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Data-driven automatic predictions of avalanche danger in Switzerland

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Avalanche forecasting implies predicting current and future snow instability in time and space. In Switzerland, avalanche bulletins are issued daily during the winter season to warn the public about the avalanche hazard, described by region with one of five danger levels. Assessing avalanche danger is by large a data-driven, yet experience-based decision-making process. It involves analysing a multitude of data diverse in scale – time and space, and concluding by expert judgment on the avalanche scenario. Numerous statistical models were developed in the past, but rarely applied due to limited usefulness in operational forecasting. Modern machine learning techniques open up new possibilities for developing support tools for operational avalanche forecasting. With this aim, we developed a data-driven approach based on the supervised Random Forest (RF) classifier to automatically predict the danger level for dry-snow avalanche conditions in the Swiss Alps. A large database of more than 20 years of meteorological data and modelled snow stratigraphy data obtained with the numerical snow cover model SNOWPACK were used to train the RF algorithm. We optimized the model and selected the best set of input features that combine meteorological variables and features extracted from the simulated profiles, resampled at the same daily resolution as the forecasts. Our target variable was the regional danger level forecast in the public bulletin. We evaluated the predictive performance of the RF model with an independent test set with data of two winter seasons (2018-2019 and 2019-2020). The test set accuracy was 72 %, which is slightly lower than the accuracy estimate of the public forecasts (about 76 %). Given this uncertainty in our target variable, we trained an optimized RF model on a subset containing so-called verified avalanche danger levels. The test set accuracy then increased to 80 %. During the winter season 2020-2021, both RF models were tested in operational setting and automatically predicted a 'nowcast' and a 'forecast' in real-time. In parallel, we also tested a deep recurrent neural network model, which used a 7-days time series with 3-hours time resolution as input and also predicted the avalanche danger level. We present a comparison of the performance of the three models. This is one of the first times that a data-driven approach is tested in real-time as a feasible tool for operational avalanche forecasting.