COMPARING MODELS OF DIFFERENT LEVELS OF COMPLEXITY FOR THE PREDICTION OF WET-SNOW AVALANCHES

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ABSTRACT: The amount and timing of infiltrating water plays an important role in determining wet-snow instability. However, the nature of water flow in snow is very complex and heterogeneous. In addition, the mechanical interaction of water and snow is poorly understood. Both facts complicate wet-snow avalanche forecasting. Due to this complexity and the poor understanding, statistical rather than physical models have been used in the past to explain wet-snow avalanche activity. Various multivariate statistical models used different input parameters with varying complexities ranging from simple air temperature recordings to modeled energy balance. We tested these statistical models for the region of Davos. Meteorological data from different automatic weather stations at three elevations (below treeline, at treeline and in the alpine) for the winter periods 2004-2005 to 2012-2013 were used and results compared to wet-snow avalanche activity data. Results show that the forecasting models using only air temperature, or which were trained with other local data, had only limited success, i.e. transferability was limited. To improve forecasting skills, it seems crucial to include information on both, boundary conditions (e.g. air temperature) and the snowpack itself (e.g. snow surface temperature). Best predictive power was obtained when we accounted for aspect, energy fluxes and state of infiltration. The results suggest that a certain complexity is necessary to correctly depict the processes favoring wet-snow avalanche activity with a model. Already now, parts of the results are in operational use to better predict days with wet-snow avalanche activity.

KEYWORDS: Wet-snow avalanches, avalanche forecasting, danger assessment.

1. INTRODUCTION

Forecasting wet-snow avalanches is notoriously difficult and mainly hindered by the fact that our understanding on the formation processes is still poor compared to dry-snow avalanche release. The lack of knowledge is driven by two facts: (1) Previous research (Brun and Rey, 1987; Schneebeli, 2004; Techel and Pielmeier, 2011; Trautman et al., 2006; Waldner et al., 2004) clearly showed that the mechanical interactions of water and snow stratigraphy are highly non-linear, spatially heterogeneous and fast changing. (2) Lack of direct information, i.e. detailed snowpack information, adds to the lack of understanding and ultimately complicates wet-snow avalanche danger assessment. Based on the above difficulties, statistical models using readily available meteorological input data, rather than purely physical modeling have been applied to explore and/or forecast wet-snow avalanche activity. The most common statistical approach for exploring and forecasting days with high wet-snow avalanche activity were until now classification trees (Baggi and Schweizer, 2009; Mitterer and Schweizer, 2013; Peitzsch et al., 2012b). Additionally, Zischg et al. (2005) presented a fuzzy-logic approach, Romig et al. (2005) used log-binominal regression analyses and applied Mitterer et al. (2013) an expert-based approach.

All statistical models used at least once within their setup air temperature, some had information on snowpack temperature (snow surface temperature, isothermal state) and only the approach by Baggi and Schweizer (2009) included information on snow stratigraphy via a capillary barrier index. Results scattered considerably, but mainly implied that avalanche days might be predicted with a probability in the range of 0.6-0.85 and non-avalanche days with a probability of about 0.8-0.9. Especially the rules within the model based on a classification tree presented by Peitzsch et al. (2012b) seemed very promising. In their work, which was not used to train the tree and obtained good results in terms of detection probability (0.91).

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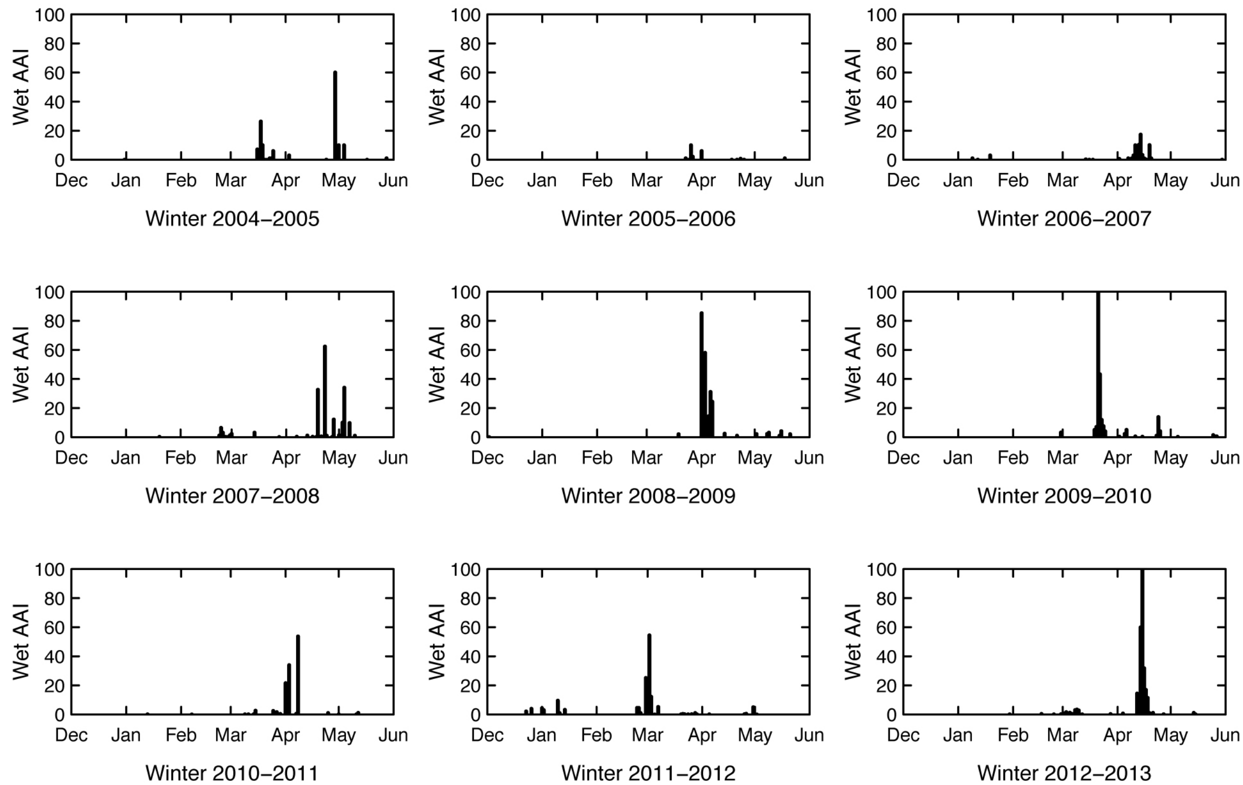

Fig. 1: Wet-snow avalanche activity (AAI) for the region of Davos, Switzerland during the nine winter seasons 2004-2005 to 2012-2013.

However, they did not report on false-alarm rates and for the following winter season (2011-2012), the model completely failed to predict days when wet-snow avalanches occurred (Peitzsch et al., 2012a). They concluded that the tree failed, because threshold values were slightly too high for a correct classification of avalanche days; forecasted non-avalanche days agreed fairly well. Also Romig et al. (2005) concluded that their model was much better in predicting days with no wet-snow avalanche activity than days with avalanches and attributed this result to the complexity of the problem.

This led us to the questions, which we tried to tackle with this presented work: Do physically more complex model settings provide better predictions for wet-snow avalanches than simpler ones, which are based on e.g. air temperature only?

2. DATA AND METHODS

2.1 Avalanche occurrence data

We used the number and sizes of wet-snow avalanches reported for the region of Davos in Switzerland during the nine winter seasons 2004-2005 to 2012-2013. For our analyses, we defined the winter season to last from 1 December to 31 May. Based on weights for the sizes and numbers per day (Schweizer et al., 2003), we calculated an avalanche activity index (AAI) for every day (Fig. 1).

For all winter seasons, the median wet-snow avalanche activity for an avalanche day was 1, i.e. that at least 1 medium-sized or 10 small avalanches were reported (Canadian size class); the mean activity was 8 and the maximum activity 101 which was reported on 21 March 2010. In total 188 days with wet-snow avalanche activity were reported, 117 days had an AAI≥1. We used different thresholds for the AAI to classify avalanche and non-avalanche days (Tbl. 1).

Tbl. 1: Different thresholds for the avalanche activity index (AAI) defining wet-snow avalanche days (Avd) and non-avalanche days (nAvD) with the corresponding number of days for the winter seasons 2004-2005 to 2012-2013.

Threshold	*Number Avd*	*Number nAvD*
AAI≥1	117	1523
AAI≥5	50	1590
AAI≥10	36	1604
AAI_{TOP10}	10	1630

2.2 *Meteorological data*

We used data from automatic weather stations at three elevations (below treeline, at treeline and in the alpine): the station SLF located in the valley bottom of Davos (1560 m a.s.l.), the station KLO (2140 m a.s.l.),) situated slightly above treeline and the station Weissfluhjoch (WFJ, 2540 m a.s.l.) well above treeline in the Alpine. Available meteorological data included air temperature (T_A), relative humidity (RH), wind speed (V_W) and direction (D_W), reflected shortwave radiation (RSWR), snow height (HS), snow surface temperature (T_{SS}) and snow temperatures at different heights within the snowpack (T_{S0}-T_{S3}). The stations reported data every 30 minutes which we then used to calculate daily averages, minimum, maximum values and sums or differences over 1, 3 or 5 days.

2.3 *Data obtained with SNOWPACK: Snow stratigraphy, temperature and energy balance*

Since some of the prediction models used snowpack parameters, but manual snow profiles were only available on an irregular basis, we run the 1-D snow cover model SNOWPACK in operational mode to obtain snowpack information. Operational mode means that we only used the values of the three weather stations as input for the snow cover simulations; no additional information on e.g. incoming longwave radiation was given to the model, even if available. Outputs were generated every 3 hours and were available for the location of the stations (i.e. flat field) and virtual north- and south-facing, 38° steep slopes. Finally, we calculated daily averages, minimum, maximum, modal values or sums and differences over 1 to 5 days. In this way we obtained grain size and grain size difference to calculate the capillary barrier index, snowpack temperatures to define when the snowpack was 0°-isothermal (Baggi and Schweizer, 2009) and calculated the LWC_{index} (Mitterer et al., 2013) which is based on energy and mass balance.

2.4 *Determining predictive skills of the prediction models*

The five statistical prediction models used in this study and their parameters are given in Tbl 2. We applied the rules of the different models to every day within our data set and calculated the probability of detection (POD), the probability of non-events (PON) and the false-alarm rate (FAR) according to Schweizer and Jamieson (2007) for the four different thresholds defining a wet-snow avalanche day (Tbl. 1).

3. RESULTS AND DISCUSSION

Fig. 2 shows the predictive performance for the five different models. Overall, all models performed well in detecting non-avalanche days (nAvd), had high values for false alarms and varied considerably in their forecasting skills for AvDs.

The models BAG and MIT1 (Fig. 2b,c) showed very poor performance for detecting AvD, but still reasonable results for detecting nAvD (PON ~0.8). For BAG, none of the largest events within our data was detected; for all other thresholds, POD was not higher than 0.25. The FAR was for all thresholds very high (0.8-0.9). With other words, the BAG model missed two thirds of the AvDs, and if the model classified an AvD it was right in only 1 out of 10 cases. MIT1 predicted Avds with a probability of 0.4-0.6, with the best performance for an AAI≥10. The results were slightly better than for BAG, but again at most only a little more than half of the avalanche days were detected by simultaneously predicting 8 to 9 times an AvD although no wet-snow avalanche occurred.

The PEI model (Fig. 2a) performed slightly better and indicated fair detection potential with values for POD of 0.55-0.69, but had the best results in detecting nAvD with a PON of 0.8 which is in agreement with former results (Peitzsch et al., 2012a). Best performance was achieved with the MIT2 (POD = 0.74-0.9) and MIT3 models (POD = 0.67-0.8). The PON for these last two models was around 0.75, false alarms were considerably high, but the overall performance in terms of the true-skill score was best for MIT2 and MIT3 (not presented in Fig. 2).The results underline that air temperature solely is not a good proxy to forecast days with high wet-snow avalanche probability (Kattelmann, 1985; Mitterer and Schweizer, 2013). In fact, the model based only on

Tbl. 2: Overview of model approach and input parameters to predict days with wet-snow avalanche activity.

Model	*Station*	*Model approach*	*Meteo*	*Snowpack*
Baggi and Schweizer (2009) (BAG)	KLO	Classification tree	3d-sum of positive T_A	Days since isothermal state Capillary barrier index
Peitzsch et al. (2012b) (PEI)	KLO+ SLF	Classification tree	Mean T_A Maximum T_A	Change in HS over 5 days
Mitterer and Schweizer (2013) (MIT1)	WFJ	Classification tree	5d-sum of positive T_A	None
(MIT2)	KLO	Classification tree	3d-sum of positive T_A	Mean daily T_{SS}
Mitterer et al. (2013) (MIT3)	KLO (south)	Expert-based	Energy balance	Mass balance

air temperature (MIT1) was the second worst. The two best models (MIT2 and MIT3) included a combination of energy input (e.g. high values of air temperature) and information on whether the snowpack was ready for snow to be melt (i.e. high snow surface temperature in MIT2) or how much water had already been melted (i.e. mass balance in MIT3). It is somewhat surprising that the BAG model performance was so poor, since it included in some way similar information on energy input (3-day sum of positive T_A) and energy state of the snowpack (days since isothermal state was reached). Especially the latter variable produced many misses as the 0°C isothermal state of the snowpack was mostly reached shortly after avalanche activity had peaked. This explains also why none of the top 10 avalanche activity days was captured with that model (Fig. 2b). There are two possible explanations for the discrepancy of our findings and the ones of Baggi and Schweizer (2009): (1) We modeled the data to calculate the two variables *Days since the isothermal state* was reached and the *Capillary barrier index*, whereas Baggi and Schweizer (2009) derived both from biweekly manually observed snow profiles. The snow cover model SNOWPACK is known to produce grain sizes, which are small compared to observed ones, which consequently changes the capillary barrier index. Measuring and/or modeling snow temperatures close to 0°C is a difficult task and the discrepancy is therefore not surprising. We were very strict in defining the isothermal state, i.e. all snow layers had to have a temperature of 0°C, and maybe this introduced the above mentioned time delay. (2) The response variable, i.e. AvD/nAvD, was slightly different for our data set than the one of the BAG model. While we considered both, loose- and slab avalanches within the avalanche activity index, Baggi and Schweizer (2009) included in their dataset only wet snow slab avalanches. In addition, the avalanches in Baggi and Schweizer (2009) were observed on predominately northeast-facing slopes, whereas our data set included mostly avalanches, which released on south-facing slopes suggesting that the tree of Baggi and Schweizer (2009) is trained on locally too specific data.

All models had high proportion of false alarms, which lowers the overall skill of the prediction. The high values for the FAR are mainly attributed to the fact that we considered the period from December to May. All winters were characterized by a short, more or less distinct period with high avalanche activity lasting for a couple of days in spring (Fig. 1). In most years, the activity dropped sharply around end of April or beginning of May. However, conditions favoring wet-snow avalanches might have prevailed. Therefore, we tried to lower the numbers of false alarm by shortening the season: 3 days after the avalanche activity had peaked the season ended. This rule should cover the fact that wet-snow avalanches become less likely the longer the snowpack is isothermal(Baggi and Schweizer, 2009). The reduced datasets we then applied to the two best models (MIT2 and MIT3). This cut the number of potential avalanche days in half, but slightly increased the misses so that the POD decreased. For MIT2, however, the FAR did not significantly decrease, since most false alarm days were during the season. In fact, the second rule of the MIT2 tree (T_{SS} < -0.7°C and 3d-sum of positive T_A ≥ 4.5°C) occurred often dur

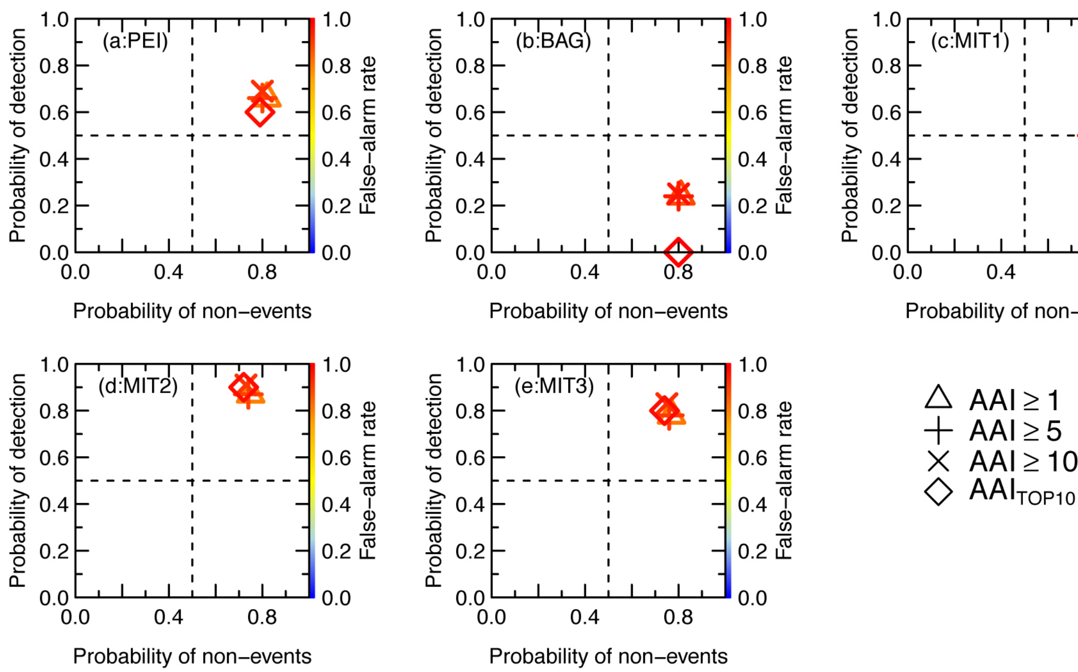

Fig. 2: Predictive performance of the models presented in Table 2 using the different thresholds for the avalanche activity index (AAI).

ing the entire season. During these days the energy balance was still negative, although air temperature was well above freezing. For the MIT3 model, though, false alarm days dropped by 80% by introducing the above cutting rule. Some years did not produce any false alarms at all. With the MIT3 model, problems with false alarms were still present for the seasons when avalanche activity peaked twice or elevation and aspect of the release zone differed considerably during the season (e.g. winter 2004-2005 or 2007-2008 in Fig. 1). Especially the latter fact makes the MIT3 model superior to the MIT2 approach.

4. CONCLUSIONS

Forecasting wet-snow avalanches is difficult due to complex interactions of meteorological conditions, snow stratigraphy and water flow through snow. Since our understanding of the mechanical processes is still fairly limited, statistical modeling was used in the past to explain days with a high probability for wet-snow avalanches. Several statistical or expert-rule based models evolved including a wide range of meteorological and snowpack parameters. We chose five different models with varying complexity to predict wet-snow avalanche days for the region of Davos, Switzerland for the winter seasons 2004-2005 until 2012-2013. Results show that the forecasting models using only air temperature (MIT1), or which were trained with local data (BAG, PEI), had only limited success. To improve the hit rate for POD and PON (e.g. MIT2 and MIT3 models), it seemed crucial to include information on both, boundary conditions (e.g. air temperature) and the snowpack itself (e.g. snow surface temperature). Still, for the two best models, the FAR was rather high, which lowered the overall predictive skill. Discarding the days after the major avalanche cycle for every winter, FAR for MIT3 decreased significantly. For MIT2, however, the numbers of false alarms remained about the same since most days with false alarms occurred before the major cycle. This reveals that three facts favor a wet-snow avalanche day and must be considered for assessing wet-snow avalanche danger: (1) High energy input at the snow surface, (2) a high snow surface temperature so that snow is melted and water is produced, and (3) an almost 0°C isothermal state of the snowpack to allow infiltration. The results suggest that a certain complexity is necessary to correctly depict the processes favoring wet-snow avalanche activity with a model. Already now, parts of the results are in operational use to better predict days with wet-snow avalanche activity.

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