions that are conducive to persistent weak layer development (Tbl. 2). Monthly summaries of snow depth, daily snowfall, and daily precipitation (SWE) may indicate if snow exists on the ground early in the season, and if it is shallow enough to create a persistent weak layer, or deep enough to create a bed surface deeper than the terrain roughness (e.g., Schweizer et al., 2009). Monthly summaries of snowfall and SWE also indicate loading during the time of weak layer development, which may compact and strengthen weak layers through overburden pressure (e.g., Brown et al., 2001). Loading could also induce avalanches that may indicate future instability, or destroy weak layers in certain areas. Calculated daily temperature gradients were summarized as a relatively direct proxy of the snowpack temperature gradient. The proportion of days in each month, or group of months, that had conditions conducive to persistent weak layer development was quantified by counting days with a calculated temperature gradient stronger than 10°C/m and a snow depth less than one meter. This variable potentially summarizes the relative amount of time that a weak layer was developing each season. The height of snow on February 1st, the day we begin considering deep slabs on persistent weak layers, is included since

Tbl. 2: Derived seasonal variables used in this study.

Derived Seasonal Variables			
Variable	*Symbol*	*Summaries*	*Time*
Height of snow (cm)	HS	avg, max	Nov, Dec, Jan
Daily SWE (cm)	SWE	total (sum)	Nov, Dec, Jan, ND, NDJ
24 hr snowfall (cm)	HN	total (sum)	Nov, Dec, Jan, ND, NDJ
Daily temperature gradient (°C/10cm)	tg	avg	Nov, Dec, Jan, ND, NDJ
Days with TG>10°C/m & HS<1m	tgcnt	proportion	Nov, Dec, Jan, ND, NDJ
Height of snow on Feb. 1st (cm)	Feb1HS	(observed value)	once/season

it may be reflective of the snow depth and potential for persistent weak layer development prior to this date.

3. RESULTS

The over-fit tree created to split seasons with avalanches on deep persistent weak layers from seasons without avalanches on deep persistent weak layers primarily split observations based on total SWE in November, December, and January (Fig. 1). Seasons with greater than or equal to 30.8cm of SWE from November through January primarily did not have deep slabs on persistent weak layers. Seasons that had less SWE from November through January were split based on the total SWE in December. Deep slabs on persistent weak layers occurred during seasons that had less than 30.8cm of SWE from November through January and less than 5.6cm of SWE in December.

Seasons with more SWE in December were split based on the maximum snow depth in November. The group of seasons with a higher maximum snow depth in November had more seasons with deep slabs than seasons without, while the opposite is true for the group of seasons with lower maximum snow depth in November.

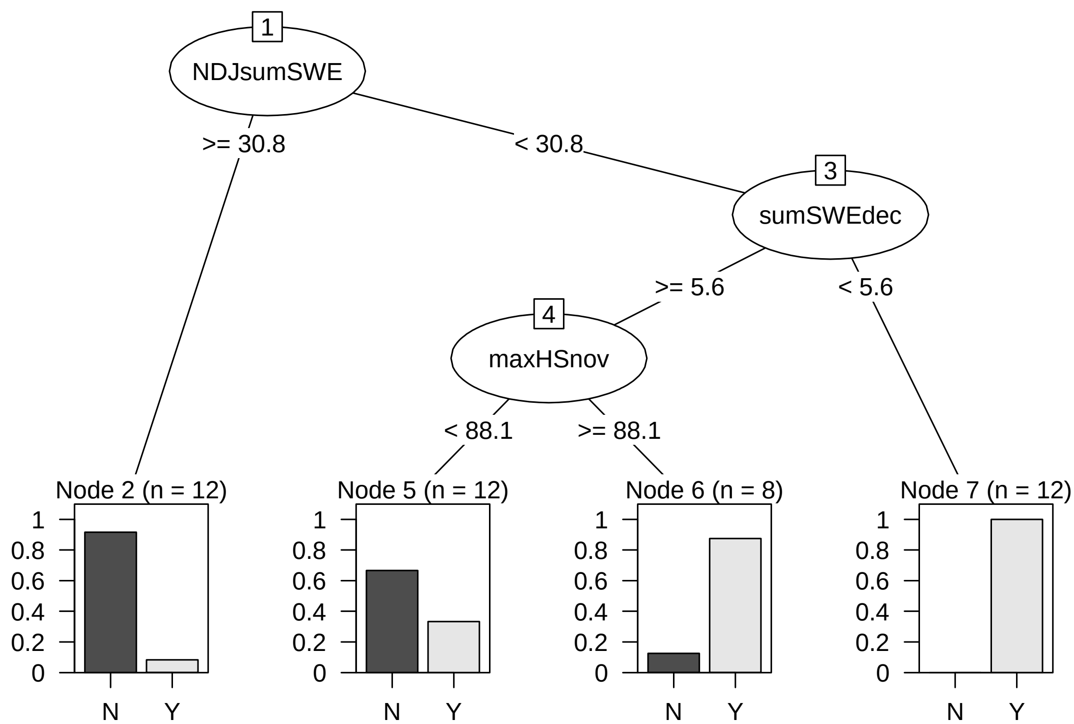

Fig. 1: Tree grown to split seasons with (Y) and seasons without (N) deep slabs on persistent weak layers. The cross validated tree consists of split number one only. (Figure created using the partykit package in R statistical software (Hothorn and Zeileis, 2013)).

The cross-validated tree, which is most suitable for predictive purposes, used only the first split of the over-fit tree (Fig. 1). It has an RPC of 0.75, TSS of 0.51, POD of 0.96 and PON of 0.55, with an FAR of 0.28 and FSR of 0.04 (Tbls. 3, 4).

Tbl. 3: Contingency tables for both the over-fit and cross-validated (CV) trees.

			Observed	
			Non Av.	*Av.*
Predicted	*Over-fit*	*Non Av.*	19	5
		Av.	1	19
	CV	*Non Av.*	11	1
		Av.	9	23

Tbl. 4: Measures of performance, described in text, for over-fit and cross-validated (CV) tree.

	RPC	*TSS*	*FAR*	*POD*	*PON*	*FSR*
Over-fit	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

4. DISCUSSION

The over-fit tree is useful for displaying the underlying structure of the data, and shows which variables are most associated with deep slabs on persistent weak layers. The first split in the over-fit tree separated seasons without deep slabs based on those seasons having greater total SWE in November, December, and January (Fig. 1). This metric indicates that wetter seasons have deep slab avalanches less frequently than dry seasons. More precipitation early in the season increases the snow depth and snow density, which would decrease the overall temperature gradient and reduce weak layer development. Furthermore, abundant precipitation early in the season helps stabilize 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 overburden pressure from load will strengthen weak layers (Brown et al., 2001).

The second split divides seasons with less SWE in November, December, and January based on total December SWE. Seasons with a drier December had deep slabs on persistent weak layers. Seasons with a relatively wet December, despite an overall relatively dry early season, had deep slabs when the maximum November snow depth was relatively deeper than seasons without deep slabs. The inclusion of maximum November snow depth 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 higher than the terrain roughness (e.g., Schweizer et al., 2009).

Total SWE in November, December, and January becomes the only split between seasons with and seasons without deep slabs after 10-fold cross-validation. The cross-validated tree provides a desirably low FSR (0.04) despite decreasing overall accuracy and skill (Tbl. 4). The inclusion of January in this cumulative SWE total implies the importance of continuous observation of meteorological conditions across all months. Considering the effect of November, December, and January SWE totals on late season deep slab stability has less uncertainty when months are combined than when they are considered 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. Observations from isolated, rather than continuous, periods of time will increase uncertainty in any avalanche forecast.

While the over-fit tree is not suitable for prediction due to over-optimism, measures of model performance are included to display the overall reduction in model performance after cross-validation (Tbl. 4). Overall accuracy (RPC) decreases after cross-validation. The only improvements after cross-validation are an increased POD and decreased FSR. Despite these improvements the overall skill (TSS) and accuracy (RPC) of this tree drop due to an increased FAR and decreased PON. The TSS may be the best measure of overall performance, and it is low (51%) for the cross-validated tree. Hendrikx et al. (2014) achieved a TSS of 47% and an RPC of 73% on the dataset used to fit their tree. Schweizer et al. (2009) had RPCs ranging from 77-89% and TSS ranging from 29-54% for various datasets. Our cross-validated tree shows similar levels of performance as trees previously applied for avalanche forecasting. These levels of model performance are too low to solely rely on for an avalanche forecast, but the models are still useful when combined with experience and knowledge of other forecasting tools and avalanche behavior.

While the achieved model performance is comparable to previous avalanche forecasting models, it should be noted that the sample size here is 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 significance of the cross-validated tree's sole predictor (total SWE in November, December, and January).

Future work will consider which meteorological metrics are responsible for the daily triggering of deep slabs on persistent weak layers. We will use classification trees with meteorological metrics summarized over several days prior to days with avalanches in order to predict days with deep slabs. This will provide both a seasonal and daily forecasting perspective to this complex issue.

5. CONCLUSIONS

We used classification trees to model seasons with deep slab avalanches on persistent weak layers. While our classification trees do not show any improvement in predictive model performance over previous work, the variables used in the trees provide valuable insight about which meteorological conditions are common during seasons with deep slab avalanches on persistent weak layers. Information regarding potential deep slab avalanche hazard can be gained by considering the season's meteorological history. The rate of snow accumulation over the early months of the season may control the cycle of strengthening and weakening of persistent weak layers, with less gradual, more abrupt, loading leading to more deep slabs. We found that seasons with an abundance of precipitation from November through January were mostly stable in regards to deep slabs. While many seasons with an overall drier early season did have deep slabs, those with a shallower snowpack in November did not. Seasonal meteorological conditions that indicate higher potential for late season deep slabs are an overall relatively dry early season combined with an early season snowpack that is shallow enough for weak layer formation, yet deep enough to form a significant weak layer or bed surface above terrain roughness.

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