STATISTICAL NOWCAST OF AVALANCHE ACTIVITY AT THE REGIONAL SCALE

Stephan Harvey [1]*, Alec van Herwijnen [1], Bettina Richter [1]

[1] WSL Institute for Snow and Avalanche Research SLF, Switzerland

ABSTRACT: Forecasting natural avalanche activity is challenging. Events are relatively rare and several contributory factors affecting the formation of dry- or wet-snow avalanches have to be evaluated. In contrast to previous statistical avalanche forecast models which focus on specific avalanche types or small scales, in this study we developed a model to predict avalanche days for an entire winter season at the regional scale. We therefore analysed an avalanche catalogue consisting of observed avalanches in the region of Davos, Switzerland, over the last 13 years (2003/04 to 2015/16). In combination with data from an automatic weather station and simulated snow cover properties from the model SNOWPACK, we trained random forest models by applying different methods to predict avalanche days. Overall, the predictive performance was in line with other similar studies. However, substantial differences in performance were observed among the 13 winter seasons. Surprisingly, the performance of models without snow cover data from the SNOWPACK simulations was very similar. These results suggest that there is no strong correlation between avalanche activity and snow cover properties, highlighting the limitations of obtained avalanche activity data through visual observations. While more work is still required, the reasonable performance of our statistical model to predict avalanche days show that automatically predicting regional avalanche activity using an automatic weather stations is feasible.

KEYWORDS: avalanche forecasting, avalanche activity, statistical model, random forest, SNOWPACK

1. INTRODUCTION

Avalanche forecasting involves the assimilation and interpretation of weather and snowpack data within a given time period and spatial extent. Based on this data, the probability, distribution as well as the size of expected avalanches is estimated, a challenging task. Forecasting natural avalanche activity is especially difficult since such avalanche events are relatively rare and are affected by various contributing factors with complex interactions.

Over the last decades various statistical approaches have been developed to automate avalanche forecasting. A popular tool is the nearest neighbours (NN) method, which has a long history (e.g. Buser, 1983; Gassner et al. 2001; Purves et al. 2003; Purves and Heierli, 2006; Zeidler and Jamieson, 2004). In recent years, other statistical machine learning methods have emerged based on optimizing a model on a training data set (e.g. Pozdnoukhov et al. 2011).

* *Corresponding author address:*
Stephan Harvey, WSL Institute for Snow and Avalanche Research SLF, Flüelastrasse 11, CH-7260 Davos Dorf, Switzerland,
phone: +41 81 417 01 29, fax: +41 81 417 01 10;
email: harvey@slf.ch

Many of these studies focused on specific avalanche types, such as storm snow (e.g. Bair, 2013; Davis et al. 1999), wet-snow (e.g. Baggi and Schweizer, 2009; Helbig et al. 2015; Mitterer and Schweizer, 2013), or glide-snow avalanches (e.g. Dreier et al. 2016; Peitzsch et al. 2012), or specific locations, such as avalanche release in forests (Teich et al, 2012). Other studies focused on forecast the avalanche danger level (e.g. Schirmer et al. 2009).

The datasets for training these models are often either limited to a relative small spatial extent or focused on dry- or wet-snow avalanches. However, avalanche observations do not always clearly distinguish between dry- or wet-snow avalanches. Often datasets include manual measurement, especially snow cover properties, which certainly limits the amount of data available. Furthermore, any model based on such data will require regular field observations for making predictions.

We investigate the predictive merit of using weather and simulated snowpack data obtained from a single automatic weather station (AWS) for naturally triggered avalanches throughout the region of Davos (Figure 1) during the winters of 2003/04 until 2015/16 (13 seasons). Simulated snow cover data were obtained with the snow cover model SNOWPACK (Bartelt and Lehning, 2002; Lehning et al. 2002a; Lehning et al. 2002b).

We used all available avalanche data (excluding glide-snow avalanches where possible) and developed random forest models (Breiman, 2001) by splitting the avalanche data in terms of typical situations for natural triggered avalanches. The avalanche activity for each season was predicted from the data of the remaining 12 other seasons. The aim of this study is to predict natural avalanche activity for the region of Davos for an entire season based on meteorological data and modeled snow cover data from a single AWS.

2. LOCATION AND DATA

In the region of Davos (175 km^2), daily avalanche observations were made by various observers at different elevations and aspects throughout the area. We used meteorological data from the AWS at Weissfluhjoch (WFJ; 2540 m a.s.l., Fig. 1). The investigated time period was from Dec 15 until April 30 for each winter between 2003 and 2016 (13 winters).

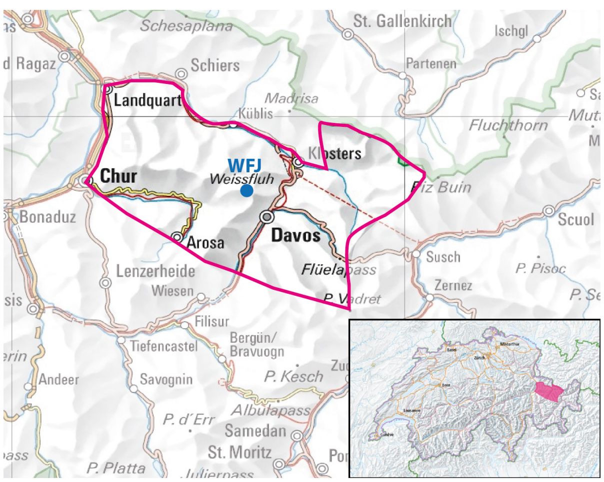

Fig. 1: Study area around Davos. The blue dot shows the location of the automatic weather station at Weissfluhjoch (WFJ).

2.1 *Avalanche data*

Based on the avalanche observations we calculated an avalanche activity index (AAI) by using a weighted sum of recorded avalanches per day with weights of 0.01, 0.1, 1 and 10 for size classes 1 to 4 (Canadian avalanche size class, McClung and Schaerer, 2006), according to Schweizer et al. (2003). Avalanches of class 5 were treated the same as class 4. Days with an AAI > 1, e.g. at least one medium sized avalanche, were considered as avalanche day.

Following Föhn and Schweizer (1995), skier-triggered avalanches and avalanches triggered by explosives were weighted with weights of 0.5 and 0.2, respectively.

Hence, 389 avalanche days and 1396 non avalanche days ensued.

2.2 *Automatic weather and simulated snowcover data*

Meteorological data was measured at 30 minute intervals. To obtain reliable data on liquid precipitation (rain), we completed the dataset with measured rain at the SwissMetNet weather station from Meteo Swiss in Davos at 1560 m a.s.l.. Based on the data from WFJ, SNOWPACK was driven to calculate various parameters. As the station WFJ is a flat field site, it cannot be regarded as representative for all avalanche release zones in steep slopes. Therefore, slope simulations for southern and northern aspects and 38° slope angle were performed.

Various variables were derived from SNOWPACK, representing important contributory factors, including:

- New snow (e.g. 24h and 72h new snow depth)
- Energy balance and liquid water content (e.g. liquid water content of uppermost 20 cm or total liquid water content, sum of positive energy balance according to Wever et al. (2016))
- Stability indices (e.g. sk38, sn38 according to Jamieson and Johnston (1998), Jamieson and Johnston (1993) and Schweizer et al. (2006))
- Critical crack length according to Gaume et al. (2016)
- Snow characteristics (e.g. sphericity, dendricity, grain type, hand hardness)

To link the frequent measured and modeled data with the daily avalanche occurrence we had to aggregate the data to daily values. Depending on the variable, we calculated daily means, minimum, maximum or sums. For new snow depth and some snow characteristics we used the daily value at 6 am.

The total dataset including all measured and modeled data contained 1785 days and 58 variables over 13 seasons.

3. METHODS

As we considered the avalanche activity throughout the entire season, various types of avalanches are included. Combining all these in one large data set may lead to over fitting (Hastie et al. 2009). To investigate if partitioning the dataset might improve the performance, we created 5 groups consisting of different "types" of avalanches (Tab.1). An avalanche day was then assigned to each group if the criteria defined in Tab. 1 were fulfilled.

Tab. 1: Criteria for assigning avalanche days for each group; hns24 is 24h new snow depth, sn38_s is stability index in southern aspect, lwc.20cm_f and lwc.20cm_s are liquid water content in uppermost 20 cm in the flat field and southern aspect, respectively, surf_erod is a parameter related to the wind erosion potential, hand_hard_f1 is the mean hand hardness in uppermost 20 cm in the flat and VW_MAX_3h is a 3h running mean of maximum wind velocity. Except for wind speed, all other parameters were modeled or derived from SNOWPACK simulations.

	Assign criterion
New snow	hns144 > 30 cm or hns72 > 20 cm or hns24 > 10 cm
Wet snow 1	sn38_s <= 2.2 and lwc.20cm_f > 1 or lwc.20cm_s > 1
Wet snow 2	sn38_s > 2.2 and lwc.20cm_f > 1 or lwc.20cm_s > 1
Wind drift	surf_erod >= 3 and hand_hard_f1 < 2 and VW_MAX_3h > 8
Everything else	Remaining days

3.1 <u>Nowcast classification</u>

Random forest (Breiman, 2001) were used to discriminate avalanche days from non-avalanche days. Random forests consist of numerous binary classification trees. Bootstrap samples are used to construct multiple trees. Each tree is grown with a randomised subset of predictors that allows the trees to grow to their maximum size without pruning.

For the classification of avalanche days, different approaches were investigated:

Method 1:
First, for each group shown in Tab. 1, the number of variables was reduced by applying different classification tree methods, including random forests, traditional classification trees (Breiman, 2001) and conditional classification trees (Hothorn et al. 2006). Highly correlated or illogical variables were eliminated by hand. Each group then consisted of 15 to 20 explanatory variables.

Random forests were then used to discriminate avalanche days from non-avalanche days for each group. The final prediction for each day was calculated as the sum of the predictions in each group. Values greater than 1 were classified as 1 (avalanche day).

Method 2:
The number of variables was not reduced, but random forests were computed separately for each assigned groups. The final prediction considering all avalanche days was summarized as for method 1.

Method 3:
The classification was computed with random forests using all 58 variables without considering separate groups over the entire season.

Method 4:
Avalanche days which were not assigned to group criteria for new snow, wet snow 1 or wet snow 2 were set to non-avalanche day.

Method 5:
Except new snow, only measured meteorological data were used in a single random forest model without considering separate groups.

3.2 <u>Validation</u>

Due to the large dataset the performance was evaluated by predicting one complete season by using the other 12 seasons as training data. This was repeated for each winter.

In order to determine how well the predicted avalanche activity for each winter reproduced the observations, the Hanssen-Kuipers skill score (HKS) and Heidke skill score (HSS) were used to evaluate the predictive performance of the models (Wilks, 1995). The probability of detection (POD; the number of correctly predicted events divided by the total number of events), probability of detection of non-events (PON; the number of correctly predicted non-events divided by the total number of non-events), probability of false detection (POFD; the number of wrong predicted events divided by the number of non-events), and false alarm ratio (FAR; the number of falsely predicted events divided by the total number of predicted events) were also calculated. These scores vary between 0 and 1. A perfect model would have HKS, HSS, POD and PON of 1, while POFD and FAR would be 0.

4. RESULTS AND DISCUSSION

Overall, the predictive performance was very similar for all methods (Tab. 2). Creating specific groups and reducing variables did not affect the performance in any significant manner.

The HSS skill score of about 0.53 is in line with other studies predicting avalanche days. Pozdnoukhov et al. (2011) reported values around 0.6 using support vector machines on a dataset from Scotland, while Dreier et al. (2016) reported values around 0.53 using random forests for predicting glide-snow avalanche days at the slope scale. Also, the HKS values are in the same range as those reported by Wever et al. (2016), who forecasted wet-snow avalanches using a similar dataset.

Tab. 2: Predictive measures ((Wilks, 1995)

	POD	PON	POFD	FAR	HKS	HSS
Method 1	0.61	0.78	0.22	0.56	0.39	0.51
Method 2	0.62	0.77	0.23	0.57	0.39	0.51
Method 3	0.61	0.80	0.20	0.54	0.41	0.53
Method 4	0.61	0.80	0.20	0.54	0.41	0.53
Method 5	0.64	0.77	0.23	0.56	0.41	0.52

Due to the unbalanced data, PON values were higher than POD values. The POD and FAR values we obtained were similar to Dreier et al. (2016) or Pozdnoukhov et al. (2008), but lower than Mitterer and Schweizer (2013), who classified wet-snow avalanches with a small dataset.

The prediction performance varied significantly among the 13 winter seasons (Fig. 2). The overall skill scores ranged from 0.38 (winter 2013/14) to 0.64 (winter 2005/06) for HSS and 0.17 (winter 2003/04) to 0.63 (winter 2006/07) for HSK (Fig.3). This shows that each winter has its own characteristics and performed differently.

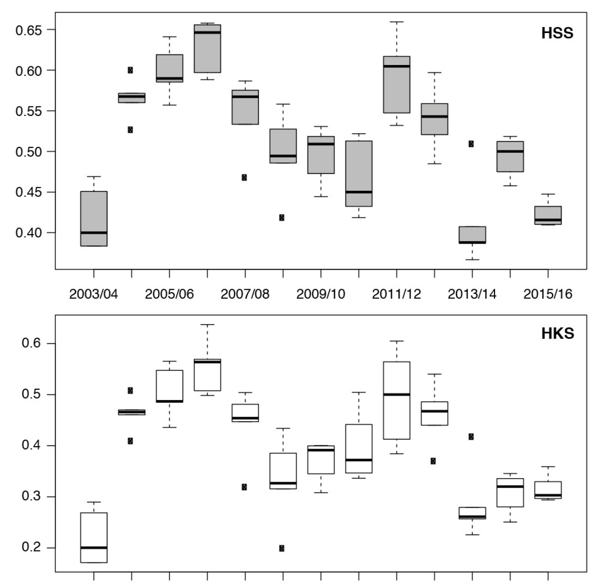

Fig. 2: Range of Heidke (HSS) and Hanssen-Kuipers (HKS) skill scores from the 5 methods for the 13 winters.

Surprisingly Method 5, which was driven without any SNOWPACK simulations (except of new snow), performed equally well. This result contradicts previous studies on wet-snow avalanches (Mitterer and Schweizer, 2013; Wever et al. 2016) where SNOWPACK simulations on energy balance and liquid water content were good predictors. Also, it is in contradiction with various studies on forecasting dry-snow avalanches, which highlighted the need to incorporate snow cover information (e.g. Schweizer and Föhn, 1996; Stoffel et al. 1998).

One reason for the low impact of SNOWPACK simulations may be the fact that typical natural avalanche cycles are mainly driven by new snow in winter and water infiltration in spring. The latter strongly correlates with maximum snow surface temperature (Pearson r = 0.65). Another reason for the discrepancy is certainly the quality of our avalanche activity data. These are strongly biased due to visibility, personality of observer, interpretation of avalanche type and size.

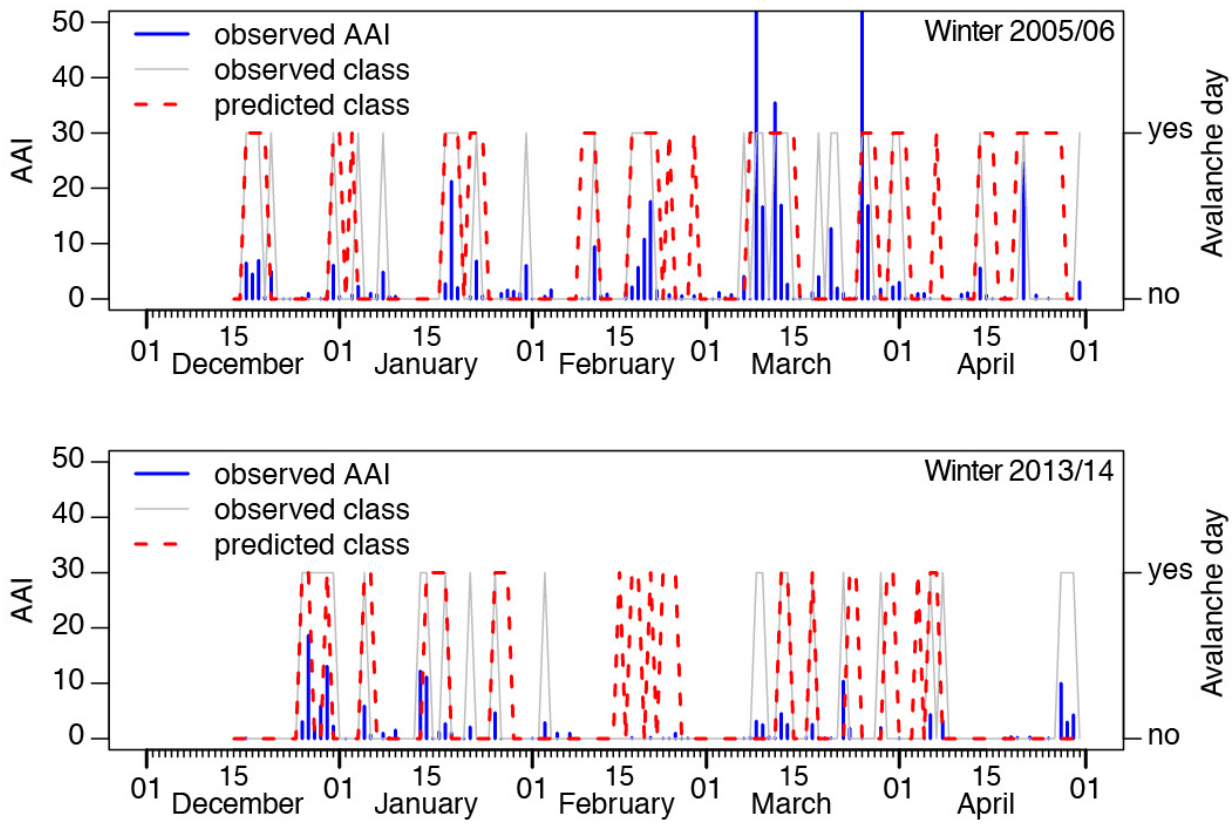

Fig. 3: Examples of 2 winters with different performance using method 3. At the top: good performance for winter 2005/06 (POD=0.78, FAR=0.49, HSS=0.62, HKS=0.55). Below: poor performance for winter 2013/14 (POD=0.52, FAR=0.69, HSS=0.38, HKS=0.26).

5. CONCLUSION

We analyzed avalanche activity in the region of Davos for 13 seasons. The goal was to predict natural avalanche activity for an entire season based on meteorological and modeled snow cover data obtained from one automatic weather station.

Overall, our model performance was similar to other studies, suggesting that avalanche days can be predicted by a unique automated weather station and SNOWPACK simulations on a regional scale.

However, the results show clear limitations due to biased and partly inaccurate avalanche data and the large spatial scale. The defined threshold for an avalanche day can include one medium sized avalanche or 10 large avalanches, which of course is not the same. Specially missed avalanche days with high AAI should be regarded further. Furthermore, winters which were poorly predicted should be investigated more closely.

Nevertheless the results show that automatically predicting avalanche activity for regional scales based on AWS data is feasible and could be a valuable tool for assisting avalanche forecasters when predicting avalanche hazard on large scales.

REFERENCES

Baggi, S. and Schweizer, J., 2009. Characteristics of wet snow avalanche activity: 20 years of observations from a high alpine valley (Dischma, Switzerland). Natural Hazards, 50(1): 97-108.

Bair, E.H., 2013. Forecasting artificially-triggered avalanches in storm snow at a large ski area. Cold Regions Science and Technology, 85: 261-269.

Bartelt, P. and Lehning, M., 2002. A physical SNOWPACK model for the Swiss avalanche warning; Part I: numerical model. Cold Regions Science and Technology, 35(3): 123-145.

Breiman, L., 2001. Random forests. Machine Learning, 45(1): 5-32.

Buser, O., 1983. Avalanche forecast with the method of nearest neighbours: an interactive approach. Cold Regions Science and Technology, 8(2): 155-163.

Davis, R.E., Elder, K., Howlett, D. and Bouzaglou, E., 1999. Relating storm and weather factors to dry slab avalanche activity at Alta, Utah, and Mammoth Mountain, California, using classification and regression trees. Cold Regions Science and Technology, 30(1-3): 79-89.

Dreier, L., Harvey, S., van Herwijnen, A. and Mitterer, C., 2016. Relating meteorological parameters to glide-snow avalanche activity. Cold Regions Science and Technology, 128: 57-68.

Föhn, P.M.B. and Schweizer, J., 1995. Verification of avalanche danger with respect to avalanche forecasting. In: F. Sivardière (Editor), Les apports de la recherche scientifique à la sécurite neige, glace et avalanche. Actes de Colloque, Chamonix, 30 mai-3 juin 1995. ANENA, Grenoble, France, pp. 151-156.

Gassner, M., Etter, H.J., Birkeland, K. and Leonard, T., 2001. NXD2000: An improved avalanche forecasting program based on the nearest neighbor method, Proceedings International Snow Science Workshop, Big Sky, Montana, U.S.A., 1-6 October 2000. Montana State University, Bozeman MT, USA, pp. 52-59.

Gaume, J., van Herwijnen, A., Chambon, G., Wever, N. and Schweizer, J., 2016. Snow fracture in relation to slab avalanche release: critical state for the onset of crack propagation. The Cryosphere Discussion: in review.

Hastie, T., Tibshirani, R. and Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer Verlag, New York, 763 pp.

Helbig, N., van Herwijnen, A. and Jonas, T., 2015. Forecasting wet-snow avalanche probability in mountainous terrain. Cold Regions Science and Technology, 120: 219-226.

Hothorn, T., Hornik, K. and Zeileis, A., 2006. Unbiased recursive partitioning: A conditional inference framework. Journal of Computational and Graphical Statistics, 15(3): 651-674.

Jamieson, J.B. and Johnston, C.D., 1993. Shear frame stability parameters for large-scale avalanche forecasting. Annals of Glaciology, 18: 268–273.

Jamieson, J.B. and Johnston, C.D., 1998. Refinements to the stability index for skier-triggered dry slab avalanches. Annals of Glaciology, 26: 296-302.

Lehning, M., Bartelt, P., Brown, R.L. and Fierz, C., 2002a. A physical SNOWPACK model for the Swiss avalanche warning; Part III: meteorological forcing, thin layer formation and evaluation. Cold Regions Science and Technology, 35(3): 169-184.

Lehning, M., Bartelt, P., Brown, R.L., Fierz, C. and Satyawali, P.K., 2002b. A physical SNOWPACK model for the Swiss avalanche warning; Part II. Snow microstructure. Cold Regions Science and Technology, 35(3): 147-167.

McClung, D.M. and Schaerer, P., 2006. The Avalanche Handbook. The Mountaineers Books, Seattle WA, U.S.A., 342 pp.

Mitterer, C. and Schweizer, J., 2013. Analysis of the snow-atmosphere energy balance during wet-snow instabilities and implications for avalanche prediction. The Cryosphere, 7(1): 205-216.

Peitzsch, E.H., Hendrikx, J., Fagre, D.B. and Reardon, B., 2012. Examining spring wet slab and glide avalanche occurrence along the Going-to-the-Sun Road corridor, Glacier National Park, Montana, USA. Cold Regions Science and Technology, 78: 73-81.

Pozdnoukhov, A., Matasci, G., Kanevski, M. and Purves, R.S., 2011. Spatio-temporal avalanche forecasting with Support Vector Machines. Natural Hazards and Earth System Sciences, 11(2): 367-382.

Pozdnoukhov, A., Purves, R.S. and Kanevski, M., 2008. Applying machine learning methods to avalanche forecasting. Annals of Glaciology, 49: 107-113.

Purves, R., Morrison, K.W., Moss, G. and Wright, D.S.B., 2003. Nearest neighbours for avalanche forecasting in Scotland - development, verification and optimisation of a model. Cold Regions Science and Technology, 37(3): 343-335.

Purves, R.S. and Heierli, J., 2006. Evaluating nearest neighbours in avalanche forecasting - a qualitative approach to assessing information content. In: J.A. Gleason (Editor), Proceedings ISSW 2006. International Snow Science Workshop, Telluride CO, U.S.A., 1-6 October 2006, pp. 701-708.

Schirmer, M., Lehning, M. and Schweizer, J., 2009. Statistical forecasting of regional avalanche danger using simulated snow cover data. Journal of Glaciology, 55(193): 761-768.

Schweizer, J., Bellaire, S., Fierz, C., Lehning, M. and Pielmeier, C., 2006. Evaluating and improving the stability predictions of the snow cover model SNOWPACK. Cold Regions Science and Technology, 46(1): 52-59.

Schweizer, J. and Föhn, P.M.B., 1996. Avalanche forecasting - an expert system approach. Journal of Glaciology, 42(141): 318-332.

Schweizer, J., Kronholm, K. and Wiesinger, T., 2003. Verification of regional snowpack stability and avalanche danger. Cold Regions Science and Technology, 37(3): 277-288.

Stoffel, A., Meister, R. and Schweizer, J., 1998. Spatial characteristics of avalanche activity in an alpine valley - a GIS approach. Annals of Glaciology, 26: 329-336.

Teich, M., Marty, C., Gollut, C., Grêt-Regamey, A. and Bebi, P., 2012. Snow and weather conditions associated with avalanche releases in forests: Rare situations with decreasing trends during the last 41 years. Cold Regions Science and Technology, 83-84: 77-88.

Wever, N., Valero, C.V. and Fierz, C., 2016. Assessing wet snow avalanche activity using detailed physics based snowpack simulations. Geophysical Research Letters, 43: 5732–5740.

Wilks, D.S., 1995. Statistical methods in the atmospheric sciences: an introduction. International Geophysics, 59. Academic Press, San Diego CA, U.S.A, 467 pp.

Zeidler, A. and Jamieson, J.B., 2004. A nearest-neighbour model for forecasting skier-triggered dry-slab avalanches on persistent weak layers in the Columbia Mountains, Canada. Annals of Glaciology, 38: 166-172.