Forecasting snow avalanches using avalanche activity data obtained through seismic monitoring

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Abstract

Accurate avalanche occurrence data are of crucial importance for avalanche forecasting, since recent avalanching provides direct evidence on snowpack instability. We therefore explore how avalanche activity data obtained through seismic monitoring can be used for avalanche forecasting. By visually inspecting data from a seismic sensor deployed in an avalanche starting zone, we obtained three avalanche catalogues for two entire winters and one period of 10 days with intense wet-snow avalanche activity. Avalanche activity was clustered in time for all catalogues, and diurnal periodicity was clearly present during spring. In winter, when dry-snow avalanches predominantly release, rather weak long-term correlations on the order of several days were found between past and future avalanche activity. We investigated the performance of a simple model to predict future avalanches based on past avalanche activity. Model performance was better in spring than in winter, especially for very short time scales of up to three hours, and for time scales around 24 hours. Furthermore, the performance of our very simple model was comparable to the performance of more sophisticated models to forecast wet-

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snow avalanche release based on meteorological input variables. While it is clear that for operational avalanche forecasting automatic avalanche detection still has to be developed, overall this work shows that avalanche activity data obtained through seismic monitoring would yield very valuable data for wet-snow avalanche forecasting.

Keywords: avalanche detection, avalanche forecasting, early warning, seismic monitoring

1. Introduction

Operational avalanche forecasting mainly relies on meteorological observations and forecasts in combination with snow cover instability observations, ideally direct observations of avalanches (e.g. McClung and Schaerer, 2006). It involves the assimilation of multiple data sources to make predictions over complex interacting processes. For many decades, avalanche forecasters have developed successful decision-making strategies to deal with this complexity (e.g. LaChapelle, 1980). These rule-based empirical strategies, sometimes applied intuitively, are employed to deal with many of the numerous processes and scales involved in avalanche formation. For instance, avalanche forecasters often rely on the observed or forecasted amount of new snow. However, the success rate of this approach is rather limited, especially for local forecasts (e.g. Schweizer et al., 2009). Employed methods in avalanche forecasting are thus still largely based on experience of the forecaster and therefore prone to subjectiveness.

Monitoring precursor signals to avalanche release could therefore potentially help to improve avalanche forecasting. Acoustic emissions (AE) can

18 provide information on the imminence of failure of a material (e.g. Michlmayr
19 et al., 2012), and AE monitoring in laboratory experiments has extensively
20 been used to better understand the failure process in various materials (e.g.
21 Lockner, 1993; Woo et al., 2008; Niemz et al., 2009; Rosti et al., 2010). On
22 the larger scale, this technique has also been used to monitor and study grav-
23 itational slope instabilities such as landslides (e.g. Spillmann et al., 2007),
24 cliff collapse (Amitrano et al., 2005), rock avalanches (e.g. Deparis et al.,
25 2008) and unstable glaciers (e.g. Faillettaz et al., 2008). However, despite
26 encouraging new results (Kapil et al., 2014; Reiweger et al., 2015), due to
27 the strong attenuation of high frequency waves in snow, the applicability
28 of AE for forecasting avalanches is likely limited. Furthermore, reliable low
29 frequency precursor signals to avalanche release have not yet been identified
30 (van Herwijnen and Schweizer, 2011a), even though previous studies sug-
31 gested that such signals exist (Gubler, 1979).

32 In the absence of reliable, non-invasive, in-situ precursor signals from the
33 snowpack associated with imminent slope instability, avalanche occurrence
34 data might offer an alternative. Indeed, recent avalanche observations, for
35 instance the number of observed avalanches within the last 24 hours, are
36 widely used for avalanche forecasting (e.g. McClung and Schaerer, 2006).
37 During snow storms, the likelihood of increased avalanching is usually obvi-
38 ous, for instance, once about 50 cm of new snow has fallen. However, due
39 to the absence of reliable avalanche observations, it often remains uncertain
40 whether many natural avalanches occur. The answer can usually only be
41 given after the storm, once visibility has improved, when the danger has al-
42 ready decreased and the peak activity has generally passed. Clearly, more

43 reliable methods to detect avalanche occurrence are required.

44 For the automated remote detection of avalanches several techniques and
45 instruments can be applied, in particular ground based and satellite radar
46 sensors (e.g. Gauer et al., 2007; Kogelnig et al., 2012; Eckerstorfer et al.,
47 2016), infrasonic sensors (e.g. Marchetti et al., 2015; Scott et al., 2007;
48 Thüring et al., 2015), and seismic sensors. The latter are well suited for the
49 remote detection of hazardous mass movements such as rockfall, landslides,
50 ice avalanches and snow avalanches (e.g. Caplan-Auerbach and Huggel, 2007;
51 Deparis et al., 2008; Suriñach et al., 2005). Seismic monitoring systems con-
52 sist of one or several seismic sensors, also called geophones or seismometers,
53 fixed in the ground or bolted to rocks to record ground vibrations gener-
54 ated by mass movements. Ives et al. (1973) were the first to show that
55 seismic monitoring equipment can be used to remotely detect avalanches. It
56 quickly became evident that such avalanche monitoring systems could po-
57 tentially provide valuable information for avalanche forecasting, since data
58 on avalanche activity represent the most direct instability data (McClung
59 and Schaerer, 2006). As noted by Harrison (1976): 'a network of a few
60 sensors which remotely could detect and locate avalanches during storm con-
61 ditions over an area of a few square miles would have important applica-
62 tion'. Since then, numerous studies have shown that, depending on the size,
63 avalanches that occur up to several kilometers away from the sensors can be
64 detected (e.g. Bessason et al., 2007; Suriñach et al., 2001; van Herwijnen and
65 Schweizer, 2011a; Lacroix et al., 2012).

66 Thus far, seismic monitoring systems are not widely used for operational
67 avalanche forecasting, in part due to the difficult task of automatically dis-

68 criminating signals generated by avalanches from background noise. Indeed,
69 while Rubin et al. (2012) obtained encouraging detection rates using various
70 machine learning algorithms for the automatic detection of avalanche signals
71 in seismic data, the high false alarm rate of around 90% showed that substan-
72 tial progress still has to be made. Nevertheless, based on visual inspection of
73 the data from one seismic sensor, van Herwijnen and Schweizer (2011b) were
74 able to obtain a database with the release times for 385 avalanches in one
75 winter using data from one sensor, with an estimated accuracy of less than
76 one minute. Similarly, Lacroix et al. (2012) visually identified 80 avalanches
77 in the data from a seismic array with seven sensors for one winter. Such
78 avalanche catalogues can be used to better understand avalanche triggering
79 mechanisms and ultimately improve avalanche forecasting, as suggested by
80 recent results presented by van Herwijnen and Schweizer (2011b), Lacroix
81 et al. (2012) and Schweizer and van Herwijnen (2013).

82 By extending the previously published avalanche data base from van Her-
83 wijnen and Schweizer (2011b), in this study we explore how avalanche ac-
84 tivity data obtained through seismic monitoring can be used for avalanche
85 forecasting. First we investigate clustering and periodicity in avalanche ac-
86 tivity and compare local avalanche activity obtained through seismic moni-
87 toring with regional avalanche activity obtained through conventional visual
88 observations. Then, we focus on exploiting avalanche activity data for lo-
89 cal avalanche forecasting (about 2 km²) at time scales of up to 7 days. To
90 evaluate the effectiveness and reliability of the forecast, we use two methods:
91 receiver operating characteristic curves (e.g. Kumar and Indrayan, 2011) and
92 error diagrams (e.g. Molchan, 1997). These diagrams allow to evaluate fore-

cast performance in terms of probability of detection, false alarm ratio and alarm duration, and have been used to evaluate forecasting models for earthquakes and volcanic eruptions (e.g. Talbi et al., 2013; Grasso and Zaliapin, 2004). Due to a lack of accurate avalanche activity data, such a rigorous performance evaluation is generally not possible in avalanche forecasting.

2. Methods and data

2.1. Sites and instrumentation

We monitored avalanche activity at two sites above Davos (Figure 1): the Wannengrat (WAN) and the Dorfberg (DFB) field sites. At both sites, we continuously record seismic data, one or several automatic meteorological stations (AMS) are present and we installed automatic cameras which allowed us to identify seismic signals generated by avalanches (van Herwijnen and Schweizer, 2011a,b). The field sites and data acquisition systems are only briefly described; a detailed description can be found in van Herwijnen and Schweizer (2011a), van Herwijnen and Schweizer (2011b) and van Herwijnen et al. (2013).

At the WAN field site, we deployed an array of 7 vertical uni-axial geophones with a natural frequency of 14 Hz in an avalanche starting zone at an elevation of about 2500 m. a. s. l. . The commercial data acquisition system (Seismic Instruments SmartGeophone system) consists of low-noise, high-precision 24-bit analog to digital converters (ADC) and data were continuously sampled at a rate of 500 Hz. The geophones were mounted in a foam housing with a density close to that of snow and placed on top of the snow cover in early winter to be buried by subsequent snowfall (van Herwij-

117 nen and Schweizer, 2011a). At the DFB field site, we deployed one vertical
118 component geophone with a natural frequency of 14 Hz on a grassy slope at
119 an elevation of about 1900 m. a. s. l. . The data acquisition system (Cirrus
120 Logic CRD5378) consists of a low-noise, high-precision 24-bit ADC and data
121 were continuously sampled at a rate of 500 Hz. The geophone was placed in
122 a waterproof plastic housing and inserted in the ground with a metal spike.

123 *2.2. Signal processing and avalanche detection*

124 Since there is considerable environmental noise in seismic data, for in-
125 stance due to airplanes, wind or ski lifts, it is important to distinguish seismic
126 signals generated by avalanches from noise (van Herwijnen and Schweizer,
127 2011b). Using avalanches identified on the images from automatic cameras
128 allowed us to visually identify typical characteristics associated with signals
129 generated by avalanches (see Figures 2 and 3 for examples). This learning
130 step was required for each site separately, since the location of the site as
131 well as local topography and geology strongly affect the seismic wave field.
132 For instance, due to its proximity to the town of Davos and a large ski area
133 (Figure 1), there was substantially more noise in the seismic data at DFB
134 than at WAN (compare the signal-to-noise levels in Figures 2 and 3). Since
135 there was a clear diurnal trend in the signal-to-noise ratio at the Dorfberg
136 field site (not shown), we are confident that the increased noise at this field
137 site is of anthropogenic nature.

138 Despite these site specific differences, seismic signals generated by avalanches
139 had unique temporal and spectral characteristics allowing us to identify them
140 in the seismic data. To do so, we performed a visual inspection of the wave-
141 form and the spectrogram (see Figures 2 and 3 for examples), i.e. the evo-

142 lution of the frequency content of the signal with time, as was done by van
 143 Herwijnen and Schweizer (2011b) and Lacroix et al. (2012). A visual inspec-
 144 tion of the seismic data is time consuming and prone to observer bias. To
 145 reduce the latter, all data were inspected by the same observer. However,
 146 in the absence of reliable automatic signal classification methods, visual in-
 147 spection of the data is thus far the only method to identify signals generated
 148 by avalanches. While we have invested much effort to obtain validation data
 149 from the field (for a detailed description see van Herwijnen and Schweizer,
 150 2011b), many of the avalanche signals identified in the seismic data were not
 151 confirmed by field observations (see Figure 4 for an example). For instance,
 152 at DFB during the spring of 2013, 25 of the 52 avalanche signals identified in
 153 the seismic data remained unconfirmed. Nevertheless, given the overall simi-
 154 larities between the seismic signals generated by avalanches, we are relatively
 155 confident in the accuracy of our visual inspection of the data.

156 *2.3. Seismic avalanche catalogues*

157 For this study, we analyzed seismic data during three distinct periods:
 158 for WAN we inspected data from one sensor inserted in the snow from two
 159 winters, namely the winters of 2009-2010 and 2010-2011, and for DFB we
 160 focused on a period of high wet-snow avalanche activity during the spring of
 161 2013. We thus have three seismic avalanche catalogues, henceforth referred
 162 to as WAN2010, WAN2011 and DFB2013, consisting of the release time t_i of
 163 each avalanche found in the seismic data. The release time was used to cal-
 164 culate the avalanche activity $N(t, s)$, consisting of the number of avalanches
 165 with $t_i \in [t - s, t)$ and s the length of the time interval in hours. For instance,
 166 for $s = 1$ hour we obtain an hourly avalanche activity, while for $s = 24$ hours

we obtain daily avalanche rates. Finally, besides the avalanche activity we also computed the waiting time between subsequent avalanches, defined as $\tau_i = t_i - t_{i-1}$.

WAN2010 consisted of 385 avalanches over a period of 108 days from 13 January to 30 April 2010 (blue line in Figure 5). WAN2011 consisted of 154 avalanches over a period of 138 days from 11 December 2010 to 27 April 2011 (red line in Figure 5). Finally, DFB2013 consisted of 52 avalanches over a period of 10 days from 1 to 11 March (green line in Figure 5). To investigate differences in dry-snow and wet-snow avalanching, we further split the WAN2010 and WAN2011 catalogues in a winter period, when the majority of avalanches consisted of dry-snow avalanches, and a spring period, when most avalanches were wet-snow avalanches. Based on field observations as well as a detailed inspection of local meteorological data, we determined that for WAN2010 the cutoff date between winter and spring was 15 March 2010, while for WAN2011 it was 25 March 2011. We will refer to these avalanche sub-catalogues as WAN2010_{winter}, WAN2010_{spring}, WAN2011_{winter} and WAN2011_{spring}. Finally, we also analyzed combined seismic avalanche catalogues, namely SEIS consisting of WAN2010, WAN2011 and DFB2013 combined, SEIS_{winter} consisting of WAN2010_{winter} and WAN2011_{winter}, and SEIS_{spring} consisting of WAN2010_{spring}, WAN2011_{spring} and DFB2013.

2.4. Regional avalanche catalog

For the region of Davos, the avalanche warning service monitors an area of 175 km² on a daily basis and information is gathered on the number, size and type (dry or wet-snow) of avalanches. The uncertainty in the time of occurrence can sometimes be large as observations cannot be made during

192 periods of bad visibility, for instance during snow storms. However, there
 193 are no consistent records of this uncertainty. For this study, we compiled
 194 a regional avalanche catalog consisting of all avalanche observations during
 195 the study period. Since there is also information on the type of avalanche,
 196 we further compiled two additional catalogues consisting of all dry-snow and
 197 all wet-snow avalanche observations during the study period. We thus have
 198 three regional avalanche catalogues, henceforth refereed to as OBS, OBS_{dry}
 199 and OBS_{wet}, consisting of the estimated release date of each avalanche ob-
 200 served in the region of Davos. We also compared the avalanche catalogues to
 201 the forecasted avalanche danger level for the region of Davos, based on the
 202 European five-degree danger scale (1: Low, 2: Moderate, 3: Considerable, 4:
 203 High, 5: Very High) (e.g. Meister, 1995; Schweizer et al., 2003).

204 For correlation analysis, e.g. between avalanche activity catalogues, we
 205 used the Spearman rank order correlation coefficient r_s . A level of significance
 206 $p = 0.05$ was chosen to decide whether the correlations were statistically
 207 significant.

208 *2.5. Model performance measures*

209 In this work we explore how avalanche activity data obtained through
 210 seismic monitoring can be used for forecasting avalanches. We therefore
 211 investigated a simple model based on past avalanche activity to predict fu-
 212 ture avalanches (Section 3.4). To evaluate the predictive performance of our
 213 model, we used common performance measures such as the probability of
 214 detection (POD) and the false alarm ratio (FAR) (e.g. Wilks, 2011), and in
 215 particular two methods: receiver operating characteristic (ROC) curves (e.g.
 216 Kumar and Indrayan, 2011) and error (ERR) diagrams (e.g. Molchan, 1997).

217 The ROC curve displays the probability of detection (POD; the number
 218 of correctly predicted events divided by the total number of events) versus the
 219 false positive rate (FPR; the number of falsely predicted events divided by the
 220 total number of non-events) for varying avalanche activity thresholds. The
 221 area under the curve (AUC) is an effective measure to assess the performance
 222 of a model (for more details, see Kumar and Indrayan, 2011). An AUC value
 223 of 1 corresponds to a perfect model, while an AUC value of 0.5 corresponds
 224 to a flip of a coin (50-50 chance).

225 Error diagrams allow to characterize model performance in terms of fail-
 226 ure to predict rate (1-POD) and total alarm duration (DUR; length of time
 227 with avalanche activity above the threshold divided by total length of the
 228 time series) for varying avalanche activity thresholds. Error diagrams thus
 229 add an important parameter when evaluating model performance, namely
 230 the total alarm duration. A DUR value close to 1 corresponds to a poor
 231 model since an alarm is raised for most of the time. The optimal avalanche
 232 activity threshold is determined by finding the minimum distance:

$$d_{min} = \min(\sqrt{(d_{ROC}^2 + d_{ERR}^2)}) \quad (1)$$

233 with $d_{ROC}^2 = FPR^2 + (1 - POD)^2$ the distance between a perfect model (point
 234 (0,1)) and the observed ROC curve, and $d_{ERR}^2 = (1 - POD)^2 + DUR^2$ the
 235 distance between a perfect model (point (0,0)) and the observed ERR curve.
 236 For the optimal activity threshold, we then determined the corresponding
 237 POD and DUR values as well as the false alarm ratio (FAR; the number
 238 of falsely predicted events divided by the total number of predicted events).
 239 Evaluating model performance can thus be done using four distinct metrics:
 240 AUC, POD, FAR and DUR. To analyze our avalanche forecasting model in

241 a comprehensive manner, we therefore determined the overall model score S
 242 defined as $S = (1 - AUC) + (1 - POD) + FAR + DUR$. A perfect model
 243 would therefore have a score of 0, while a score of 2 or more would imply
 244 poor model performance.

245 3. Results and discussion

246 Information on the size and type of the avalanches detected in the seismic
 247 data was generally not available. For the WAN2010 catalog, most avalanches
 248 occurred after the cutoff date between winter and spring (red dashed line in
 249 Figure 5), suggesting that the majority of avalanches in this catalog were wet-
 250 snow avalanches. For WAN2011, the avalanches were more or less equally
 251 split between winter (88) and spring (66) (blue dashed line in Figure 5).
 252 Finally, for the DFB2013 catalog, 27 of the 52 avalanches were seen on the
 253 images from the automatic cameras. All these were wet-snow avalanches,
 254 indicating that the avalanches in this catalog were most probably all wet-
 255 snow avalanches.

256 Based on an analysis of the avalanches observed on the images from the
 257 automatic camera, van Herwijnen et al. (2013) determined that avalanche
 258 length ranged from 13 to almost 700 meters. Furthermore, they showed
 259 that avalanche length was proportional to the square of seismic signal dura-
 260 tion T . For WAN2010, van Herwijnen and Schweizer (2011b) showed that
 261 many signals identified in the seismic data were generated by wet loose snow
 262 avalanches. While some of these loose snow avalanches were relatively small,
 263 others entrained the entire snow cover, resulting in larger avalanches which
 264 generated relatively long ($T > 20$ s) seismic signals (see Figure 6 and 7 in van

265 Herwijnen and Schweizer, 2011b). Furthermore, they showed that the cumu-
 266 lative distribution of T^2 followed a power law with an exponent of 2.5 ± 0.4 ,
 267 similar to the exponent of 2.2 ± 0.1 measured for snow slab avalanche scaling
 268 based on slab width field measurements (Faillettaz et al., 2004). Overall,
 269 results from van Herwijnen et al. (2013) and van Herwijnen and Schweizer
 270 (2011b) suggest that T^2 provides some basic information on avalanche size,
 271 albeit indirect. The distributions of T^2 thus suggest that the DFB2013 cat-
 272 alog contained the largest avalanches, while the WAN2011 catalog contained
 273 the smallest avalanches (Figure 6).

274 *3.1. Clustering in avalanche activity and periodicity*

275 The hourly avalanche activity observed at our seismic monitoring sta-
 276 tions was clustered in time (Figure 5). Indeed, for WAN2010 there were
 277 two very distinct peaks in the avalanche activity, around 20 March and at
 278 the end of April. Even though avalanche activity was substantially lower for
 279 WAN2011, there were also several periods with above average avalanche ac-
 280 tivity (e.g. early March and early April). Finally, in the much shorter catalog
 281 of DFB2013, avalanche activity was highest near the end of the period.

282 To verify the non-random distribution of avalanche occurrence in more
 283 detail, we determined the coefficient of variation η of the waiting time τ ,
 284 defined as the ratio between the standard deviation and the mean of τ (Mar-
 285 zocchi and Zaccarelli, 2006). For a Poisson process, i.e. a uniform distri-
 286 bution in time, τ obeys an exponential distribution and $\eta = 1$. Clustered
 287 events are characterized by $\eta > 1$. The assumption that the occurrence times
 288 obey a Poisson process was rejected for all catalogues (Table 1), except for
 289 WAN2010_{winter}.

290 To further investigate clustering, the cumulative distribution of τ was
 291 analyzed for all seismic avalanche catalogues (Figure 7). Clearly, for all cata-
 292 logues the waiting times were not uniformly distributed, except for WAN2010_{winter}.
 293 For short time scales, the waiting times were less clustered than a Poisson
 294 process, while for longer time scales τ was more clustered. By comparing
 295 the observed cumulative distributions with the expected exponential distri-
 296 bution (dashed lines in Figure 7), one can determine a threshold time t_r
 297 above which larger waiting times are more frequent than expected (Tatard
 298 et al., 2010). For WAN2010 and DFB2013 t_r was around 12 hours, while
 299 for WAN2011 it was more than 40 hours (Figure 7a and Table 1). When
 300 analysing the winter and spring catalogues separately, the lowest t_r values
 301 were found for the spring catalogues (Table 1, Figure 7b and 7c). Overall,
 302 these result show that avalanches do not occur randomly. This was expected
 303 since avalanches result from the complex interaction between meteorologi-
 304 cal disturbances (e.g. precipitation or incoming solar radiation) and existing
 305 weaknesses within the snow cover, acting over various time scales. Our re-
 306 sults suggests that in spring avalanches are clustered for time scales on the
 307 order of several hours to one day, while in winter clustering time scales are
 308 on the order of a few days.

309 To investigate periodicity in the avalanche activity, we calculated the
 310 covariance of the hourly avalanche activity

$$C(r, s) = \frac{1}{n} \sum_{t=1}^{t=n-r} N(t, s) N(t + r, s) \quad (2)$$

311 with r the lag time and $s = 1$ hour. The normalized covariance $\frac{C(r)}{C(0)}$ exhibited
 312 a first zero crossing after a lag time of 12 hours and a secondary maximum
 313 for a lag time of 24 hours, especially for WAN2010 and DFB2013 (Figure 8a).

314 This suggests that there generally was a daily pattern in avalanche activity,
 315 which comes as no surprise since we mostly detected wet-snow avalanches,
 316 which typically release during the day when the energy input into the snow
 317 cover is greatest (e.g. Mitterer and Schweizer, 2013; Helbig et al., 2015).
 318 This periodicity in wet-snow avalanching is further highlighted when we an-
 319 alyze $\frac{C(r)}{C(0)}$ for winter and spring separately (Figure 8b). For WAN2010_{winter},
 320 WAN2011_{winter} and SEIS_{winter} the normalized covariance rapidly decreased
 321 to values close to zero for lag times larger than two hours (Figure 8b), sug-
 322 gesting there was no discernable periodicity in dry-snow avalanche activity.
 323 For WAN2010_{spring}, WAN2011_{spring} and SEIS_{spring}, on the other hand, a clear
 324 daily pattern emerged with a minimum in $\frac{C(r)}{C(0)}$ after a lag time of 12 hours
 325 and a secondary maximum for a lag time of 24 hours (Figure 8c).

326 *3.2. Comparison with regional avalanche activity and avalanche danger level*

327 From an avalanche forecasting perspective, observations of recent avalanche
 328 occurrences are regarded as unambiguous information on snow cover insta-
 329 bility (e.g. McClung and Schaerer, 2006). Avalanche observations are there-
 330 fore commonly considered as the best predictor for future avalanches. The
 331 area monitored by our seismic monitoring stations is approximately 2 km²
 332 (van Herwijnen and Schweizer, 2011b; van Herwijnen et al., 2013). To eval-
 333 uate how representative the avalanche activity from the seismic sensors is
 334 from an avalanche forecasting perspective, we therefore compared daily seis-
 335 mic avalanche activity with the avalanche activity observed in the region of
 336 Davos. There was a weak positive correlation between regional avalanche
 337 activity recorded through conventional visual observations and avalanche ac-
 338 tivity recorded through seismic monitoring, although for DFB2013 the corre-

339 lation was not significant (Table 2 and Figure 9). These results suggest that
340 increased regional avalanche activity generally also coincided with increased
341 local avalanche activity near the seismic monitoring stations.

342 Despite the small area covered by the seismic stations, compared to about
343 175 km² for the visual observations in the region of Davos, all the major
344 regional wet-snow avalanche periods were well captured (compare solid red
345 and dashed green lines in Figure 9). This is also reflected by the significant
346 positive correlation between the observed wet-snow avalanche activity and
347 seismic avalanche activity, except again for DFB2013. While for DFB2013
348 the overall pattern in avalanche activity corresponded well with observed
349 wet-snow avalanches, the absence of a significant correlation was due to the
350 fact that the peak in avalanche activity at the seismic station was on 8
351 March, while it was a day later for the regional observations (Figure 9c).
352 Indeed, when shifting the visual observations of regional avalanche activity
353 backward by one day, the correlation became very strong and significant for
354 all observed avalanches ($r_s = 0.88$, $p < 10^{-3}$) as well as for the wet-snow
355 avalanches ($r_s = 0.86$, $p < 10^{-3}$). Finally, there was a major avalanche cycle
356 at the end of April 2010 in the WAN2010 catalog which was not as prevalent
357 in the OBS_{wet} catalog. The reason for this is unknown, even though in general
358 avalanche observers tend to underreport avalanches this late in the season,
359 especially smaller wet-snow avalanches.

360 Dry-snow avalanche cycles were generally less well captured through seis-
361 mic monitoring, with the exception of an avalanche cycle in March 2011
362 (Figure 9b), as reflected by a lack of correlation between OBS_{dry} and seismic
363 avalanche activity (Table 2). These results suggest that wet-snow avalanches

364 generate larger seismic signals than dry-snow avalanches of comparable size,
 365 as previously reported (Biescas et al., 2003; van Herwijnen and Schweizer,
 366 2011a). Furthermore, our results suggest that monitoring a relatively small
 367 area with one seismic station can provide reasonable estimates for regional
 368 wet-snow avalanche activity. For dry-snow avalanches, on the other hand,
 369 monitoring a larger area by deploying more seismic stations is likely required
 370 to estimate regional activity.

371 Regional avalanche activity data obtained through conventional visual ob-
 372 servations are widely used in avalanche forecasting. For the region of Davos, it
 373 therefore comes as no surprise that there was a significant positive correlation
 374 between forecasted avalanche danger level and observed regional avalanche
 375 activity from the previous day (Table 3). While this was the case for both
 376 dry-snow and wet-snow avalanche danger, the correlation was strongest for
 377 dry-snow avalanche danger (Table 3 and Figure 10a). Similar to regional
 378 avalanche observations, local daily avalanche activity observed through seis-
 379 mic monitoring generally increased with increasing forecasted avalanche dan-
 380 ger level, even though the correlation was somewhat weaker (Table 3). How-
 381 ever, when looking at dry-snow and wet-snow avalanche danger separately,
 382 a correlation only existed for wet-snow avalanche danger (Table 3 and Fig-
 383 ure 10b). Overall, this suggests that local avalanche activity data obtained
 384 through seismic monitoring could yield valuable data to estimate the regional
 385 avalanche danger level, in particular for wet-snow avalanches.

386 *3.3. Correlation of past and future avalanche activity*

387 The observed correlation between avalanche activity and forecasted avalanche
 388 danger level does not necessarily imply that past avalanche activity is in-

389 dicative of future activity. To investigate this issue more closely, we com-
 390 puted an additional time series $N_{future}(t, s)$ consisting of the number of
 391 avalanches with $t_i \in [t, t + s)$. The Spearman correlation coefficient $r_s(s) =$
 392 $cor(N(t, s), N_{future}(t, s))$ then provides an indication whether future avalanche
 393 activity correlated with past activity.

394 For the avalanche catalog OBS, the correlation coefficient $r_s(s)$ was rela-
 395 tively low and mostly not significant ($p > 0.05$). Nevertheless, $r_s(s)$ exhibited
 396 two significant maxima at 24 and 96 hours (black solid line in Figure 11).
 397 A very similar pattern was also present for OBS_{wet} with overall larger and
 398 significant $r_s(s)$ values (red solid line in Figure 11). These results highlight
 399 once more that during our study period, the majority of avalanches consisted
 400 of wet-snow avalanches. For dry-snow avalanches, on the other hand, $r_s(s)$
 401 values were lowest, not significant and the trend was different: $r_s(s)$ increased
 402 up to 72 hours and decreased thereafter (blue solid line in Figure 11).

403 The correlation coefficients $r_s(s)$ for the combined seismic catalog SEIS,
 404 as well as the $SEIS_{winter}$ and $SEIS_{spring}$ catalogues were generally larger and
 405 statistically significant (black, blue and red dotted lines in Figure 11). Nev-
 406 ertheless, trends $r_s(s)$ observed in $SEIS_{winter}$ and $SEIS_{spring}$ showed some sim-
 407 ilarities with those observed in OBS_{dry} and OBS_{wet} . Despite some differences
 408 in the exact location of local minima and maxima and, of course, the value
 409 of the correlation coefficient, the overall trends in $r_s(s)$ exhibited similar fea-
 410 tures (compare blue and red dotted lines with blue and red solid lines in
 411 Figure 11). Indeed, $r_s(s)$ exhibited a local maximum at 24 hours and local
 412 minima at 72 and 168 hours for $SEIS_{spring}$ (red dotted lines in Figure 11).
 413 For $SEIS_{winter}$, on the other hand, $r_s(s)$ reached its maximum at 96 hours

414 and decreased thereafter.

415 The increased temporal resolution obtained through seismic monitor-
416 ing allowed us to investigate $r_s(s)$ in greater detail, especially for shorter
417 time windows ($s < 24$ hours), which is not possible with conventional daily
418 avalanche observations. At these shorter time scales, substantial differences
419 were observed for $\text{SEIS}_{\text{winter}}$ and $\text{SEIS}_{\text{spring}}$. While $r_s(s)$ generally increased
420 from 1 to 24 hours for $\text{SEIS}_{\text{winter}}$, for $\text{SEIS}_{\text{spring}}$ there was a very pronounced
421 local minimum at 12 hours and the strongest correlation was observed for
422 the shortest time scale of 1 hour. Overall, these results suggest that differ-
423 ent processes with different characteristic time scales were responsible for the
424 triggering of dry and wet-snow avalanches in our avalanche catalogues, in line
425 with the results shown in Figure 7 and 8. Avalanche activity in spring closely
426 relates to air temperature and incoming shortwave radiation (e.g. Mitterer
427 and Schweizer, 2013; Helbig et al., 2015), both of which exhibit strong diurnal
428 trends. Avalanche activity in winter, on the other hand, typically relates to
429 precipitation (i.e. storm cycles) (e.g. van Herwijnen and Schweizer, 2011a),
430 for which the normalized covariance exhibited a secondary maximum around
431 70 hours (not shown), consistent with the long-term correlations observed in
432 Figure 11.

433 3.4. *Simple avalanche forecasting model*

434 The results shown in Figure 11 suggest that past dry-snow avalanche ac-
435 tivity is only indicative of future avalanche activity when considering large
436 time windows, typically on the order of 3 to 4 days. For wet-snow avalanches,
437 on the other hand, past avalanche activity is only indicative of future avalanche
438 activity for much shorter time windows, either 1 to 3 hours or around 24

439 hours. From an avalanche forecasting perspective, this suggests that using
 440 past avalanche activity to make predictions about future avalanches in spring
 441 will only be reliable for short time scales on the order of hours, while in winter
 442 reliability should increase for time scales longer than about 48 hours.

443 To verify this hypothesis, we evaluated a simple model based on past
 444 avalanche activity to predict future avalanches. The model is very similar
 445 to the model used by Grasso and Zaliapin (2004) and Schmid et al. (2012)
 446 for predicting volcanic eruptions, and is based on the detection of a thresh-
 447 old value on an hourly avalanche activity function $A(t, \Delta)$ (Figure 12), i. e.
 448 we want to forecast avalanches on an hourly basis. When an avalanche is
 449 detected at time t_i , $A(t, \Delta)$ is raised by 1 for a duration Δ :

$$A(t, \Delta) = A(t, \Delta) + 1 \text{ for } t \in (t_i, t_i + \Delta]. \quad (3)$$

450 An alarm is triggered when $A(t, \Delta)$ exceeds a predefined threshold value A_0 .
 451 Thus, the model has two tunable parameters, namely the alarm duration Δ
 452 and the avalanche activity threshold A_0 . Prediction is correct if an avalanche
 453 occurs at hour t while $A(t, \Delta) > A_0$ (green arrows and dots in Figure 12).
 454 However, all other hours with $A(t, \Delta) > A_0$ are still considered false alarms
 455 (red dots in Figure 12).

456 We evaluated model performance on the SEIS_{winter} and SEIS_{spring} cata-
 457 logues. For $\Delta = 24$ hours, the predictive skills of our forecasting model are
 458 illustrated in Figure 13. Clearly, for an alarm duration of 24 hours, the model
 459 is more accurate in spring than in winter, as reflected by the higher AUC
 460 value. For the optimal avalanche activity threshold (1 avalanche in winter
 461 and 5 in spring; dots in Figure 13), the POD, FAR and DUR values were
 462 also poorer in winter (0.64, 0.96 and 0.47, respectively) than in spring (0.71,

463 0.80 and 0.27, respectively).

464 Overall, model performance was better in spring than in winter for the
465 entire range of alarm durations Δ in terms of model score S and for most
466 of the individual model performance measures (Figure 14). During winter,
467 model performance somewhat improved with alarm duration. For $\Delta > 24$
468 hours, the model resulted in reasonable POD values between 0.6 and 0.7,
469 but very high FAR values of about 0.95 (solid lines in Figure 14b). The
470 improvement of the overall model score S for larger Δ in winter is mostly
471 attributed to a decrease in the total alarm duration (DUR; black solid line in
472 Figure 14b). During spring, model performance decreased with increasing Δ ,
473 predominantly due to increases in FAR and DUR. However, for Δ between
474 24 and 48 hours, model performance briefly improved, with typical POD and
475 FAR values of around 0.7 and 0.8, respectively, and DUR values around 0.2.
476 This quantitative model performance evaluation shows that based on past
477 avalanche activity, avalanches in spring can more accurately be forecasted
478 than avalanches in winter. Furthermore, it confirms our hypothesis that past
479 wet-snow avalanche activity is indicative of future avalanches for time scales
480 of a day or less, while for dry-snow avalanches this is only the case for longer
481 time scales.

482 There is a clear link between model performance and the time scales iden-
483 tified in the avalanche catalogues (Sections 3.1 and 3.3). In winter, avalanche
484 activity was clustered for $t_r > 53$ hours ($SEIS_{winter}$ in Table 1), and model
485 performance generally improved for time scales *larger* than t_r . In spring, on
486 the other hand, avalanche activity was clustered for $t_r > 10$ hours ($SEIS_{spring}$
487 in Table 1), while our forecasting model performed best for time scales *shorter*

488 than t_r . While these results seem contradictory, they can be explained based
 489 on the correlation analysis of past and future avalanche activity (Figure 11).
 490 Indeed, in winter past and future avalanche activity were mostly uncorrelated
 491 for time scales shorter than t_r (blue dashed line in Figure 11), suggesting that
 492 past avalanche activity can only be used for predictions over long time scales
 493 ($t > t_r$). In spring, the correlation of past and future avalanche activity was
 494 strongest for time scales shorter than t_r and for time scales around 24 hours,
 495 while for even longer time scales the correlation decreased (red dashed line
 496 in Figure 11). This suggests that avalanche prediction in spring based on
 497 past avalanche activity is only effective for shorter time scales ($t < t_r$), in
 498 line with the results of our forecasting model (Figure 14).

499 To the best of our knowledge there are no other published studies in which
 500 an attempt was made to automatically forecast avalanches based on past
 501 avalanche activity. In most studies almost exclusively meteorological param-
 502 eters were used as input (e.g. Brabec and Meister, 2001). However, Schweizer
 503 and Föhn (1996) considered snow instability information, and Schirmer et al.
 504 (2009) achieved the best results with a nearest neighbor method which used
 505 the avalanche danger level of the previous day as additional input. For local
 506 forecasting, for instance, Schweizer et al. (2009) used critical new snow depths
 507 measured at two different elevations to forecast large dry-snow avalanches in
 508 a single avalanche path at time scales ranging from 24 to 120 hours. While
 509 their model worked well in terms of POD, with values mostly above 0.7, the
 510 FAR values were generally very high, typically above 0.9. With regard to
 511 wet-snow avalanches, Mitterer and Schweizer (2013) evaluated several mod-
 512 els with a variety of meteorological input variables to forecast avalanches in

513 the region of Davos at time scales ranging from 24 to 72 hours. Model per-
 514 formance was good with POD values around 0.9 and FAR values around 0.3.
 515 On the other hand, Helbig et al. (2015) used a relatively simple model based
 516 on air temperature and incoming shortwave radiation to forecast wet-snow
 517 avalanches over entire Switzerland at time scales of 24 hours, with typical
 518 POD values around 0.6 (FAR values were not reported due to the absence
 519 of reliable avalanche occurrence data). It is somewhat surprising that POD
 520 values of our very simple model based on past avalanche activity is compa-
 521 rable to more sophisticated models, both in winter and in spring. This may
 522 partly be attributed to the fact that we use data that are directly related to
 523 instability, whereas most other models use meteorological data which only
 524 provide an indirect indication of snow instability (e.g. LaChapelle, 1980; Mc-
 525 Clung, 2002). While our FAR values are much higher, we would like to point
 526 out that since we are using an hourly alarm function, the obtained FAR
 527 values are very conservative (see Figure 12). Finally, by including the error
 528 diagram in our analysis we have included the total alarm duration in our
 529 analysis, which thus far has not been done for avalanche forecasting.

530 **4. Summary and outlook**

531 By performing a visual inspection of the waveform and the spectrogram of
 532 seismic data recorded in avalanche starting zones, we obtained avalanche cat-
 533 alogues for two entire winters (2010 and 2011) and one period of 10 days with
 534 intense wet-snow avalanche activity in the spring of 2013. These avalanche
 535 catalogues, consisting of the release times of each avalanche found in the
 536 seismic data, were used to investigate clustering and periodicity in avalanche

537 activity, and to perform a detailed investigation of how such avalanche ac-
538 tivity data could be used for local avalanche forecasting (at spatial scales of
539 2 km²) at time scale of up to 7 days.

540 Avalanches were strongly clustered in time. The waiting time between
541 avalanches departed from a Poisson process for waiting times larger than t_r ,
542 ranging from 9 to 107 hours. Avalanche activity also exhibited some period-
543 icity, in particular during spring when the covariance of avalanche activity
544 displayed a clear diurnal trend. This comes as no surprise, since it is well
545 known that in spring avalanches typically release during the day, when the
546 energy input into the snow cover is greatest.

547 Observed seismic avalanche activity compared fairly well with conven-
548 tional visual avalanche observations for the region of Davos, a region of about
549 175 km². This was especially true for wet-snow avalanches, for which all the
550 major regional wet-snow avalanche periods were well captured through seis-
551 mic monitoring. Dry-snow avalanches, on the other hand, were less frequent
552 in our seismic avalanche catalogues, and most dry-snow avalanche cycles
553 were not well captured through seismic monitoring. These results suggest
554 that monitoring over a larger area by deploying several seismic stations is
555 likely required to provide robust estimates of regional dry-snow avalanche
556 activity.

557 Since past avalanche activity is often used in avalanche forecasting, we
558 explored the suitability of highly resolved avalanche occurrence data for fore-
559 casting purposes. First, we showed that depending on the considered time
560 scale, past avalanche activity is correlated with future avalanche activity.
561 During winter, i.e. for dry-snow avalanches, only long-term correlations were

562 observed for time scales larger than 3 days, likely related to the frequency of
563 precipitation events. During spring, on the other hand, short-term correla-
564 tions were observed, typically for time scales less than 3 hours or around 24
565 hours, likely related to diurnal patterns in energy input into the snow cover
566 (e.g. air temperature and incoming shortwave radiation).

567 Based on these results, we evaluated the performance of a simple model
568 based on past avalanche activity to predict future avalanches, similar to mod-
569 els used for predicting volcanic eruptions (e.g. Grasso and Zaliapin, 2004;
570 Schmid et al., 2012). Model performance was better in spring than in win-
571 ter, especially for very short time scale of up to three hours, and for time
572 scales around 24 hours. For time scales of several days, model performance
573 somewhat improved in winter. While we are not aware of any previous at-
574 tempts to automatically forecast avalanches based on past avalanche activity,
575 the probability of detection of our very simple model was comparable to the
576 performance of much more sophisticated models based on meteorological in-
577 put variables (Schweizer et al., 2009; Mitterer and Schweizer, 2013; Helbig
578 et al., 2015).

579 This work is a first attempt to evaluate the predictive power of past
580 avalanche activity for avalanche forecasting in a quantitative manner. By
581 evaluating model performance in terms of probability of detection, false alarm
582 ratio and total alarm duration, our results suggest that using avalanche ac-
583 tivity for avalanche forecasting is more effective in spring than in winter.
584 Future model improvements will include scaling the avalanche activity func-
585 tion with seismic signal duration, since signal duration can serve as a proxy
586 for avalanche size (van Herwijnen et al., 2013; van Herwijnen and Schweizer,

2011b). Our analysis was based on visual inspection of the seismic data,
which is a time consuming endeavor. For operational avalanche forecasting,
automatic avalanche detection is therefore required (e.g. Rubin et al., 2012),
especially when focusing on natural avalanche activity. Nevertheless, the re-
sults reported here clearly show that if highly resolved avalanche occurrence
data can be obtained in near real-time, this would be extremely useful for
avalanche forecasting.

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References

- Amitrano, D., Grasso, J., Senfaute, G., 2005. Seismic precursory patterns
before a cliff collapse and critical point phenomena. *Geophys. Res. Lett.*
32, 41–55.
- Bessason, B., Eiriksson, G., Thorarinsson, O., Thorarinsson, A., Einarsson,
S., 2007. Automatic detection of avalanches and debris flows by seismic
methods. *J. Glaciol.* 53, 461–472.
- Biescas, B., Dufour, F., Furdada, G., Khazaradze, G., Surinach, E., 2003.
Frequency content evolution of snow avalanche seismic signals. *Surv. Geo-
phys.* 24, 447–464.

- 610 Brabec, B., Meister, R., 2001. A nearest-neighbor model for regional
611 avalanche forecasting. *Annals of Glaciology* 32, 130–134.
- 612 Caplan-Auerbach, J., Huggel, C., 2007. Precursory seismicity associated with
613 frequent, large ice avalanches on Iliamna volcano, Alaska, USA. *Journal*
614 *of Glaciology* 53, 128–140. doi:10.3189/172756507781833866.
- 615 Deparis, J., Jongmans, D., Cotton, F., Baillet, L., Thouvenot, F., Hantz,
616 D., 2008. Analysis of rock-fall and rock-fall avalanche seismograms in the
617 French Alps. *B. Seismol. Soc. Am.* 98, 1781–1796. doi:10.1785/0120070082.
- 618 Eckerstorfer, M., Bhler, Y., Frauenfelder, R., Malnes, E., 2016. Remote sens-
619 ing of snow avalanches: Recent advances, potential, and limitations. *Cold*
620 *Reg. Sci. Technol.* 121, 126 – 140. doi:10.1016/j.coldregions.2015.11.001.
- 621 Faillettaz, J., Louchet, F., Grasso, J.R., 2004. Two-threshold model for scal-
622 ing laws of noninteracting snow avalanches. *Phys. Rev. Lett.* 93, 208001.
623 doi:10.1103/PhysRevLett.93.208001.
- 624 Faillettaz, J., Pralong, A., Funk, M., Deichmann, N., 2008. Evidence of log-
625 periodic oscillations and increasing icequake activity during the breaking-
626 off of large ice masses. *J. Glaciol.* 54, 725–737.
- 627 Gauer, P., Kern, M., Kristensen, K., Lied, K., Rammer, L., Schreiber, H.,
628 2007. On pulsed doppler radar measurements of avalanches and their im-
629 plication to avalanche dynamics. *Cold Regions Science and Technology* 50,
630 55–71.
- 631 Grasso, J., Zaliapin, I., 2004. Predictability of volcano eruption: Lessons

632 from a basaltic effusive volcano. *Geophysical Research Letters* 31.
633 doi:10.1029/2003GL019022.

634 Gubler, H., 1979. Acoustic emission as an indication of stability decrease in
635 fracture zones of avalanches. *J. Glaciol.* 22, 186–188.

636 Harrison, J., 1976. Seismic signals from avalanches. Armstrong and Ives
637 (Eds.), *Avalanche release and snow characteristics*. Institute of Arctic and
638 Alpine Research, University of Colorado. Occasional Paper No. 19 , 145–
639 150.

640 Helbig, N., van Herwijnen, A., Jonas, T., 2015. Forecasting wet-snow
641 avalanche probability in mountainous terrain. *Cold Regions Science and*
642 *Technology* 120. doi:10.1016/j.coldregions.2015.07.001.

643 van Herwijnen, A., Dreier, L., Bartelt, P., 2013. Towards a basic avalanche
644 characterization based on the generated seismic signal. *Proc. 2013 Int.*
645 *Snow Sci. W.*, Grenoble, France , 1033–1037.

646 van Herwijnen, A., Schweizer, J., 2011a. Seismic sensor array for monitoring
647 an avalanche start zone: design, deployment and preliminary results. *J.*
648 *Glaciol.* 57, 257–264.

649 van Herwijnen, A., Schweizer, J., 2011b. Monitoring avalanche activity using
650 a seismic sensor. *Cold Reg. Sci. Tech.* 69, 165–176.

651 Ives, J., Harrison, J., Armstrong, R., 1973. Development of methodology for
652 evaluation and prediction of avalanche hazard in the san juan mountain
653 area of southwestern colorado. interim report for period august 1972 -

654 august 1973. Institute of Arctic and Alpine Research, Boulder, Colorado,
655 INSTAAR- I 4-06-7 I 55-2 .

656 Kapil, J., Datt, P., Kumar, A., Singh, K., Kumar, V., Satyawali, P., 2014.
657 Multi-sensor couplers and waveguides for efficient detection of acoustic
658 emission behavior of snow. *Cold Regions Science and Technology* 101, 1 –
659 13. doi:<http://dx.doi.org/10.1016/j.coldregions.2014.01.003>.

660 Kogelnig, A., Wyssen, S., Pichler, J., 2012. Artificial release and detection
661 of avlanches: Managing avalanche risk on traffic infrastructure, a case
662 study from Austria, in: *International Snow Science Workshop ISSW 2012*,
663 Anchorage AK, U.S.A., 16-21 September 2012, pp. 535–540.

664 Kumar, R., Indrayan, A., 2011. Receiver Operating Characteristic (ROC)
665 Curve for Medical Researchers. *Indian Pediatrics* 48, 277–287.

666 LaChapelle, E., 1980. The fundamental processes in conventional avalanche
667 forecasting. *J. Glaciol.* 26, 75–84.

668 Lacroix, P., Grasso, J.R., Roulle, J., Giraud, G., Goetz, D., Morin, S., Helm-
669 stetter, A., 2012. Monitoring of snow avalanches using a seismic array:
670 Location, speed estimation, and relationships to meteorological variables.
671 *J. Geophys. Res. - Earth* 117, F01034. doi:10.1029/2011JF002106.

672 Lockner, D., 1993. The role of acoustic-emission in the study of rock fracture.
673 *Int. J. Rock Mech. Min.* 30, 883–899.

674 Marchetti, E., Ripepe, M., Ulivieri, G., Kogelnig, A., 2015. Infrasound ar-
675 ray criteria for automatic detection and front velocity estimation of snow

676 avalanches: towards a real-time early-warning system. *Nat. Hazards Earth*
677 *Syst. Sci. Discuss.* 3, 2709–2737.

678 Marzocchi, W., Zaccarelli, L., 2006. A quantitative model for the time-size
679 distribution of eruptions. *Journal of Geophysical Research-Solid Earth*
680 111. doi:10.1029/2005JB003709.

681 McClung, D., 2002. The elements of applied forecasting - Part II: The phys-
682 ical issues and the rules of applied avalanche forecasting. *Nat. Hazards* 26,
683 131–146.

684 McClung, D.M., Schaerer, P., 2006. *The Avalanche Handbook*. The Moun-
685 taineers, Seattle, Washington, U.S.A.

686 Meister, R., 1995. Country-wide avalanche warning in Switzerland, in: *Pro-*
687 *ceedings International Snow Science Workshop, Snowbird, Utah, U.S.A.,*
688 *30 October-3 November 1994, ISSW 1994 Organizing Committee, Snow-*
689 *bird UT, USA.* pp. 58–71.

690 Michlmayr, G., Cohen, D., Or, D., 2012. Sources and characteris-
691 tics of acoustic emissions from mechanically stressed geologic gran-
692 ular media a review. *Earth-Science Reviews* 112, 97 – 114.
693 doi:http://dx.doi.org/10.1016/j.earscirev.2012.02.009.

694 Mitterer, C., Schweizer, J., 2013. Analysis of the snow-atmosphere energy
695 balance during wet-snow instabilities and implications for avalanche pre-
696 diction. *The Cryosphere* 7, 205–216.

697 Molchan, G., 1997. Earthquake prediction as a decision-making problem.
698 *Pure and Applied Geophysics* 149, 233–247.

699 Niemz, P., Brunner, A., Walter, O., 2009. Investigation of the mechanism of
700 failure behaviour of wood based materials using acoustic emission analysis
701 and image processing. *Wood Res.* 54, 49–62.

702 Reiweger, I., Mayer, K., Steiner, K., Dual, J., Schweizer, J., 2015. Measuring
703 and localizing acoustic emission events in snow prior to fracture. *Cold
704 Regions Science and Technology* 110, 160 – 169.

705 Rosti, J., Koivisto, J., Alava, M.J., 2010. Statistics of acoustic emission in
706 paper fracture: precursors and criticality. *J. Stat. Mech. - Theory E.* 2010,
707 P02016. doi:10.1088/1742-5468/2010/02/P02016.

708 Rubin, M., Camp, T., van Herwijnen, A., Schweizer, J., 2012. Automati-
709 cally detecting avalanche events in passive seismic data. *Proc. 11th Int.
710 Conf.Mach. Learn. Appl.* 1, 13–20.

711 Schirmer, M., Lehning, M., Schweizer, J., 2009. Statistical forecasting of
712 regional avalanche danger using simulated snow-cover data. *J. Glaciol.* 55,
713 761–768.

714 Schmid, A., Grasso, J.R., Clarke, D., Ferrazzini, V., Bachelery, P.,
715 Staudacher, T., 2012. Eruption forerunners from multiparameter
716 monitoring and application for eruptions time predictability (Piton
717 de la Fournaise). *Journal of Geophysical Research-Solid Earth* 117.
718 doi:10.1029/2012JB009167.

719 Schweizer, J., Föhn, P., 1996. Avalanche forecasting - An expert system
720 approach. *J. Glaciol.* 42, 318–332.

- 721 Schweizer, J., van Herwijnen, A., 2013. Can near real-time avalanche occur-
722 rence data improve avalanche forecasting? Proc. 2013 Int. Snow Sci. W.,
723 Grenoble, France , 195–198.
- 724 Schweizer, J., Kronholm, K., Wiesinger, T., 2003. Verification of regional
725 snowpack stability and avalanche danger. Cold Reg. Sci. Technol. 37, 277–
726 288.
- 727 Schweizer, J., Mitterer, C., Stoffel, L., 2009. On forecasting large and infre-
728 quent snow avalanches. Cold Regions Science and Technology 59, 234 –
729 241.
- 730 Scott, E., Hayward, C., Kubichek, R., Hamann, J., Pierre, J., Comey,
731 B., Mendenhall, T., 2007. Single and multiple sensor identification of
732 avalanche-generated infrasound. Cold Reg. Sci. Technol. 47, 159–170.
- 733 Spillmann, T., Maurer, H., Green, A., Heincke, B., Willenberg, H., Husen,
734 S., 2007. Microseismic investigation of an unstable mountain slope in the
735 Swiss Alps. J. Geophys. Res. - Sol. Ea. 112. doi:10.1029/2006JB004723.
- 736 Suriñach, E., Furdada, G., Sabot, F., Biescas, B., Vilaplana, J.,
737 2001. On the characterization of seismic signals generated by snow
738 avalanches for monitoring purposes. Ann. Glaciol. 32(7), 268–274.
739 doi:doi:10.3189/172756401781819634.
- 740 Suriñach, E., Vilajosana, I., Khazaradze, G., Biescas, B., Furdada, G., Vila-
741 plana, J., 2005. Seismic detection and characterization of landslides and
742 other mass movements. Nat. Hazards Earth Syst. Sci. 5(6), 791–798.

- 743 Talbi, A., Nanjo, K., Zhuang, J., Satake, K., Hamdache, M., 2013. Interevent
744 times in a new alarm-based earthquake forecasting model. *Geophysical*
745 *Journal International* 194, 1823–1835. doi:10.1093/gji/ggt194.
- 746 Tatard, L., Grasso, J.R., Helmstetter, A., Garambois, S., 2010. Character-
747 ization and comparison of landslide triggering in different tectonic and
748 climatic settings. *Journal of Geophysical Research-Earth Surface* 115.
749 doi:10.1029/2009JF001624.
- 750 Thüring, T., Schoch, M., van Herwijnen, A., Schweizer, J., 2015. Robust
751 snow avalanche detection using supervised machine learning with infra-
752 sonic sensor arrays. *Cold Regions Science and Technology* 111, 60 – 66.
- 753 Wilks, D., 2011. Statistical methods in the atmospheric sciences. volume 100
754 of *International Geophysics Series*. 3rd ed., Academic Press, San Diego
755 CA, U.S.A.
- 756 Woo, S., Choi, N., Cho, N., 2008. Characterization of the
757 fracture process of notched glass fiber/aluminum hybrid laminates
758 by acoustic emission. *Compos. Sci. Technol.* 68, 1521–1530.
759 doi:10.1016/j.compscitech.2007.10.020.

Table 1: Overview of the total number of avalanches N , the coefficient of variation η of the waiting time, and the threshold time t_r for the avalanche catalogues.

catalog	N	η	t_r (hours)
WAN2010	385	2.3	11
WAN2010 _{winter}	58	0.95	107
WAN2010 _{spring}	327	3.1	8
WAN2011	154	2.5	42
WAN2011 _{winter}	88	2.3	55
WAN2011 _{spring}	66	2.1	25
DFB2013	52	1.9	12
SEIS _{winter}	146	1.9	53
SEIS _{spring}	445	2.9	10

Table 2: Correlation analysis between daily regional avalanche activity recorded through conventional visual observations and daily avalanche activity recorded through seismic monitoring. The Spearman correlation coefficient r_s as well as the significance level p are shown.

	OBS		OBS _{dry}		OBS _{wet}	
catalog	r_s	p	r_s	p	r_s	p
WAN2010	0.26	8×10^{-3}	-0.18	0.06	0.28	3×10^{-3}
WAN2011	0.37	$< 10^{-3}$	0.11	0.21	0.35	$< 10^{-3}$
DFB2013	0.58	0.06	-0.04	0.90	0.42	0.19

Table 3: Correlation analysis between avalanche danger rating and previous day avalanche activity. The median daily avalanche activity as well as the interquartile range (in brackets) are shown for each danger level as well as the Spearman correlation coefficient r_s and the significance level p .

Catalog	Danger rating all					Danger rating dry					Danger rating wet			
	1	2	3	r_s	p	1	2	3	r_s	p	2	3	r_s	p
OBS	0(0)	0(3)	4(20)	0.29	$< 10^{-3}$	0(0)	0(0)	2(14)	0.33	$< 10^{-3}$	0(0)	0.5(13)	0.27	0.04
SEIS	1(2)	0(1)	1(3)	0.19	$< 10^{-3}$	1(1)	1(3)	1(2)	0.06	0.36	1(4)	3(8)	0.24	0.05

Figure 1: Overview of the field sites instrumented with seismic monitoring systems around Davos, Switzerland. Also shown are the main roads, railway line, mountain cable ways and the locating of automatic meteorological stations (AMS).

Figure 2: (a,b) Images from the automatic camera at DFB taken on 3 March 2013 at 12:44 and 12:46 showing the release of an avalanche (arrow). (c) Seismic waveform recorded at DFB on 3 March 2013 between 12:00 and 13:00. The arrow shows the signal generated by the avalanche. (d) Corresponding spectrogram showing the frequency content of the signal with time. The black arrow shows the signal generated by the avalanche.

Figure 3: (a,b) Images from the automatic camera at WAN taken on 20 March 2010 at 12:44 and 12:48 showing the release of an avalanche (arrow). (c) Seismic waveform recorded at WAN on 20 March 2010 between 12:00 and 13:00. The arrow shows the signal generated by the avalanche. (d) Corresponding spectrogram showing the frequency content of the signal with time. The black arrow shows the signal generated by the avalanche.

Figure 4: Seismic signals generated by avalanches and environmental noise for two hours on 23 March 2010. Top: spectrogram showing the frequency content of the signal with time. The black arrows show confirmed avalanches, based on images from automatic cameras. The red arrows show visually picked avalanches without confirmation. The blue arrows show airplane signals. The magenta arrow shows the noise band from ski lifts. Bottom: corresponding waveform.

Figure 5: Hourly avalanche activity observed through seismic monitoring for WAN2010 (red line), WAN2011 (blue line), and DFB2013 (green line). The cutoff date between winter and spring for WAN2010 was 15 March 2010 (red dashed line) and for WAN2011 it was 25 March 2011 (blue dashed line).

Figure 6: Cumulative distribution of the square of seismic signal duration T for WAN2010 (red line), WAN2011 (blue line), and DFB2013 (green line).

Figure 7: Cumulative distribution of avalanche waiting time τ . The dashed lines represent the corresponding exponential distribution computed for each catalog. (a) For WAN2010 (red line), WAN2011 (blue line), and DFB2013 (green line). (b) For WAN2010_{winter} (red line), WAN2011_{winter} (blue line) and SEIS_{winter} (black line). (c) For WAN2010_{spring} (red line), WAN2011_{spring} (blue line) and SEIS_{spring} (black line).

Figure 8: Normalized covariance $C(r,1)/C(0,1)$ of hourly avalanche activity with lag time r . (a) For WAN2010 (red line), WAN2011 (blue line), and DFB2013 (green line). (b) For WAN2010_{winter} (red line), WAN2011_{winter} (blue line) and SEIS_{winter} (black line). (c) For WAN2010_{spring} (red line), WAN2011_{spring} (blue line) and SEIS_{spring} (black line).

Figure 9: Comparison of dry-snow (blue line) and wet-snow (red line) daily avalanche activity observed through conventional visual observations in the region of Davos with avalanche activity observed through seismic monitoring (green dashed lines) for the three avalanche catalogues (a) WAN2010, (b) WAN2011, (c) DFB2013.

Figure 10: (a) Avalanche activity observed through conventional visual observations with forecasted dry-snow (blue) and wet-snow (red) avalanche danger rating for the region of Davos. (b) Same for avalanche activity observed through seismic monitoring. On each box, the notch shows the location of the median, the edges of the box are the 1st and 3rd quartiles, the whiskers show the range of observed values that fall within 1.5 times the interquartile range above and below the interquartile range, and the crosses show outliers.

Figure 11: Correlation coefficient $r_s(s)$ between past and future avalanche activity with windows length s . $r_s(s)$ was computed for the OBS avalanche catalogues (circles and solid lines with colors as indicated in the legend) as well as for the SEIS avalanche catalogues (squares and dotted lines with colors as indicated in the legend). Filled symbols indicate correlation coefficients which were significant ($p \leq 0.05$), while open symbols indicate correlation coefficients which were not significant ($p > 0.05$)

Figure 12: Simple model to predict avalanches based on the avalanche activity function $A(t, \Delta)$ (blue line). The tunable parameters are the alarm duration Δ and the avalanche activity threshold A_0 (blue dashed line). The arrows indicate avalanche events; red arrows are missed events, green arrows are correctly predicted events. The red open circles depict false alarms and the green open circles correct alarms.

Figure 13: (a) ROC curve for an alarm duration Δ of 24 hours for the SEIS_{winter} (blue) and SEIS_{spring} (red) avalanche catalogues. The black line shows the line of random chance (50-50 chance) and the blue and red dots show the optimal model performance. (b) Error diagram for an alarm duration Δ of 24 hours for the SEIS_{winter} (blue) and SEIS_{spring} (red) avalanche catalogues. The black line shows the line of random chance (50-50 chance) and the blue and red dots show the optimal model performance.

Figure 14: (a) Forecasting score S with alarm duration Δ for the $SEIS_{winter}$ (blue) and $SEIS_{spring}$ (red) avalanche catalogues. (b) Individual performance measures POD (blue), FAR (red), AUC (green) and DUR (black) with alarm duration Δ for the $SEIS_{winter}$ (solid) and $SEIS_{spring}$ (dashed) avalanche catalogues.