GENERATING MAPS FOR OPERATIONAL AVALANCHE WARNING WITH MACHINE LEARNING ALGORITHMS

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ABSTRACT: Snow avalanche warning services use a wide range of tools to ensure that users of their bulletins receive reliable and consistent information. This study describes a new tool for predicting maps of danger levels, avalanche problems, snowpack stability, and trends for incidents for the upcoming 2.5 days. The input consists of topographical data, meteorological data from the nowcast tool INCA, and data from the numerical weather prediction model AROME. Additionally, snow depth data available on a 1 km grid from SNOWGRID-CL is used. Machine learning methods were applied. The most suitable algorithm was determined for each target variable (danger level, avalanche problems, extended column tests, incident trend). The results are detailed maps for the development of the target variables for the next 2.5 days. During the model development, preliminary results were shared with practitioners, so that feedback could be utilized immediately.

KEYWORDS: Prediction, risk assessment, random forest, support vector machine, nearest neighbor, multi-output classifier

1. INTRODUCTION

Automating the estimation of avalanche danger has a long history. Initially, various methods were tested using meteorological conditions as input (Obled and Good, 1980). Later, topographic variables and new methods were added (Purves et al., 2003). Finally, the output of physically-based snow models was used (Schirmer et al., 2009; Vionnet et al., 2012; Fromm and Schönberger, 2022; Maisson et al., 2024). In most cases, the main objective was estimating the avalanche danger levels for the current day.

This study focuses on the prediction of the spatio-temporal avalanche danger for the upcoming days. This includes the avalanche danger levels, avalanche problems, snowpack stability, and trends for avalanche incidents.

2. DATA

The bulletin data for the algorithms was assembled for the provinces of Salzburg and Tyrol, Austria (Figure 1). The period from 2016 to 2022 was used as a training dataset, 2022-2023 for validation, and 2023-2024 for testing (unseen data). The danger level and the avalanche problems were extracted from CAAML-files (Haegeli et al., 2010; Lanzanasto et al., 2023) provided by the avalanche warning services of Salzburg and Tyrol.

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Figure 1: Map of the study area. The dark lines show the provinces of Salzburg and Tyrol.

Daily snow depth data on a 1 km grid of Austria was used from SNOWGRID-CL (Olefs et al., 2020). The data of the meteorological variables for training and testing comes from the nowcast tool INCA (Haiden et al., 2011). Predictions were carried out using AROME data (Termonia et al., 2018), which contain forecasts for the upcoming 60 h (GeoSphere Austria, 2023).

The digital elevation model from Austria in 10 m grid resolution (Geoland, 2021) was upscaled to a coarser grid (1 km).

The snow stability data of the extended column test (ECT, Simenhois and Birkeland, 2009) and accident data were used from the Avalanche Warning Service Information System (LAWIS), which collects snow and avalanche data (Zenkl and Kritz, 2024).

3. METHODS

In this study, we developed three procedures running in a sequence (Figure 2). The first is focused on the danger level and the avalanche problems; the second procedure deals with the stability of the snowpack, which has a higher spatial variability; in the third step, conclusions are drawn about the tendency of incidents.

The concept of a step-by-step calculation was adopted from a preliminary version of the model (Schönberger and Fromm, 2024). However, the algorithms in the individual steps were further evaluated and optimized.

Forecasts for the next 2.5 days were calculated using data from a numerical weather prediction model. It was applied once a day and results were shared with practitioners. This semi-operational application enabled us to obtain feedback, which was used to optimize the setup of the model and the type of visualization.

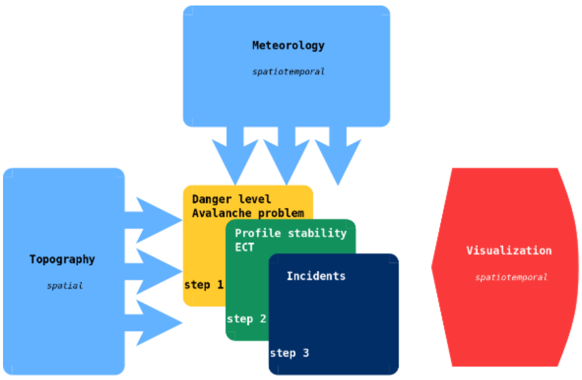

Figure 2: Overview of the step-by-step application of the procedures (adapted: Schönberger and Fromm, 2024).

3.1 *Step 1: danger level and avalanche problems*

The input consists of values that represent the properties on the grid point at the respective time and of time series that describe the meteorological development in advance. The variables are aspect, slope angle, curvature, and snow depth. The time series variables are air temperature, relative humidity, precipitation, wind speed, and global radiation.

The avalanche danger level is estimated by using a random forest regressor (Ho, 1995). The interpretation as a regression problem makes it possible to use the first decimal place to describe the trends within the levels.

The avalanche problems are classification problems that contain the class of the avalanche problem and eight aspects. Thus, a random forest classifier was coupled with a multi output classifier (Géron, 2018). Two avalanche problems were considered for each time step.

3.2 *Step 2: profile stability, ECT*

Additional to the input variables in step 1, the calculated avalanche danger level was used as input for estimating the profile stability. The three variables of the ECT are determined by three sub-steps.

First, the depth of the weak layer is estimated with a random forest regressor. Secondly, it is calculated whether the fracture will propagate or not. Additionally, the depth of the weak layer was used as input. The best results were achieved with a k-nearest neighbor classifier. In the third step, the calculated fracture propagation was added as input and the number of taps was estimated by using a support vector machine (Platt, 2000). The selection of algorithms and their sequence played an important role in achieving useful results.

3.3 *Step 3: incidents*

The calculated avalanche warning levels and the calculated variables of the ECT serve as input for the estimation of incidents. A support vector machine was used for this task.

4. RESULTS

An example (2024-02-23) is used to illustrate the results, because this date is one of the test dates that were not included in the model development (unseen data). Different time steps of the prediction were chosen to highlight features on the maps.

4.1 *Maps of avalanche danger level*

Figure 3 shows the calculated danger levels for the mountainous part of Austria on 23 February 2024, in the afternoon. The black lines highlight the study areas (Salzburg and Tyrol). The slider can be adjusted by the user to view the time steps in the future. Snow-free areas are transparent. The algorithms estimate danger level 2 in the western part, danger level 3 in the eastern part, and danger levels up to 4 along the Main Alpine Ridge. Figure 4 summarizes the danger levels determined by the corresponding avalanche warning services. In the north-west part of the study area, danger level 1 was predicted at lower elevations. Towards the east, the danger increased and reached level 4 above 2,000 m a.s.l.

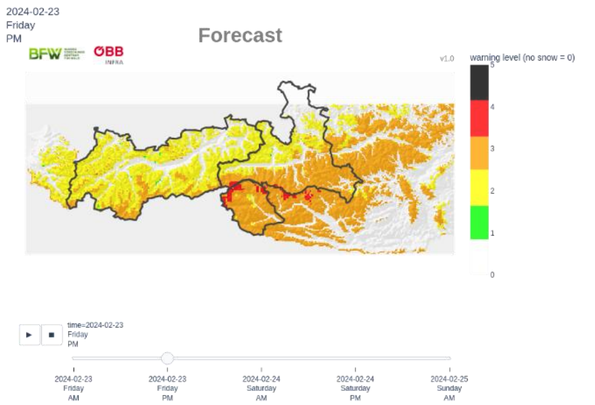

Figure 3: Calculated avalanche danger levels for 23 February 2024 afternoon.

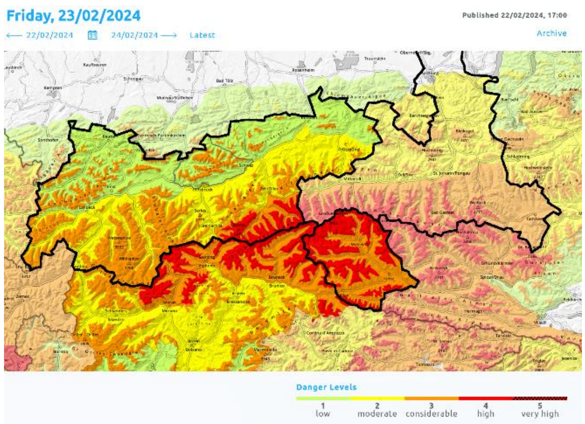

Figure 4: Avalanche danger levels from the avalanche.report for 23 February 2024.

4.2 Maps of avalanche problems

The calculated first avalanche problem was mainly drifting snow or new snow (Figure 5). The second avalanche problem was mainly gliding snow; persistent weak layers were expected in the eastern part of the study area (Figure 6).

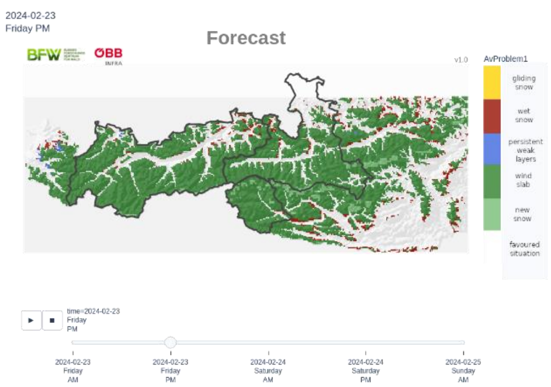

Figure 5: Calculated first avalanche problem for 23 February 2024 afternoon.

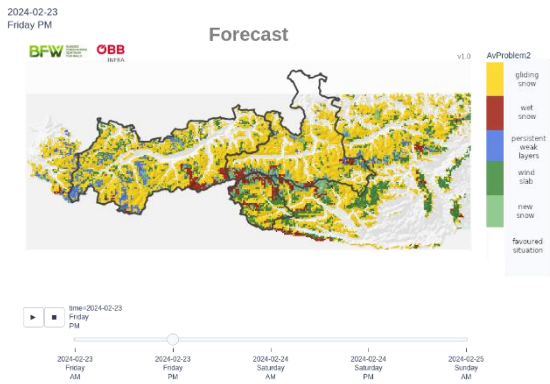

Figure 6: Calculated second avalanche problem for 24 February 2024 afternoon.

4.3 Maps of snow stability

The estimations for the ECT show variations between the area north and south of the Main Alpine Ridge (Figure 7). In Tyrol (west), the variations also depend on the aspects.

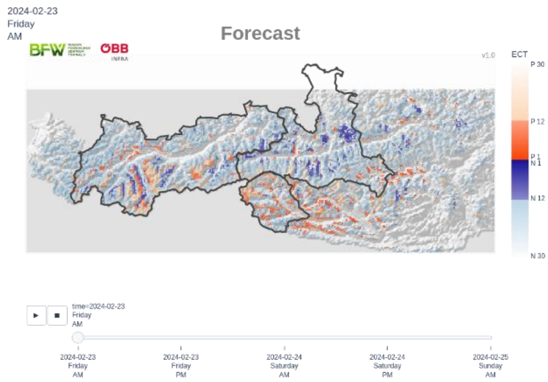

Figure 7: Calculated number of taps of ECT and propagating / not propagating for 23 February 2024 morning.

4.4 Maps of index for incidents

The calculated index for incidents is clearly influenced by the topography (Figure 8). In contrast to the danger levels, higher values were predicted in the west of the study site. The dots indicate incidents recorded by LAWIS. 16 incidents were reported on 24 February, one and two incidents occurred on 23 and 25 February, respectively.

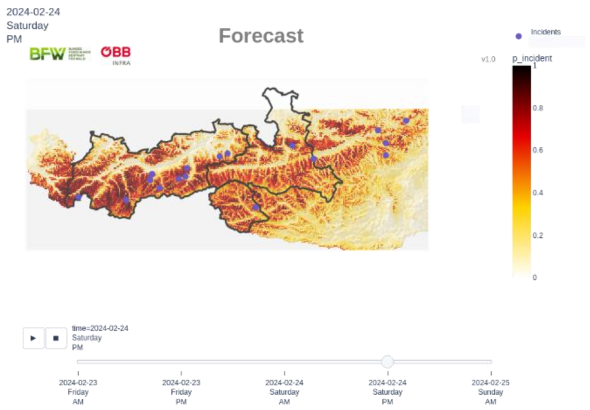

Figure 8: Calculated trend for avalanche incidents for 24 February 2024 afternoon.

5. DISCUSSION

The presented model was applied to the Austrian Alps. This means that the model was only trained with data from the study area (Salzburg and Tyrol) however predictions were also made outside this area. The results show improvements compared to previous analyses (Schönberger and Fromm, 2024) and that the model is transferable to neighboring regions.

A comparison of model results with bulletin data were made for a day with a wide range of danger levels. The differences between the calculated danger levels and the danger levels determined by the corresponding avalanche warning services can be used to estimate the quality of the predictions (Figure 3, Figure 4). Danger level 4 was predicted in the correct region. However, its spatial extent was partially underestimated. The results for danger level 3 are largely in agreement; a slight underestimation only occurs in the west of the study area. Instead of danger level 1, level 2 was calculated in the north. However, this occurred at lower elevations, where snow-free conditions prevailed, which is shown transparently for the calculations.

The calculated avalanche problems correspond well with the avalanche bulletins. The avalanche problems snow gliding and new snow or drifting snow were identified.

The predictions of the calculated ECT vary strongly in time and space, which was already expected during the development of the model (step 2), due to difficulties in identifying algorithms and their sequence.

The number of avalanche incidents increased on 24 February (Figure 8). The calculated values can be used to identify temporal trends, but the spatial information is limited.

6. CONCLUSIONS

In this study, topographic properties and the spatio-temporal data from a numerical weather prediction model was used to estimate snow avalanche conditions.

Preliminary results were shared with avalanche warning services and practitioners. Their feedback was used to optimize the useability and the visualization (e.g. zoom options, download speed).

In contrast to the bulletin, the results are available on a grid. It is important to consider this when determining statistical metrics so that comparisons with other studies are possible.

In the future, we also want to implement the model systematically with the ÖBB avalanche warning commissions in winter to receive daily feedback.

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