DATA-DRIVEN MODELS USED IN OPERATIONAL AVALANCHE FORECASTING IN SWITZERLAND

Alec van Herwijnen*, Stephanie Mayer, Cristina Pérez-Guillén, Frank Techel, Martin Hendrick, Jürg Schweizer

WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland

ABSTRACT: One of the main challenges in avalanche forecasting is the complexity of the snowpack and its interactions with the environment. Traditional methods rely on expert knowledge to analyze snow and weather data, field observations and weather predictions, which is time-consuming and partly subjective. In contrast, data-driven models can analyze large amounts of data faster and may identify patterns that are difficult for humans to detect. Such models are based on statistical or machine learning algorithms that learn from past data to make predictions about new situations. Data-driven models are increasingly used in avalanche forecasting, as they can provide more objective and timely predictions, assisting forecasters in decision-making. Here, we present three recently developed models used in operational avalanche forecasting in Switzerland. The data-driven models use machine-learning algorithms with meteorological and simulated snow stratigraphy data as input to predict (1) the avalanche danger level, (2) snowpack instability and natural avalanche probability, and (3) wet-snow avalanche probability. The models were trained on historical data and typically have an accuracy of about 75%. During the last three winter seasons, we tested these models in operational avalanche forecasting for the Swiss Alps at SLF. Models 1 and 2 were consulted daily, while model 3 only in potential wet-snow avalanche situations. Preliminary results suggest that the models performed equally well in nowcast mode, when driven with measured data, as in forecast mode, when driven with data from numerical weather prediction models. Overall, the positive feedback we received from the forecasters shows that data-driven models can successfully be integrated into operational forecasting systems.

Keywords: Avalanche forecasting, machine learning, data-driven models.

1. INTRODUCTION

Snow avalanches range among the most prominent natural hazards threatening people and infrastructure in snow-covered mountains. With the ever-growing number of people and goods crossing mountainous regions, guaranteeing public safety and mobility is becoming increasingly important. Avalanche safety services therefore regularly assess the avalanche danger and implement appropriate mitigation measures. However, the ability to forecast avalanches in space and time is limited by current experience-based forecasting practices. Indeed, increasingly large data volumes covering a wide range of data qualities and spatio-temporal scales, such as hourly meteorological measurements, highly resolved meteorological forecasts, daily field observations, or weekly snow profiles, are mostly manually analyzed to assess snow instability in time and space (McClung and Schaerer, 2006). A major challenge is the lack of timely data, particularly during periods of increased avalanche danger, as traditional observations are then not possible. Improving the spatio-temporal resolution of predictions is only possible with numerical models.

Snow cover models were developed to derive snow instability from simulated stratigraphy (vertical layering) at single points, allowing for a more objective approach than time-consuming manual profiles to avalanche forecasting. Crocus (Brun et al., 1992) and SNOWPACK (Bartelt and Lehning, 2002) are the most advanced snow cover models. To obtain spatial snow instability information, snow cover models typically run on a network of AWS, or in semi-distributed or gridded approaches (Morin et al., 2020). However, the absence of thoroughly validated methods to assess snow cover instability from simulated stratigraphy hindered the integration of snow cover models into operational forecasting (Morin et al., 2020). Statistical methods were also developed as alternatives for assessing snow instability. These mostly focused on using machine learning method to estimate avalanche activity (e.g. Purves et al., 2003; Hendrikx et al., 2014) or the avalanche danger (Schweizer and Föhn, 1996; Schirmer et al., 2009). Nevertheless, very few of these models were used operationally due to a lack of input data, transferability to other regions, or snow stratigraphy/instability input. Fortunately, new meth-

*Corresponding author address:
Alec van Herwijnen, WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland; tel: +41 81 4170 161
email: vanherwijnen@slf.ch

ods and models were recently developed to exploit snow cover models (e.g. Mayer et al., 2022; Viallon-Galinier et al., 2023), bringing us closer to the practical implementation of objective methods for avalanche forecasting.

Increases in computation power and data combined with modern machine learning techniques now offer exciting new possibilities for operational avalanche forecasting. Recently, random forest (RF) classifiers were developed to predict the danger level for dry-snow conditions (Pérez-Guillén et al., 2022), wet-snow avalanche activity (Hendrick et al., 2023), and snow instability (Mayer et al., 2022). These RF classifiers show very promising results (Techel et al., 2022), and were tested during the last three winter seasons in real-time for operational avalanche forecasting in Switzerland. Avalanche forecasters responded with very positive feedback to the results, underscoring the operational potential of these classifiers. Here, we provide an overview of the models and show examples of the visualizations used in operational forecasting.

2. MODELS

Over the last few years, we developed three different classifiers to predict (1) the avalanche danger level, (2) snow instability from simulated stratigraphy, (3) wet-snow avalanche probability. The backbone for these models consists of meteorological data from a network of automatic weather stations (AWS) and from snow cover simulations obtained with the model SNOWPACK (Bartelt and Lehning, 2002; Lehning et al., 2002). Here, we briefly describe each model and provide references where the reader can find more detailed information.

2.1. Avalanche danger level

Assessing the avalanche danger level has traditionally been an experience-based decision-making process where human experts, avalanche forecasters examine diverse data and draw conclusions based on their expertise – with obvious potential for bias. By applying machine learning techniques to the output from physical snow cover models and quality-checked regional danger ratings, we developed a fully data-driven approach to evaluate the regional avalanche danger level for dry-snow conditions in the Swiss Alps (Pérez-Guillén et al., 2022). Using a large data set of more than 20 years of human danger level predictions, AWS data and SNOWPACK simulations, we trained a random forest (RF) classifier to predict the avalanche danger level. The accuracy of the model, i.e. the percentage of correct danger level predictions, was around 75%, similar to the agreement rate between regional forecasts and local assessments based on field observations (Techel and Schweizer, 2017). The model consistently performed well across the Swiss Alps, encompassing diverse climatic regions, although some regional variations were observed.

2.2. Snow instability

Snow stratigraphy and snow instability data are crucial components to assess avalanche danger. Manual snow observations, including snow profiles and stability tests, are therefore commonly used. However, such data are sparse in time and space, and snow cover models can provide valuable alternative data. While instability indices describing the mechanical processes of dry-snow avalanche release have been implemented into snow cover models (e.g. Bellaire et al., 2018; Reuter and Bellaire, 2018; Richter et al., 2018), there exists no readily applicable method that combines these metrics to reliably predict snow instability. We therefore trained an RF classifier to assess snow instability from SNOWPACK output (Mayer et al., 2022). We did so by manually comparing snow profiles observed in the Swiss Alps with their simulated counterparts. We then used the observed stability test result and an estimate of the local avalanche danger level to construct a binary target variable (stable vs. unstable). The snow instability classifier then aggregates six snow stratigraphy features to determine the probability of instability for each layer in the snowpack. Although the subset of training data only consisted of about 150 profiles labeled as either unstable or stable, the model classified profiles from an independent validation data set with an accuracy of 88%. Model predictions were also in line with observed avalanche activity in the region of Davos for five winter seasons.

2.3. Wet-snow avalanche probability

Wet-snow avalanches are triggered by the infiltration of liquid water into the snowpack. Release mechanisms are generally not well understood, making process-based prediction difficult. A simple proxy of water infiltration is therefore often used for forecasting, namely the mean liquid water content (LWC) of the snowpack (e.g. Bellaire et al., 2016; Wever et al., 2016; Mitterer et al., 2013). While indices based on LWC thresholds are generally effective in detecting the onset of wet-snow avalanche cycles, as these coincide with rapid increases in LWC, such indices are not well-suited to predict the end of avalanche periods. We therefore developed an RF classifier to predict the local wet-snow avalanche activity at the locations of automated weather stations (Hendrick et al., 2023). Model input consisted of measured meteorological data and SNOWPACK variables computed for

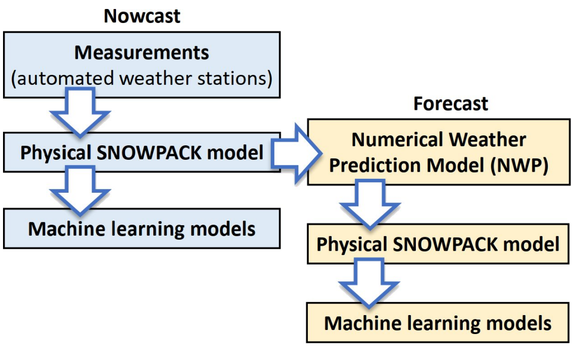

Figure 1: Model chain used to test the machine learning models in operational avalanche forecasting.

38-degree slopes facing the 4 cardinal directions. Based on concurrent avalanche observations, we defined a binary target variable to discriminate days with wet-snow avalanche activity from days without any activity in a stringent manner. Overall, model performance was good, with a precision of about 75%, and beyond the stringent definition of wet-snow avalanche days, model predictions also correlated with wet-snow avalanche activity over the entire Swiss Alps. While model development and validation were done in nowcast mode, we also studied model performance in 24-hour forecast mode by using input variables computed from a numerical weather prediction model, showing similar performance.

3. OPERATIONAL IMPLEMENTATION

Since the winter season 2020-2021, the Swiss avalanche forecasting service at SLF started using the models described above in operational context. The operational model chain used for real-time testing of the RF models consists of the following steps (Figure 1):

1. Measurements are transmitted from automated weather stations to a server at SLF once an hour.
2. Based on these data, every 3 hours, snow cover simulations are performed with SNOWPACK for the locations of the IMIS stations and for four virtual slope aspects (N, E, S, W).
3. The input features required for the models are then extracted from the SNOWPACK output and the respective predictions are calculated.

In addition, the models were also tested in a forecast mode for the coming 24 hours. With the most recent nowcast SNOWPACK run, the forecast simulations are driven with the numerical weather prediction model COSMO-1 (developed by the Consortium for Small-scale Modeling; `https://www.cosmo-model.org/`, last access: 31 May 2022) operated by the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss), downscaled to the locations of the AWS (Figure 2). Model predictions are visualized in two ways:

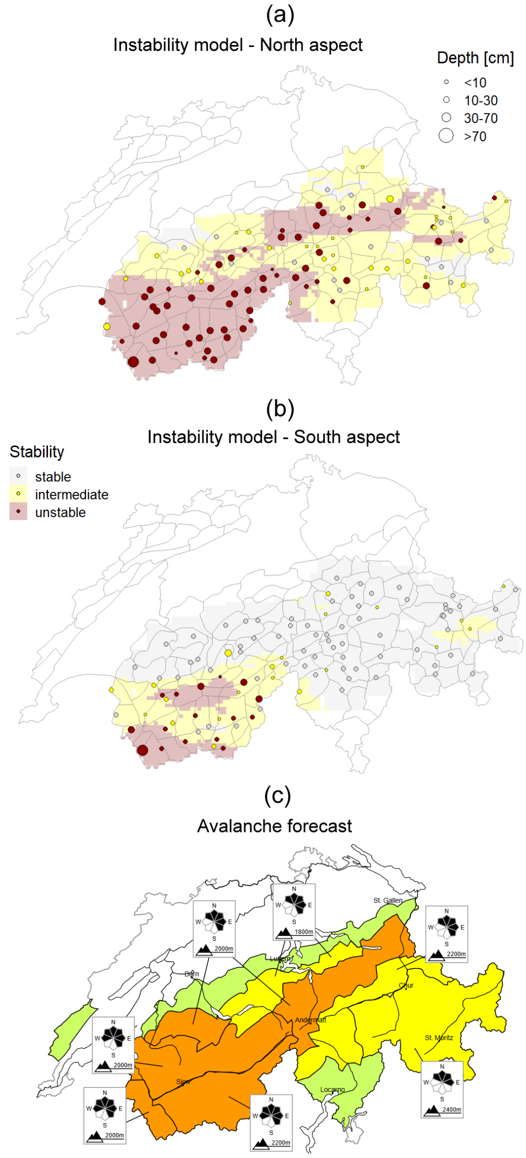

Figure 2: (a) Output of the snow instability model on 10 March 2023 for north-facing virtual slopes showing the probability of instability (colors) and the depth of the weak layer (size of the dot). The dots show the predictions at the location of the AWS, where the size of the dot scales with the depth of the weakest layer in the profile (see legend). The probability of instability is classified as either stable [0,0.5), intermediate [0.5,0.77) or unstable [0.77,1]. The colors on the map show linear interpolated results on a 1 km grid. (b) Output of the snow instability model for south-facing virtual slopes. (c) Avalanche forecast for 10 March 2023.

1. Maps showing the individual predictions at the locations of the AWS for each simulated slope aspect and simple interpolations between AWS (Figure 2).
2. Time series (not shown) or plots with elevation summarizing aspect-specific predictions (Figure 3).

An example of a visualization on a map showing the predictions of the snow instability model for 10 March 2023 is shown in Figure 2. These maps combine information on the degree of instability (using three categories) as well as the depth of the weakest layer, which is a rough proxy for the potential avalanche size. On this day, 20 to 40 cm of new snow had fallen in the northern and western Swiss Alps. The model predicted that the snowpack was mostly unstable in these regions, and the instability was more pronounced on north-facing slopes (Figure 2a) than on south-facing slopes (Figure 2b). The predictions were in good agreement with the forecasted avalanche danger level (Figure 2c).

An example of a visualization summarizing the predictions of the wet-snow avalanche activity model with elevation for 1 May 2023 is shown in Figure 3. These plots show the distribution of the predicted wet-snow avalanche probabilities binned with elevation, to highlight large-scale trends across the entire Swiss Alps. On this day, many wet-snow avalanches released throughout the Swiss Alps. The wet-snow avalanche activity model predicted the highest wet-snow avalanche probability on north-facing slopes between 1800 and 2400 m a.s.l. (Figure 3a), whereas the probabilities were lower for south-facing slopes (Figure 3b). This was in good agreement with avalanche observations from that day, which showed relatively wide-spread wet-snow avalanche activity throughout the Swiss Alps (Figure 3c). As many south-facing starting zones had already avalanched earlier in the spring season, most avalanches on this day released from north-facing slopes, as predicted by the model.

4. PRACTICAL EXPERIENCE

The RF classifiers presented above were primarily developed within different research projects at SLF. Typically, the integration of scientific findings into operational forecasting tends to be a rather slow process. In this case, however, the projects were carried out in close collaboration with avalanche forecasters, enabling us to rapidly evaluate and integrate these models into the operational avalanche warning service. The machine learning models have now undergone testing for three winter seasons, and in the following we summarize the perceptions of avalanche forecasters regarding their performance and highlight their main advantages.

Model	Performance	Added value
Danger level	About as good as our own assessment	Identifying spatial patterns
Snow instability	As good or better than our own assessment	Identifying spatial patterns and temporal evolution
Wet-snow	As good or better than our own assessment	The start of wet-snow avalanche cycles

Table 1: Overview of perceived performance and added value of each model.

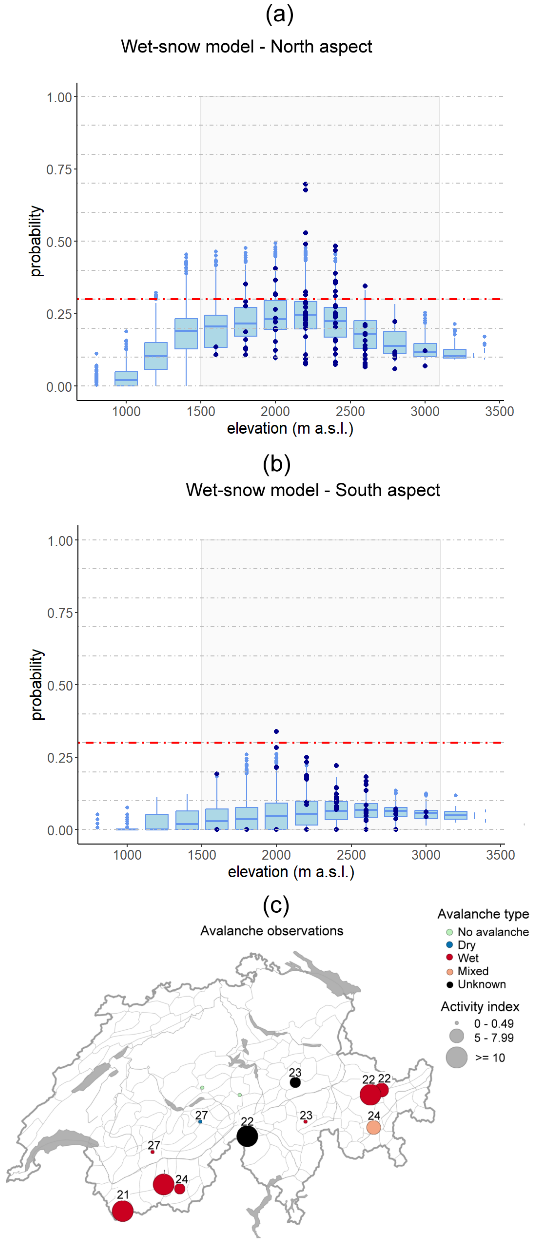

Figure 3: (a) Predictions of the wet-snow avalanche model for north-facing virtual slopes on 1 May 2023. The boxplots show the distribution of the interpolated predictions by elevation binned in 200 m intervals. The dashed red line is the best-discriminating threshold between avalanche-days and non-avalanche days in forecast mode according to Hendrick et al. (2023). The shaded grey area represents the elevation range where AWS are available. The dark blue points are the predictions at AWS. (b) Predictions of the wet-snow avalanche model for south-facing virtual slopes. (c) Avalanche observations on 1 May 2023. Colors indicate the type of avalanche, and the size of the circles corresponds to the avalanche activity index. The number above the circle shows the elevation of the starting zones (e.g., 21 = 2100 m a.s.l.).

Within the avalanche warning service, the models are regarded as a valuable and unbiased second opinion in the decision-making process. They are generally considered to be on par with, if not superior to, the assessments made by forecasters (Table 1). The primary benefit of these models, along with the visual representation of their output, lies in the ability to identify spatio-temporal patterns, that are usually difficult to assess. This is particularly helpful when conditions are rapidly changing and evolving.

5. CONCLUSIONS

Machine learning methods are ideally suited to tackle the non-linear, multi-variable complexity involved in avalanche forecasting. A crucial aspect here is data quality, as collecting and maintaining high-quality data is paramount for effectively training and validating machine learning models. Such models can efficiently analyze and process large volumes of data, including snowpack measurements, meteorological measurements, and forecasts. Additionally, machine learning models have the potential to learn from new data, enhancing the accuracy of avalanche forecasts over time. In this context, we recently developed and implemented three random forest classifiers to predict the avalanche danger level for dry-snow conditions, dry-snow instability and wet-snow avalanche probability. The models were rapidly integrated into avalanche forecasting, in part due to their ability to offer objective assessments based on data-driven analysis. The models are a valuable addition to traditional forecasting methods by providing novel information on spatio-temporal patterns that are otherwise difficult to assess. In the future, fully data-driven model chains combining (1) improved physical snow cover models, (2) gridded meteorological input data at fine spatial resolutions and (3) new machine learning methods, will play an increasingly vital role in avalanche forecasting. Beyond collecting high-quality ground truth data for training and validation, the main challenges will lie in effectively aggregating the outputs of the growing number of models, and developing intuitive visualizations that effectively communicate the model output to forecasters and decision-makers.

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