ON STABILITY MEASUREMENTS AND MODELING

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ABSTRACT: Recent developments in snow stability modeling demonstrated the great potential of numerical snow cover modeling for avalanche forecasting. The recently developed metrics provided promising results, possibly even superseding traditional stability indices. To further validate these results, we compared the temporal evolution of various stability metrics to a unique data set of measurements including snow stratigraphy, snow microstructure and stability at the Steintälli site (Davos, Switzerland). From January to March 2016, we measured the shear strength of a prominent weak layer of depth hoar crystals with the shear frame and the critical crack length in propagation saw tests. Concurrently, we characterized snow microstructure with the snow micro-penetrometer (SMP) and ran the numerical snow cover model SNOWPACK with the data from the automatic weather station at the site. Our results show that initially, strength and toughness were low, but increased with time; they were correlated. Also, load increased with time, and strength and toughness were correlated with load. While in the field we monitored the most prominent weak layer in the snowpack, the modelled stability metrics indicated that different weak layers, closer to the snow surface, were more prone to fail later in the season. The three stability metrics we compared showed similar temporal trends and performance with regard to avalanche activity in the region of Davos and forecast danger levels. Our detailed site-specific validation indicates that numerical stability metrics provide valuable data for avalanche forecasting though different indices show different behavior at times calling for specific interpretation.

KEYWORDS: snow stability, avalanche forecasting, numerical modeling, failure initiation, crack propagation

1. INTRODUCTION

In avalanche forecasting, we consider the future weather and its impact on the snow cover, which essentially represents the past weather. Future weather is provided by high resolution regional numerical weather prediction models (NWPs). The snow stratigraphy can be modelled as well, typically by either Crocus or SNOWPACK (Morin et al., 2020) and potentially critical weak layers are often well reproduced (Bellaire and Jamieson, 2013). As the snowpack is a complex sequence of snow layers of different properties its interpretation with respect to snow instability is difficult. While in the field snow stability tests provide useful information, comparable measures for modeled snow stratigraphy are less obvious, apart from stability indices such as the skier stability index SK38, which proved to be a good indicator based on manually measured shear strength (Jamieson, 1995). While the skier stability index can easily be calculated for each layer in simulated snow stratigraphy (sk38) based on parameterizations of shear strength (Jamieson and Johnston, 2001), it is not straightforward to find the potentially critical weak layer(s). The layer with the minimum value of sk38 would be the obvious candidate, but it is often not, since layers just below the penetration depth typically obtain low values of sk38. Hence, in analogy to the idea of the lemons (McCammon and Schweizer, 2002; Schweizer and Jamieson, 2007) some attempts aimed at finding the potentially critical weaknesses in simulated profiles based on structural differences such as grain size and hardness across layer boundaries (Bellaire et al., 2006). Monti et al. (2012) adjusted the threshold sum approach (TSA) to simulated profiles. Furthermore, Monti and Schweizer (2013) suggested to consider relative rather than absolute thresholds for the structural instability parameters creating the RTA (relative threshold sum approach). Combining the RTA (to find potential weaknesses) with the sk38 calculated for the depth of these weaknesses provides a measure of instability. Based on a small dataset of observed stability they preliminarily concluded that the RTA-sk38 combination was useful to discriminate between poor/fair and good stability. However, the approach was never really validated, partly since it was presumably not properly implemented into the operational version of SNOWPACK.

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Considering the avalanche formation process, SK38 relates to failure initiation, the critical cut length r_c as observed in a PST is a measure of the propensity for crack propagation. Accordingly, also the critical cut length was implemented in numerical snow cover models (Gaume et al., 2017). A validation study pointed toward some deficiencies in the parameterization and suggested a possible improvement (Richter et al., 2019).

With these developments, two variables were available reflecting the improved understanding of dry-snow avalanche release that should allow for the interpretation of snow layering in terms of stability – and holding the promise that high resolution (in space and time) numerical snow instability prediction is within reach. One of the first attempts to follow this process-based avenue was reported by Reuter and Bellaire (2018).

Recent developments towards numerical avalanche prediction based on machine learning (ML) methods also considered snow stratigraphy variables in the set of explanatory variables in addition to other output variables provided by numerical snow cover models. These variables were related to different types of target variables or labels such as the avalanche danger level, avalanche activity (Hendrick et al., 2023; Viallon-Galinier et al., 2023) and snow instability ($P_{unstable}$; Mayer et al., 2022). Analyzing variable importance provided results that partly were plausible, and partly not. Variable importance varied for standard metrics of instability, such as sk38 or r_c. Alternatively, Reuter et al. (2022) provided a process-based approach to derive the most critical avalanche problems (pAp) by identifying and tracking weak layers and assess snow instability considering the processes of failure initiation and crack propagation.

Hence, it is presently unclear how the different approaches compare, given contrasting results, for instance, for the skier stability index. Should the stability related variables still be considered or are they outperformed and superseded by (in part black-box) output of ML models? We compare the RTA-sk38 approach, the instability metric $P_{unstable}$ and the process-based approach (pAp: weak layer tracking; sk38, r_c). We analyze how these approaches perform during the winter season 2015/16 at our study site Steintälli where we collected a comprehensive set of field measurements including shear strength to which we can compare the model results.

2. METHODS

2.1 Field measurements

We performed manual snowpack observations on 9 days between early January to mid-March 2016 at the automated weather station (AWS) Steintälli (2442 m a.s.l.) above Davos (Eastern Swiss Alps; Tab. 1). We recorded a detailed snow profile, performed stability tests (CT: compression test; ECT: extended column test) and propagation saw tests (PST; 3-5 per day). In addition, we pulled shear frames (250 cm^2; 8-16 per day) on a layer of depth hoar (2-4 mm in size) that had formed at the snow surface during December 2015 and got buried on 31 December 2015; it formed a persistent weak layer (PWL) throughout January, February and March 2016. By mid-March the PWL was deeply buried.

The manual snow stratigraphy observations were completed with snow micro-penetrometer measurements (SMP; 7-24 per day; Schneebeli and Johnson, 1998); the SMP data quality, however, was insufficient and could not be analyzed on the last measurement day (10 March 2016). SMP data analysis was performed as described in detail in Schweizer et al. (2016). From the SMP signal we derived the following mechanical properties: weak layer thickness h_{WL}, density ρ_{WL}, modulus E_{WL}, strength σ_c, and fracture energy w_{fSMP} (Reuter et al., 2019). The PST's were filmed and with PTV analysis from the videos the following properties were extracted: critical cut length a_c, slab modulus E^*, and specific fracture energy of the weak layer w_{fPST} (van Herwijnen et al., 2016).

Table 1: Field data

Date	Days since burial	Slab thickness (m)	Slab density (kg m^{-3})	Shear strength ± SE (Pa)	Stability test results	
					Compression test	Extended column test
6 Jan 2016	6	0.23	159	731±54	CT17 SC	ECT18/np
15 Jan 2016	15	0.56	130	894±64	NA	ECT15/15
22 Jan 2016	22	0.75	237	1173±76	CT11 SC	ECT11/11
29 Jan 2016	29	0.62	281	1302±75	CT11 SC	ECT11/11
4 Feb 2016	35	0.92	259	1320±55	CT13 SC	ECT21/21
9 Feb 2016	40	0.88	287	1500±49	CT21 SC	ECT21/21
18 Feb 2016	49	0.83	311	1654±89	CT15 SC	ECT27/27
26 Feb 2016	57	1.15	311	1556±64	CT14 SC	ECT21/21
10 Mar 2016	70	1.31	308	1768±113	CT23 SC	ECT29/29

Toughness was approximated from weak layer fracture energy w_{fPST} and modulus E_{WL}:

$$K_c = \sqrt{\frac{E_{\mathrm{WL}}\, w_{\mathrm{fPST}}}{1-\nu^2}} \quad \text{with } \nu = 0.25.$$

Apart from the persistent weak layer monitored in detail, four additional persistent weak layers were manually identified in simulated stratigraphy (Table 2; Figure 1).

Table 2: Persistent weak layers present at the Steintälli field site in Winter 2015/16. PWL 2-5 characterized as simulated by SNOWPACK. Slab thickness *H* at 10 March 2016.

PWL number	Burial date	Grain type, size (mm)	*H* (m)
1	31 Dec	DH, 2-4 (1.9)	1.31
2	7 Jan	DH, 1.6	NA
3	29 Jan	FC, 1.4	0.89
4	10 Feb	DH, 1.6	0.58
5	1 Mar	FC, 1.3	0.38

2.2 Snow cover simulation

At the AWS Steintälli, the short- and longwave incoming and outgoing radiation are measured, in addition to snow depth, air and snow surface temperature, relative humidity, wind speed and direction. Therefore, we ran the numerical snow cover model SNOWPACK (Version 3.0.0) using all these measurements. The resulting snow cover evolution is shown in Figure 1.

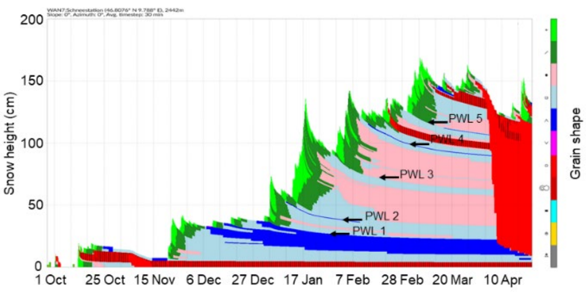

Figure 1: Snow cover evolution at AWS Steintälli during winter 2015/16 as simulated with SNOWPACK. Colours refer to grain types. Arrows point to the five manually identified persistent weak layers (PWL). PWL 1 is the layer we specifically tracked in the field from January to March 2016.

2.3 Stability modeling

Based on the manual measurements, we calculated the skier stability SK38 based on shear strength, slab density and the additional skier stress $\Delta\tau = 155/H$ accounting for skier penetration but not slab layering (Jamieson and Johnston, 1998; Monti et al., 2016). From the SNOWPACK simulations, we extracted for each layer once a day at 11:00 LT (local time) the RTA, the skier stability index sk38, the critical crack length r_c, and the stability metric P_{unstable}. As for the skier stability index SK38 calculated from the field measurements, we did not consider slab layering in modeled sk38. For the critical cut length, we considered the parameterization suggested by Richter et al. (2019). For the probability of instability P_{unstable} we extracted the maximum value and the depth where it was maximal. In addition, potential weak layers were identified with an algorithm described by Reuter et al. (2022), where the layers are tracked from their burial date on. From the potential weak layers identified by the algorithm, we only considered persistent avalanche problems (pAp) and used the weak layer depth of these problems. We then analyzed sk38 and r_c for the depth of the most relevant critical weak layer. To rate stability (stable vs. unstable), we considered the following thresholds: RTA > 0.8, sk38 < 1, r_c < 0.3 m, and $P_{\mathrm{unstable}} > 0.77$ (Mayer et al., 2022; Monti and Schweizer, 2013; Reuter et al., 2022).

3. RESULTS

3.1 Field measurements

The manual measurements of weak layer density, shear strength and the thereof derived skier stability index show in general the same increasing trend with time as the corresponding modeled SNOWPACK parameters (Fig. 2). Modeled strength, which is parameterized from density, increased more prominently than the manually measured strength. The modeled strength was lower initially and higher at the end of the observation period than the values measured with the shear frame. Accordingly, the modeled skier stability index was also lower initially and higher after mid-February than the stability index calculated from the measurements. The critical cut length increased, in general; the values modeled, however, increased too strongly compared to the measurements, which varied between 20 and 35 cm. The stability tests (CT/ECT) confirmed the increasing trend of stability; failure initiation became increasingly harder, while crack propagation remained possible. On the last field day, 70 days after burial, the critical crack length was still only 32 cm ± 9.8 cm and the crack propagated to the very end. On the other hand, weak layer specific fracture energy and toughness increased in line with the load on the weak layer and shear strength (Fig. 3). These mechanical properties were correlated with load ($r_P \gtrsim 0.7$, $p < 0.01$). Given the overall rather satisfactory agreement between measurements and model results, we will in the following compare the various modeled instability metrics.

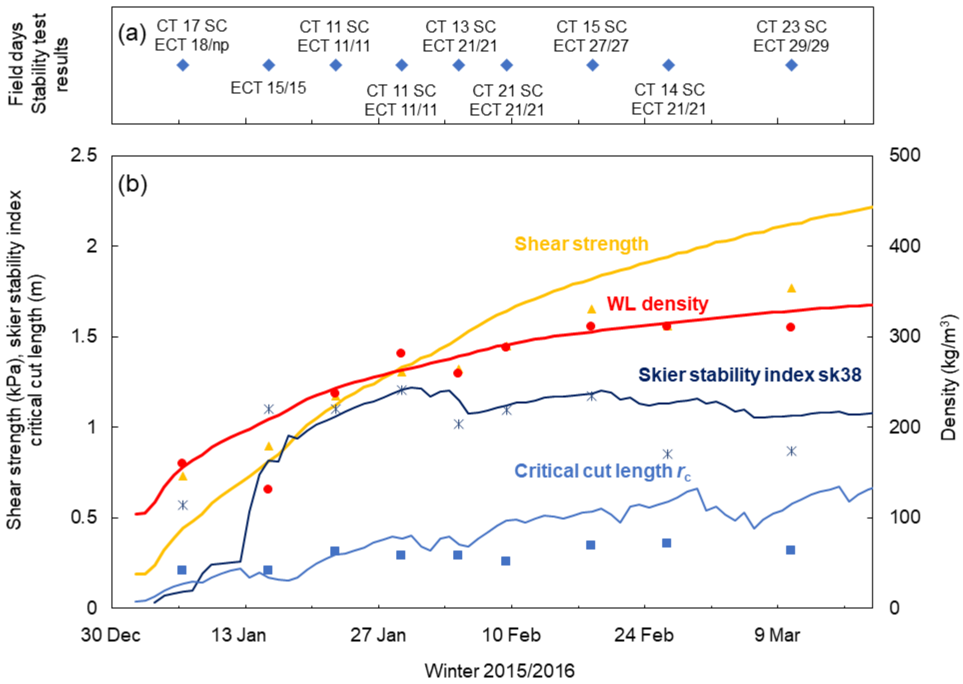

Figure 2: Field measurements and model results for the persistent weak layer buried on 31 December 2015 (PWL 1). (a) Results of stability tests (CT, ECT) on the 9 measurement days. (b) Comparison of measurements and model results for: weak layer density, shear strength, skier stability index and critical cut length. Continuous lines show SNOWPACK parameters, symbols (of the same color) the measurements.

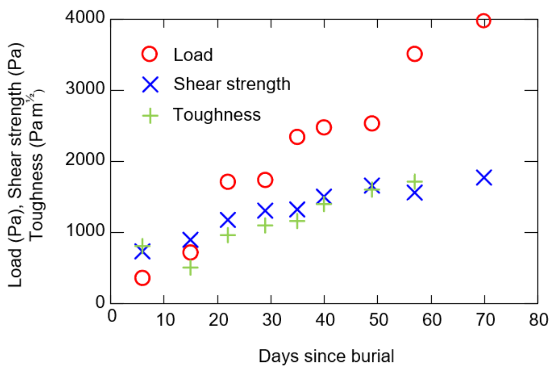

Figure 3: Load, shear strength and fracture toughness for PWL 1 buried on 31 December 2015.

3.2 Stability modeling

Assessing snow instability requires determining the most relevant critical weak layer, i.e. we only considered one weak layer per profile (or date). While performing stability tests in the field, the weak layer shows up automatically. In snow cover simulations, in contrast, weak layer detection is the first step in stability assessment. Figure 4 shows weak layer identification by $P_{unstable}$, RTA, and pAp, i.e. the weak layer tracking algorithm by Reuter et al. (2022) for persistent avalanche problems. For $P_{unstable}$, the most critical weakness is where $P_{unstable}$ is at its maximum. For RTA, we considered all layers with RTA > 0.8 and thereof selected the layer with the lowest value of sk38 (which we termed the most relevant critical weak layer). Similarly, for pAp, we also considered the persistent weak layer where sk38 was minimal.

With the $P_{unstable}$, and RTA methods, the automatically identified weak layer depth coincided at most times with the depth of one of the five manually identified PWLs. Until 1 February, $P_{unstable}$ suggested the depth of the most critical weak layer to be a few centimeters below PWL 1, then it jumped between PWL 1 and PWL 3, and subsequently PWL 4. As of 20 February, it consistently stayed at PWL 4, and finally at PWL 5 (after 7 March). On the other hand, RTA initially suggested the depth of the most critical weak layer to be below PWL 1, above the crust that had formed very early in the winter (Fig. 1).

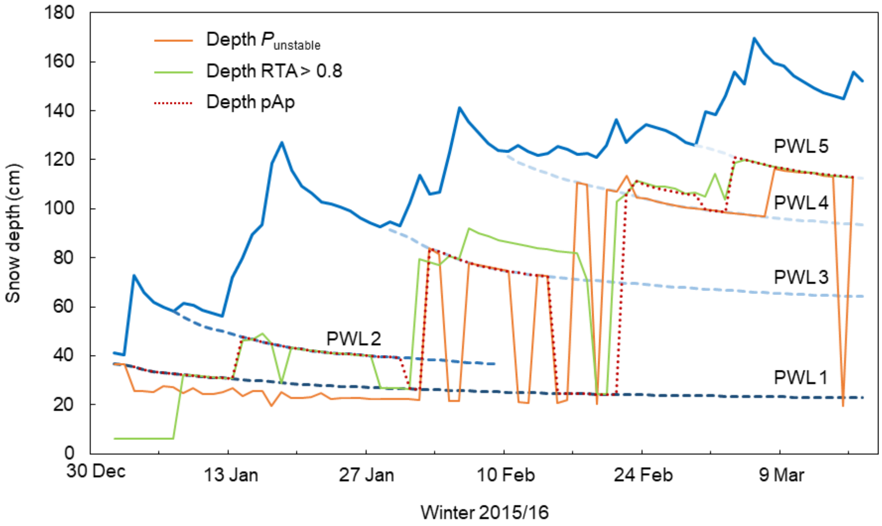

Figure 4: Snow depth and depth of the five manually identified persistent weak layers (PWL 1-5) in winter 2015/16 at Steintälli, and depth of most relevant critical weak layer as identified by the maximum value of P_{unstable}, RTA > 0.8 and min(sk38), and the weak layer tracking algorithm pAp and min(sk38).

By 8 January, the depth coincided with PWL 1 for 6 days, and then until the end of January fluctuated between PWL 1 and 2. Subsequently, until mid of February the suggested depth was either below or above PWL 3, and as of 21 February, it was near PWL 4, until it finally (by 5 March) jumped to PWL 5. With the weak layer tracking approach to identify persistent avalanche problems pAp, the suggested weak layer depth almost always coincided with one of the five manually identified PWL's and there were less jumps between layers. The depth followed initially PWL 1, moved up to PWL 2 when a suitable slab existed. By 31 December the next weak layer, PWL 3, was identified but only two days later a "healthy" slab existed. During these two days, the most relevant critical weak layer became PWL 1 again, as sk38 at the depth of PWL 1 was lower than of PWL 2. Subsequently, for the next weeks, the most relevant critical weak layer became PWL 3, and then, the above described pattern repeated until there was a "healthy" slab above PWL 4. All three methods indicated an additional PWL between layers 4 and 5, which was buried on 20 February. It was, however, not very prominent and consisted of small facets below a crust. Still, it was also found in the field on 26 February by the stability tests, but not subsequently on 10 March 2015.

Finally, we considered the numerically modelled stability metrics for the most relevant critical weak layers indicated by the different models, as shown in Figure 4. For P_{unstable}, the stability is simply the value of P_{unstable} at that particular depth, for RTA > 0.8 and pAp, it is the minimum value of sk38 as provided by SNOWPACK. For pAp, the skier stability index and the critical cut length are shown since both metrics are relevant for stability assessment.

Figure 5 shows the temporal evolution of the various stability metrics and indicates the periods where they were in the unstable range (P_{unstable} > 0.77, sk38 < 1, r_c < 0.3). Given the various PWL's in winter 2015/16, the numerically modeled stability metrics suggested long periods of instability, also reflected in the forecast avalanche danger level (Fig. 5e), with overall similar trends for the three approaches. In mid-January, early February and early March the periods of instability coincided. In between, all metrics indicated periods with somewhat higher stability, expect for the critical cut length which stayed low in mid-February. However, the time of transition between stable and unstable often differed. All modelled metrics indicated increasing stability when the highest avalanche activity was observed on 9 February 2016. However, this was a particular event with rain up to 2400 m a.s.l. so that the AAI included various types of avalanches, not only those running on PWLs. On the other hand, the activity on 1 February was well anticipated by all metrics. The probability of instability P_{unstable} often increased the earliest, while sk38 lagged slightly behind since the slab was still thin and soft, for instance, on 31 January 2016.

4. SUMMARY

We followed snow stability at the AWS Steintälli from January to March 2016. By combining field measurements and numerical modeling we gained insight into the performance of three numerical stability approaches.

The field measurements for a particular persistent weak layer revealed that the numerical modeling of snow stratigraphy and mechanical properties agreed satisfactorily overall. Weak layer shear strength as measured with the shear frame as well as specific fracture energy increased with time, in line with the increase in load. Similar trends were previously observed (e.g., Chalmers and Jamieson, 2001; Schweizer et al., 2016). While during PST experiments, cracks still propagated to the very end, failure initiation in the deeply buried PWL became increasingly less likely, as exemplified in mid-February. While the specific fracture energy of the weak layer increased, in line with increasing load, the increase in load caused the crack propagation propensity, assessed as critical crack length, to remain rather high.

The modelled stability metrics often indicated similar behavior, in terms of weak layer depth as well as stability. All three approaches most of the time followed the five manually identified persistent weak layers, with the weak layer tracking algorithm by Reuter et al. (2022) showing closest agreement. Based on this analysis and the previous ones (Reuter et al., 2022), we conclude that the relevant layers for dry-snow instabilities can be automatically identified in simulated snow stratigraphy.

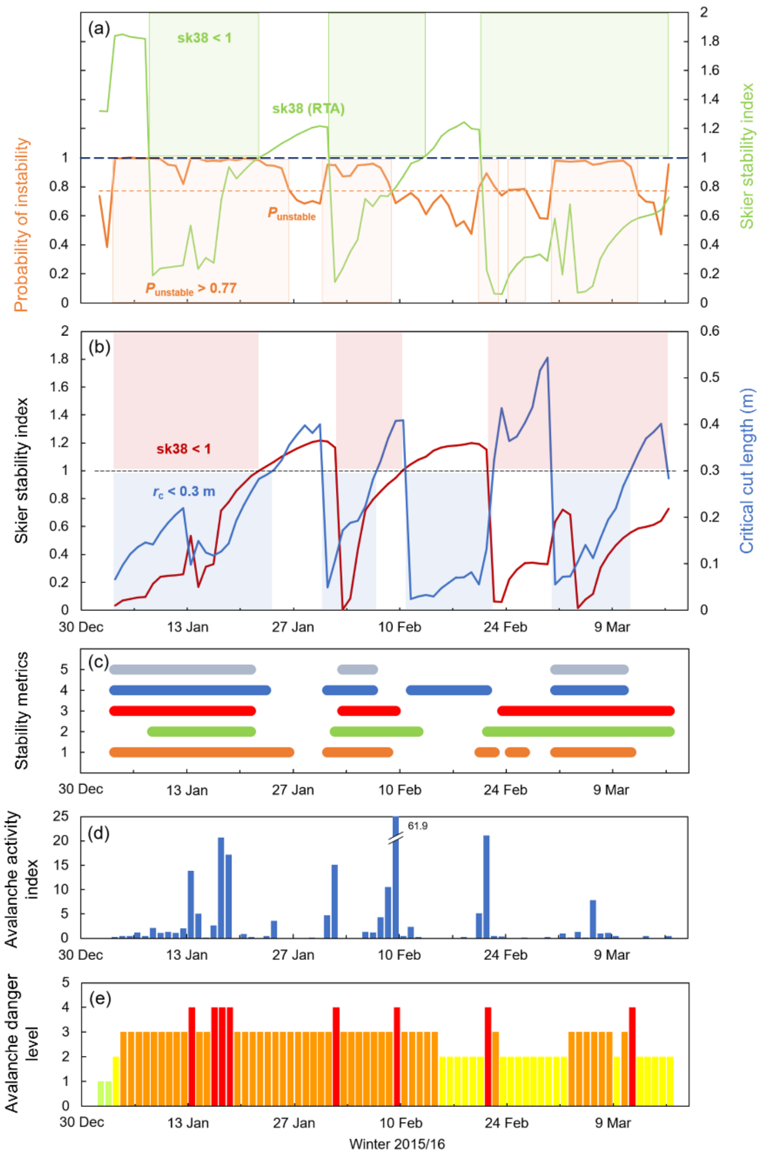

Figure 5: Modelled stability metrics as provided by (a) the probability of instability $P_{unstable}$ and the skier stability index sk38 as identified with RTA, and (b) skier stability index and critical cut length as identified with pAp layer tracking. The light shaded areas indicate the periods of instability; for pAp those can be further restricted to the times when both metrics indicated instability. (c) Summary of times of instability according to the stability metrics (1) $P_{unstable}$, (2) RTA-sk38, (3) pAp-sk38, (4) pAp-r_c, and (5) pAp-sk38∩r_c. (d) Avalanche activity index (AAI) as observed in the region of Davos; the index is a weighted sum including all types of avalanches recorded (Schweizer et al., 2003). (e) Avalanche danger level as forecast for the region of Davos.

In the present analysis we only considered one weak layer, the most prominent. Especially the RTA-sk38 approach is actually meant to identify all potentially unstable weak layers (RTA > 0.8) within a simulated snow profile not only the one showing the lowest value of sk38 as done in the present analysis for allowing straight forward comparisons between the different approaches. With this being considered, the weak layer detection would obviously improve (Fig. 6).

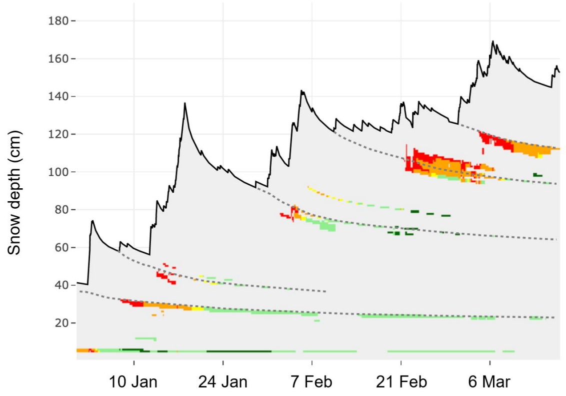

Figure 6: Skier stability index sk38 (colors) for all layers with RTA > 0.8. (red: $0 < sk38 \le 0.5$, orange: $0.5 < sk38 \le 0.95$, yellow: $0.95 < sk38 \le 1.05$, light-green: $1.05 < sk38 \le 1.5$, dark-green: $sk38 > 1.5$).

With regard to stability, differences between the three approaches were not particularly prominent. On about half of the days the stability class (stable/unstable) agreed, and the trends were similar, for instance, when P_{unstable} decreased, sk38 increased. Interestingly, P_{unstable} was negatively weakly correlated ($p < 0.01$) with pAp-sk38 and pAp-r_c, the stability metrics from the avalanche problem detection.

For the one winter season, we considered in our study, when the snowpack included several persistent weak layers, we did not observe that process-based approaches such as the skier stability index performed much worse than the ML approach. Some recent studies employing the random forest method with many different snowpack variables resulted in somewhat contradictory findings on the value of traditional stability parameters (Mayer et al., 2022; Pérez-Guillén et al., 2022; Viallon-Galinier et al., 2023). However, we certainly only followed one winter season at a specific location whereas the numerical models include data from many winters and locations. Still, it might be instructive when validating the output of ML models to look at the various stability metrics for several relevant weak layers, and their temporal evolution. In conclusion, our detailed analyses suggest that ML-based as well as process-based methods are useful to estimate stability and the depth of the most relevant critical weak layer, equivalent to fracture depth, and thus relevant for avalanche size.

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