REAL TIME SNOW SLOPE STABILITY MODELING OF DIRECT ACTION AVALANCHES

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ABSTRACT: Improved prediction of the timing of direct action avalanches that occur during storms is needed for highway forecasting operations. A SNOw Slope Stability model (SNOSS) compares the overburden stress caused by new snow to the estimated strength within the new snow. This provides estimates of the stability of the new snow layer and whether a regional direct action avalanche cycle can be expected. For the first time during the winter of 2011/2012, SNOSS was run in real time at Banner Summit, Idaho for the Idaho Transportation Department (ITD) and Little Cottonwood Canyon, Utah for the Utah Department of Transportation (UDOT). SNOSS results were displayed automatically on a webpage hourly, using weather observation downloaded from MESOWEST. Little Cottonwood Canyon has a unique dataset of weather and avalanche observations dating back to the early 1970's. We investigate SNOSS performance using detailed avalanche observations from avalanche forecasters and infrasound arrays. We present SNOSS model runs for the years 2001-2010 and compare the results to detailed avalanche observations. The results of the study will be used to improve the real time application of SNOSS, to provide a useful tool for avalanche forecasters.

1. INTRODUCTION

Avalanche forecasting models ingest weather and snowpack data in order to determine if the complex interaction of weather and snowpack data will lead to avalanche activity. Similar to an avalanche forecaster, the model attempts to use the available weather, snowpack, and avalanche information to determine if the current and future conditions will lead to avalanche activity. Avalanche forecasting models will never replace the experience and knowledge of an avalanche forecaster, but will help communicate how the multitude of information relates to avalanche activity.

Previous studies have primarily used meteorological data to predict avalanche activity. The classification schemes use either manually collected weather data (Davis et al., 1999; Floyer and McClung, 2003) or data from automatic weather stations (Hendrix et al., 2005; Cordy et al., 2009; Eckerstorfer and Christiansen, 2011). The most popular method is to forecast avalanche days – i.e. whether or not an avalanche has occurred over a specified time window. These studies reported results that vary between 70-85% correct classification rate for both natural and artificially released avalanches. The model results are simple to interpret but require a significant amount of past avalanche data to test the model and performance improves with the quality of the meteorological data available. The limitations of statistical avalanche forecasting models based on weather data are the lack of information of the snowpack properties, and the requirements that they are tuned for any individual site. For example, information about existing weak layers within the snowpack is not used nor estimated. However, acquiring hourly or daily snowpack data is not feasible for most areas. Models applied to different locations have different model parameters and predictor variables, and therefore can not be applied to locations without historical data.

Snowpack modeling can provide the required hourly snowpack property information that would be needed for avalanche forecasting models. Snowpack models typically use a minimum of hourly precipitation and temperature measurements and from these measurements, construct and evolve the snowpack through time.

The physically based SNOWPACK model (Bartelt and Lehning, 2002; Lehning et al., 2002a,b) has been used to create snow profiles during times of avalanche activity. Using the model outputs of snow strength, the stability of the snowpack can be assessed (Lehning et al., 2004; Schweizer et al., 2006; Schirmer et al., 2010). However, SNOWPACK has not been compared with a large database of avalanche activity to test the model results.

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The French SAFRAN-Crocus-MEPRA (SCM) chain (Durand et al., 1999) is an operational avalanche forecasting model that uses meteorological data as input to the snowpack model Crocus. The results from Crocus are analyzed with an expert system of rules (MEPRA) to determine if natural or skier triggered avalanche activity will occur.

This study aims to use the much simpler and more computationally efficient model, SNOw Slope Stability (SNOSS, Conway and Wilbour, 1999) to model the snowpack using only an input of hourly precipitation and temperature measurements. SNOSS models the densification of each new snow layer through time, and uses density to estimate strength (Jamieson and Johnston, 2001). Stability indices are calculated to estimate avalanche regional activity. Currently, SNOSS has been adapted to process and output results real time for two highway departments during the winter of 2011/2012.

2. STUDY SITES

2.1 Highway 21, Idaho

The Idaho Transportation Department (ITD) forecasts for Highway 21 located 2.5 hours northeast of Boise, Idaho in an intermountain climate. The area typically sees moderate snowfall (300" average), extremely cold temperatures between storms, and rain on snow events throughout the winter. ITD has a limited explosive avalanche mitigation program due to the complex terrain of the start zones and highway location. Avalanche activity is mainly direct action avalanches due to storm snow or rain on snow, with at least one major wet slide cycle during the spring. Both lanes of Highway 21 are frequently covered during avalanche cycles and the road is often closed for several days at a time. Avalanche detection is performed using two experimental infrasound arrays that can accurately time avalanche events when manual observations are not possible due to road closure. Future work involves expanding this infrasound array network to include real time avalanche event information.

2.2 Little Cottonwood Canyon, Utah

The Utah Department of Transportation (UDOT) has an avalanche forecasting program for the Little Cottonwood Canyon road from Salt Lake City to Alta, Utah in the Wasatch Mountains. UDOT has an extensive explosive avalanche mitigation program employing multiple Avalaunchers and large artillery. Avalanche records affecting the road date back to 1974 and provide a large dataset of high quality avalanche observations alongside a long history of weather observations. A significant amount of the avalanches in the area are direct action avalanches due to storm snow and occur during or directly after a storm. However, the climate is intermountain and can produce a depth hoar at the base of the snowpack during the early season. Here we focus on slide paths with multiple events per year to target direct action events.

Avalanche records between years 2001-2010 were used along with data from Alta Guard and Alta Baldy weather stations.

3. SNOW SLOPE STABILITY MODEL

A simple 1-D SNOw Slope Stability (SNOSS) model (Conway and Wilbour, 1999) is currently used operationally in maritime snow climates at Snoqualmie Pass, Washington and Milford Sound, New Zealand, whose snowpack typically consists of dense snow with very few persistent weak layers. SNOSS has shown promising results in these areas for forecasting direct action avalanche release at a regional scale. Recently, Marshall et al. (2008) used SNOSS at Red Mountain Pass, Colorado to successfully predict direct action avalanches in a continental climate.

The basis for SNOSS is to compare the overburden shear stress caused by the new snow with the estimated shear strength of layers within the snowpack. The ratio of the overburden shear stress to the shear strength is the stability index (Föhn, 1987) and as the value approaches 1, the probability of an avalanche theoretically increases. However, past studies have shown that

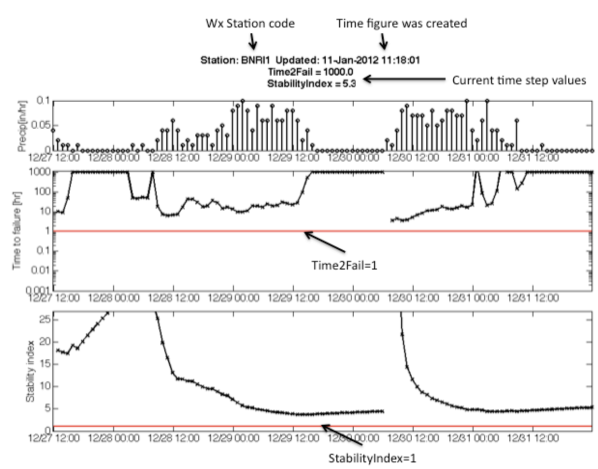

Figure 1: Real time SNOSS webpage output, updated when a new precipitation measurement is acquired. The top panel shows the hourly precipitation measurement, middle panel is the time to failure, and the bottom panel is the stability index.

avalanches typically occur at a higher stability index value that varies between sites (Conway and Wilbour, 1999; Lehning et al., 2004; Schweizer et al., 2006). This is possibly due to a difference in forcings and snowpack properties between available weather stations and starting zones.

4. REAL TIME RESULTS

SNOSS has been adapted to run real time on any combination of weather stations with hourly precipitation and air temperature measurements. The following are the steps for applying SNOSS in real time, implements with a combination of Linux shell scripts and MATLAB code:

1) Download data from the MESOWEST server for the desired stations and perform quality control on new data.
2) If there is a new precipitation measurement, run SNOSS and update the results.
3) Display the data on a webpage (figure 1) in an easy to interpret manner (http://cgiss.boisestate.edu/~hpm/SNOSS/).
4) Wait for next measurement from weather station.

The figure displayed on the webpage (figure 1) currently tracks the basal layer from the beginning of the current storm. After 12 hours of no new precipitation, SNOSS will begin tracking basal layer of the next storm, when precipitation resumes. Figure 1 shows the typical results that were displayed for the winter of 2011/2012 and how to interpret the figure. As the stability index approaches 1 (the horizontal red line), the probability of natural avalanches increases. The time to failure is the time in hours until the layer will reach a stability index of 1 given the current conditions and rates of change.

This was the first implementation of the results figure and will be modified based on the

Variables	
Weather	**SNOSS**
Alta Guard AWS	Stability index
Total water weight	
Temperature, Avg	
Alta Baldy AWS	
Wind speed, Avg	
Wind gust, Avg	
Wind direction, Avg	
Temperature, Avg	
Combined	
Snow drift	

Table 1. Predictor variables derived from weather data and SNOSS results. All variables were calculated for each avalanche and non avalanche day.

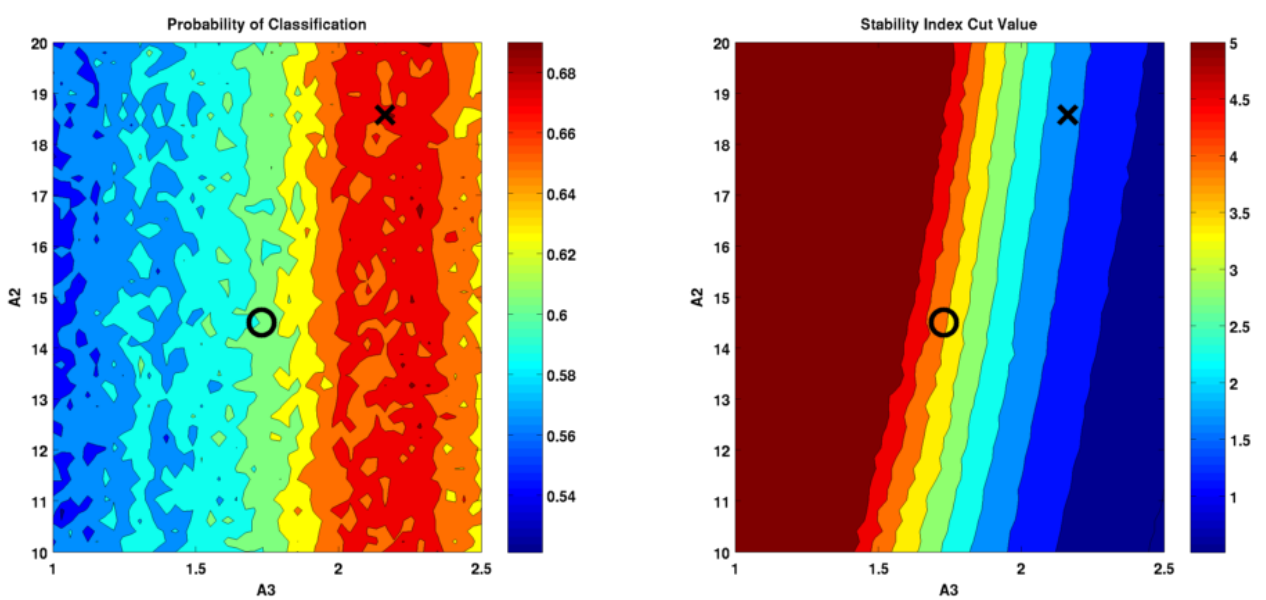

Figure 2. Different values of A2 and A3 were used in SNOSS to calculate the stability index. A single value of stability index was used to classify between avalanche and non avalanche days. The maximum correct classification (marked with an X) was 70% with A2 = 18.57 and A3 = 2.16. These values found that the best stability index split was 1.8. The Jamieson and Johnston (2001) values are shown with a circle for new snow, decomposing fragments, and rounds.

avalanche forecasters need. During the past season, the avalanche forecasters on Highway 21 used SNOSS to determine qualitatively what values of the stability index and time to failure were useful for predicting direct action avalanches.

5. NATURAL AVALANCHE PREDICTION

5.1 Avalanche days definition

A small subset of the total avalanche records for Utah between 2001 and 2010 were used to test natural avalanche prediction. Each season of weather and avalanche data was searched using a moving 12 hour window for natural avalanches as well as times with significant storms that did not produce avalanches. Each 12 hour window was classified as an avalanche day or non avalanche day depending on whether or not a natural avalanche occurred within that window. The criterion for a storm was more than 1.3 cm of water, less than 2 degrees C at the peak weather station, and less than 2 hours elapsed since the last precipitation measurement. These criteria produced 49 avalanche days and 506 non avalanche days.

Weather predictor variables were created from 72 hours of weather data prior to the end of each time window (table 1). The snow drift parameter is the total water weight measured at Alta Guard multiplied by the average peak wind speed raised to the fourth power (Hendrix et al., 2005). Using 72 hours of weather data, SNOSS model outputs were also created using the precipitation measurement at Alta Guard and air temperature from Alta Baldy.

5.2 Determine weak layer shear strength

The first objective was to tune the shear strength versus density relationship in SNOSS to the avalanche data. Jamieson and Johnston (2001) compared shear frame measurements with snow density and expressed the shear strength as:

$$\Sigma = A2\left(\frac{\rho_{snow}}{\rho_{ice}}\right)^{A3}$$

with ρ_{snow} as the snow density and ρ_{ice} as the density of ice. For new snow, decomposing fragments and rounds A2 = 14.5, and A3 = 1.73. For facets and depth hoar A2 = 18.5 and A3 = 2.11.

SNOSS was run for all 49 avalanche days and 506 non avalanche days with varying values of A2 and A3. The training and test set had equal numbers of avalanche and non avalanche days. The best single value of the stability index to split between days was determined using the training set, then evaluated using the test set. This process was repeated 100 times for each combination of A2 and A3. The results of classification are shown in figure 2. The highest average classification rate from the test set gave the values of A2 and A3. The stability index value was optimized to find the best split between days. Since the stability index is a ratio with the strength, the stability index value will change to accommodate the change in A2.

The results for A3 are significantly different from Jamieson and Johnston (2001) findings for new snow, decomposing fragments, and rounds with A2 = 18.57 and A3 = 2.16. Jamieson and Johnston values were tuned to the Canadian Rockies, which have slightly different properties than the Wasatch Mountains. With the new values of A2 and A3, the accuracy of SNOSS for the Little Cottonwood Canyon area is significantly improved.

5.3 Classification of avalanche days

Classification trees (Breiman, 1993) were used to classify avalanche days versus non avalanche days using the predictor variables in table 1. The objective was to determine if SNOSS variables could improve the classification rate over using only basic weather information.

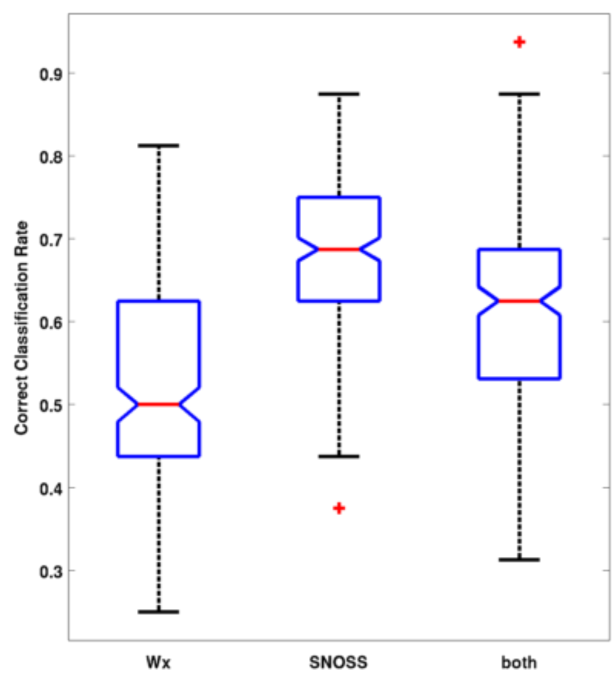

Figure 3. Classification results using weather variables, SNOSS variables (one stability index value), and both weather and SNOSS variables.

were performed using weather variables, SNOSS variables, and combination of weather and SNOSS variables. For each scenario, a training and test set were randomly created ensuring an equal number of avalanche and non avalanche days were in each set. A single classification tree was created on the training set and tested with the test set. The probability of correct classification was calculated from the test set. The random selection of the training set and creation of classification trees was repeated 200 times to determine how well a future measurement could be classified. Only a single value of the stability index was used to classify between days. The results are shown in figure 3.

The results show that using weather predictors do no perform as well (0.52 ± 0.11) as solely using the stability index (0.67 ± 0.1). This shows that classification of avalanche days can be increased significantly using information from snowpack models.

6. CONCLUSION

In this paper, we have presented how SNOSS has been adapted for real-time data analysis for use in operational avalanche forecasting programs. The season of 2011/2012 was the first winter of use and SNOSS has proven to be a useful tool for estimating how the snowpack will react to new storm snow.

Natural avalanche data from Little Cottonwood Canyon was used to tune the snowpack shear strength to best predict when avalanches would occur. These values agree very well with results from Jamieson and Johnston (2001) but for different grain types.

Avalanche days and non avalanche days were classified using weather variables, the stability index, and a combination of both variables. A single stability index value could correctly classify avalanche days with a 67% correct classification rate, a 15% improvement over only weather variables. These results suggest that using a snowpack model like SNOSS can be used to determine the stability index, which can significantly improve forecasting for direct action natural avalanches.

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