Discussion of "A data exploration tool for averaging and accessing large data sets of snow stratigraphy profiles useful for avalanche forecasting"

Author response 2

Herla et al.

June 25, 2022

Dear editor, dear referees,

We thank both referees, Frank Techel and Christoph Mitterer, for their supportive reviews, their thoughtful suggestions and their constructive feedback that helped us improve the manuscript considerably. This document provides the changes we have made to the manuscript prompted by the reviewers' comments and suggestions.

We thank the editor for changing our manuscript type from "Brief Communication" to "Research Article". This gave us the necessary space to adequately address the referees' comments.

In the following, we highlight in a point-by-point manner how we addressed the referee's suggestions. Given page and line numbers refer to the track-changes document of our revised manuscript. In addition to the changes emphasized in this Author Response, we also edited the entire manuscript in detail to improve clarity and readability.

Responses to Referee #1 (Frank Techel)

1.1 General Comment

Referee Comment: *Dear editor, dear authors, the manuscript by Herla et al. introduces a novel method that allows the synthesis of a large number of simulated snow cover simulations resulting in an average profile, which can further be queried if an in-depth analysis is of interest to the user. The proposed method builds upon and expands previous research in this direction. Furthermore, the presented algorithm provides a solution to facilitate the interpretation of snow cover simulations for regional avalanche forecasting.*

The manuscript is well written, concise, but still easy to follow. The figures are of high quality, supporting the understanding of the described workflow (Fig. 1) and the visualizations obtained with the algorithm (Fig. 2 and 3).

Author Comment: Thank you for your positive and encouraging feedback! We value and appreciate your suggestions and respond to them in a point-by-point manner below.

1.2 Elaborate on testing of algorithm

Referee Comment: *On l. 104, the authors state that their testing has shown that the rules applied for initiating the algorithm consistently produced reasonable results. While the described rules (l87-95) do indeed sound plausible, no further detail regarding the testing is provided. - Please elaborate on this testing. For instance, provide a reference if the tests you have made are described elsewhere. What do you mean when you say that "reasonable" average snow profiles are produced? Does reasonable mean that you compared these profiles with observations or is this based on feedback from avalanche forecasters?*

Author Response: In the revised manuscript, we elaborate on the testing of the algorithm by adding the new Section 4.1, *Comparison against medoid approach* (P13 L270):

> "To quantitatively estimate the performance of the averaging algorithm given the presented data set, we compared the aggregated snow profiles from three different approaches by their root mean squared errors (RMSE):
>
> 1. the medoid approach, which identifies the one profile from the profile set that is most similar to all other profiles (Herla et al. 2021),
> 2. the default averaging approach described in Sect. 2 and 3.1,
> 3. the timeseries averaging approach described in Sect. 3.2,
>
> We performed this quantitative comparison of methods for every 7th day of the season. The RMSE were computed analogously as described in Sect. 2.
>
> Since the medoid approach follows a simple and transparent concept that has been shown to perform as well or better than more sophisticated sequence aggregation methods (Paparrizos and Gravano 2015), it represents a meaningful benchmark. However, the medoid calculations for the 32 days took 28 hours, while the averaging calculations took less than 30 minutes. Despite this immense difference in computational cost, both averaging approaches yielded similar RMSE compared to the medoid approach (Fig. 6). This result suggests that the performance of the aggregation is more influenced by the specifics of the profile set than the peculiarities of the aggregation algorithm. The averaging algorithm presented in this paper therefore performs at least equally well at a much lower computational cost and comes with considerable additional benefits, such as the capabilities of retrieving underlying distributions and producing consistent time series."

Furthermore, we added the following new paragraph (P15 L322):

> "While we have not examined the performance of the algorithm in operational avalanche forecasting explicitly, extensive testing by the research team during the development and informal explorations by Avalanche Canada forecasters have shown that the presented DBA approach creates representative snow profiles that summarize the most important snowpack features and highlight the existence of prevalent weak layers and slabs in a meaningful way. However, further explorations are required to better understand the full operational value of our algorithm."

1.3 Capabilities of the algorithm during wet snow conditions and melting

Referee Comment: *Section 3.2 and Figure 3 show an example of an average snow profile over the course of a season. This example is helpful as it nicely illustrates the potential of the presented algorithm for the analysis of snow-cover simulations at a regional scale. However, from the perspective of a potential user of this algorithm, it would be useful if you could address the following* *two points: (1) In this example, the early part of the season is presented, but the melting season is missing. This makes me wonder whether the algorithm works equally well in spring when the snowpack height and the number of simulated layers decrease with increasing wetting. As the first wetting of the snowpack is highly relevant for forecasting wet-snow avalanches, snowpack characteristics like the advance of the wetting front are very important pieces of information (e.g. Wever et al., 2018). - I suggest expanding the average profile shown in Figure 3 well into spring; or, in case the algorithm is less reliable during the melting period, to mention this limitation.*

Author Response: Thank you very much for bringing this up! We added the new Section 3.3, *Performance of the algorithm during melt season conditions in spring* (P11 L245):

> "Physically-based snowpack models are also useful for assessing wet snow avalanche conditions by predicting the depth and the timing of layers accumulating liquid water in the snowpack (Wever et al. 2018). Wever et al. (2018) demonstrate that physically-based snowpack models are capable of simulating the timing of the so-called wetting front within an accuracy of ± 1 day. They also show that the modeled depth of their wetting front correlates well with observed avalanche sizes. While their approach appears promising, its operational application is currently limited to few model grid points because of the lack of spatiotemporal presentation methods that can display this type of complex information effectively. As a consequence, existing operational products for wet snow avalanches are currently limited to bulk indices that represent conditions averaged over the entire snow column (Mitterer et al. 2013; Bellaire et al. 2017; Morin et al. 2020). Hence, wet avalanche forecasting could benefit substantially from data synthesis methods that allow efficient monitoring of the wetting front within regional scale data sets of simulated snow profiles.
>
> To demonstrate the capabilities of our averaging algorithm in supporting wetting and melting conditions, we extracted a set of 46 lower elevation grid points from our data set of simulated snow profiles. The snowpack at all of these grid points became isothermal before the end of April (Fig. 5d–f show the individual grid points at March 23, March 25, and April 20, respectively). Similarly to the performance of the algorithm with mid-season profiles, the average time series precisely follows the median snow height during melting of the snowpack (Fig. 5c). Furthermore, the averaged profile allows for the monitoring of the median depth of the wetting front as it penetrates into the snowpack (Fig. 5c). In our example, all grid points were entirely sub-freezing and dry before March 23, when warmer air masses (Fig. 5a), cloud cover, and small amounts of liquid precipitation (Fig. 5b) led to the first wetting of the snow surface (Fig. 5c, e). In the consecutive month, the median depth of the wetting front remained constant at roughly 30 cm. A slightly more pronounced rain event on April 19 led to most grid points becoming entirely isothermal (with a frozen surface crust) (Fig. 5c, f). In addition to providing information on the location of the wetting front, distributions or summary statistics of the liquid water content could easily be computed for each averaged layer similarly to extracting or visualizing distributions or summary statistics of the stability of each averaged layer (not shown).
>
> Similarly to extracting or visualizing distributions or summary statistics of the stability of each averaged layer, distributions or summary statistics of the liquid water content could easily be computed for each averaged layer (not shown)."

1.4 Include summary of observed weak layers

Referee Comment: *(2) I personally would have greatly appreciated if this example would have been supported with the (observed) weak layer summary in the region. From what I remember,* *the main author presented such a comparison at a conference last year (Herla et al., 2021), showing that the average profile captures most of the weak layers tracked by the field observers. While not a full validation, this would help the reader to understand that the average snow profile, synthesizing snowpack simulations driven with an NWP model, captures the most important snowpack features in the region.*

Author Response: We agree with the referee and added observed weak layers in Fig. 4 of the revised manuscript. We also added the following new paragraph (P9 L229):

> "Avalanche forecasters in Canada routinely label weak layers that likely remain hazardous for multiple storm periods with date tags to facilitate effective communication and tracking. Hence, the resulting list of persistent weak layers represents those layers that the forecasters were most concerned about and that also likely caused avalanches. While a full and detailed validation of our model chain is beyond the scope of this paper (Herla et al., in prep.), the visual comparison of the tracked weak layers and the time series of the average profile presented in Fig. 4 demonstrates that the regionally synthesized snowpack simulations reliably captures the most relevant snowpack features in the region. In an operational context, this visual comparison of simulated and observed weak layer summaries can provide a real-time validation perspective that very efficiently communicates potential discrepancies between modeled weak layers and reality. This allows forecasters to quickly assess when the simulations require cautious interpretation or whether more observations are necessary to verify a yet unobserved weak layer."

Responses to Referee #2 (Christoph Mitterer)

2.1 General Comment

Referee Comment: *Dear editor, dear authors, the presented brief communication by Florian Herla and collegues describes the use of a specific averaging technique, the Dynamic Time Warping Barycenter Averaging (DBA) in the field of Dynamic Time Warping (DTW) with pure focus on analysing modelled snow stratigraphy. While the appraoch and methods are not novel, it is the first time that these set of methods was applied to modelled snow stratigraphy and to the field of avalanche forecasting. Large parts of the devleopped DTW method for modelled snow stratigraphy were presented in an earlier manuscript by Herla et al (2021). The focus and added value on the presented manuscript compared to the already published content by Herla et al (2021) is on (1) the newly added averaging technique DBA (section 2), (2) some added features on the layer matching appraoch (lines 73-79) and (3) two newly presented sets of figures (Fig. 2 and 3) for better communicating the obtained results.*

The text is well written and most of the prestented Figures are clear, easy to understand and enjoyable. Sometimes explanations are a bit to short and due to the nature of a brief communication explanations are sometimes not easy to grasp for an uniformed reader. In addiation, I would suggest improving Figure 1.

Even though parts of the content were already described in Herla et al (2021), I like the idea of this brief communication since the authors focus more on the quality of the results while within the other publication the architecture of the algorithm covered most parts of the reading. Nevertheless, I would expect a little more quantitative presentation on some of the descriptions, which leads me to my four general comments that may improve the quality of the manuscript: [continued below]

Author Comment: Thank you for your encouraging review and your thoughts on improving the manuscript, we much appreciate it. Since changing of the manuscript type allowed us to elaborate more, we added more detail and context at several locations throughout the manuscript. Thank you for bringing this up!

2.2 Improve Figure 1

Referee Comment: *As stated, Figure 1 is a bit confusing and hard to understand. Could you maybe use less profiles in between and describe the workflow a bit more in detail within the graph. In addition, add some more description within the caption.*

Author Response: Yes, we removed some profiles to make Fig. 1 less overwhelming, and we changed the caption of the figure to include the workflow of the algorithm.

2.3 Elaborate on influence of initial conditions

Referee Comment: *You state that for the DBA it is essential to start the interation by choosing initial condition profiles strategically (line 89). How influential is that condition of the initial profile? Or with other words, if I miss to chose my starting position carefully, does the algorithm support me and is able to find weak layers that I just missed when picking the starting conditions. Can you quantify that by adding some noise to your initial profile?*

Author Response: We added more details on how our algorithm automatically picks strategically meaningful initial conditions (P3 L109):

> "Since it is important that relevant thin weak layers are represented in the average profile, we designed the following selection routine for initial conditions. The

profiles-to-be-averaged are organized into several tiers based on the total number of layers of interest and the number of depth ranges [1] occupied by at least one layer of interest. Tier 1 contains all profiles with the maximum total number of layers of interest and the maximum number of occupied depth ranges. Tier 2 consist of the remaining profiles with the maximum number of occupied depth ranges and an above-average number of layers of interest, and tier 3 includes all remaining profiles with fewer occupied depth ranges but still an above-average number of layers of interest. Depending on how many initial conditions are requested by the user, the algorithm picks profiles from the three tiers in descending order. [...]"

Furthermore, we added the new Section 4.2, *Impacts of the data set and the initial condition on the resulting average profile* (P13 L287):

> "The initial condition profile can have substantial influence on the resulting average profile. It is not uncommon that a weak layer that exists in the majority of profiles is not captured in the final average profile if it is not already included in the initial condition profile. It is therefore crucial to select the initial condition profile with care, and to re-run the algorithm for several different initial conditions as detailed in Sect. 2.
>
> If a prevalent weak layer is not included in the initial condition profile, the odds that the layer will be present in the final average profile depend on the following factors:
>
> - the *prevalence* of the layer in the profile set: the more profiles contain the layer, the more likely it will be included in the final result, because more opportunities exist that the layer is aligned onto the same reference layer.
> - the *thickness* of the layer: the thicker the layer, the more likely it will be present in the final result, because it increases the chances of the layer to be aligned. However, this factor is often not relevant, because most weak layers are thin.
> - the *distinctness* of adjacent layers in the profiles: the more distinct or specific the adjacent layers of the weak layer, the more likely it is that it will be in the final result. This is caused by the underlying snow profile alignment algorithm (Herla et al. 2021) that focuses on matching entire layer sequences and not only individual layers. Distinct layer sequences adjacent to weak layers can therefore be thought of as anchor points during layer matching that tremendously increase the odds that an entire group of layers is matched correctly and thus included in the average profile.
>
> While the prevalence of a layer and the characteristics of the adjacent layers are attributes of the data set, the initial condition is the only factor that can be tuned. Since our algorithm automatically picks (multiple) suitable initial conditions by default (see Sect. 2), it is very unlikely that only unsuitable starting conditions are chosen accidentally. However, Fig. 7 explicitly illustrates the effect of the initial condition profile to provide more information on the intricacies of our algorithm.
>
> A scarcely distributed surface hoar layer that is included in 40 % of grid points can be found roughly 20 cm below the new snow within a thick sequence of unspecific bulk layers (Fig. 7a—the layer is emphasized in all panels by slightly more salient and black color). The occurrence frequency threshold to include weak layers in the average profile is set to 30 % in this example. Five out of six initial condition profiles that include that layer (Fig. 7b) lead to average profiles that also contain that layer (Fig. 7c), even though the three influencing factors are all adverse: the layer's

[1] The default depth ranges are [0, 30), [30, 80), [80, 150), [150, Inf) (cm), but can be modified by the user if necessary.

prevalence is low (it only exists in a few more profiles than the minimum threshold), it is very thin, and the bulk layer sequences around the weak layer are not distinct and can be found in many other locations of the profiles as well. Panels d and e of Fig. 7 further illustrate the importance of the presence of the layer of interest in the initial condition profile because all of the average profiles that were initialized with profiles that lacked the surface hoar layer (Fig. 7d) did not include the layer as well. If, however, the surface hoar is adjacent to a distinct crust (Fig. 7f), the resulting average profiles do contain both the crust and surface hoar layer (Fig. 7g) even if they are not present in the initial condition profile. This experiment demonstrates that the odds of a specific layer being present in the final result depend on the interplay of the presented factors and that our routine for the strategic selection of initial conditions is a capable way for employing the algorithm to our best benefit."

2.4 Elaborate on testing of algorithm

Referee Comment: *Related to that are your statements on the testing. I would like to see some more quantitative results and more in-depth description on how you did that. Reading phrases like (...)consistently produce reasonable average snow profiles suitable for avalanche forecasting. (Line 105), are with low support and not helpful for the interested reader or an avalanche forecaster that wants to apply your findings. In addition, I would be curious what you think is suitable for avalanche forecasting and what is not ;-).*

Author Response: This has been answered in detail in Author Comment 1.2.

2.5 Include better stability index

Referee Comment: *I like Fig. 2 very much. It will be very helpful in daily routines of avalanche forecasting centers. However, I have some issues with how the content of Fig. 2b was produced. You basically applied the approach by Schweizer and Jamieson (2007) which turned out to be inpropriate or at least less helpful when applied to simulated snow cover data (Monti and Schweizer, 2013). Main reason for that is the fact that the thresholds by Schweizer and Jamieson (2007) were obtained with statistics based on observed snow stratigraphy parameters which may differ compared to simulated ones (especially grain size). That's why Monti and Schweizer (2013) introduced the relative threshold sum appraoch and I would love to see if there are particular differences for the presented example. In fact, I would expect, e.g. the facets below the thick layer of RGs (I assume this to be the slab) to give more indication towards instability. This in turn would give you the option to included FCs as weak layers as well. At the moment the representation of Fig. 2b is heavily driven by grain size only, since the used underlaying snow cover model classifies the weak layer DH and SH mainly based on their size.*

Author Response: It is very encouraging to hear that you think our approach of making underlying distributions in the data set accessible will be helpful for operational avalanche forecasting. With regards to the threshold sum approach (TSA) by Schweizer and Jamieson (2007), we agree with you in that it is not a state-of-the-art stability index for simulated profiles. It is, however, a conceptually straightforward approach that is very tangible to many practitioners due to its application in the field. Since our figure aims at presenting the general capabilities of our algorithm, we believe it is most valuable to keep the complexity of the presented stability assessment low at this point in the paper. To address your suggestion of comparing the presented TSA approach to more sophisticated stability indices, we follow up our general overview figure with Fig. 3. This new figure highlights very strongly that our approach of making underlying distributions of the data set accessible is not confined to a single and particular property, but can be applied to any available variable in the user's data set. We also added the following new paragraph to describe the new figure (P6 L183):

> "To illustrate the value of our summary perspective on large volumes of snowpack simulations for avalanche research beyond operational avalanche forecasting, Fig. 3 demonstrates how our approach can be used to systematically compare different stability indices that have been used for characterizing instability in simulated profiles. Panels a–e in Fig. 3 visualize the stability distribution of each layer analogously to Panel b in Fig. 2 for the relative threshold sum approach RTA (Monti and Schweizer 2013), the multi-layered skier stability index SK38ML (Monti et al. 2016), the joint RTA and SK38ML approach (Monti et al. 2014; Morin et al. 2020), the critical crack length (RC) (Richter et al. 2019), and the most recent random forest classifier p_unstable (PU) (Mayer et al. 2022). We classified each stability index into categories, such as *very poor, poor, fair, good*, based on thresholds published in the respective papers. For the two approaches that include SK38ML, we use the most recent thresholds published in Fig. 5 of Morin et al. (2020). Since Richter et al. (2019) derived no thresholds for RC values that correspond to layers with poor stability, we use a threshold for the class *very poor* derived from an unpublished analysis by Mayer et al. (2022) and a threshold for the class *poor* that has been derived from manual observations of critical cracks lengths in unstable layers (Reuter et al. 2015). Not surprisingly, the two related indices TSA (Fig. 2b) and RTA (Fig. 3a) that use purely structural considerations show a very similar pattern. The SK38ML shows a similar pattern to RC, which changes entirely when combined with RTA: potentially unstable weak layers are selected with RTA and then evaluated with SK38ML (Monti et al. 2014; Morin et al. 2020). Since RC is one of the input variables to PU, both are generally similar to each other, while PU substantially reduces the layers with poor stability. Instead of comparing these indices for one simulated profile, our approach allows for valuable large-scale comparisons based on many profiles, which were previously inaccessible."

Furthermore, we added Panel b to Fig. 4, which visualizes the proportion of grid points that promote poor layer stability in the time series of the average profile, and added the following new paragraph (P9 L239):

> "In addition to understanding the evolution of the predominant snowpack features, it is equally important for forecasters to understand the evolution of the *stability* of these snowpack features. As discussed earlier, the average profile stores information about underlying distributions in the profile set, which allows us to visualize the proportion of grid points with poor stability for each layer in the time series of the average profile (Fig. 4b). This visualization takes the concept from Fig. 3e to a temporal context and makes it effortless for users to understand temporal trends in the layerwise stability predictions of *all* profiles within the entire data set within a single, very familiar visualization.

2.6 Details of snowpack model

Referee Comment: *Can you please give some more insights of the model behind the modelled snow stratigraphy data? Are you using SNOWPACK or Crocus?*

Author Response: We use a weather and snowpack model chain. Our weather model HRDPS (Milbrandt et al. 2016) has a 2.5 km resolution and provides the meteorological forcing for the model SNOWPACK (Bartelt et al. 2002; Lehning et al. 2002b,a).

We added the following new paragraph (P4 L140):

”In this section we present several application examples to illustrate the capabilities of our algorithm. While the snow profile data set used in these examples was simulated with the Canadian weather and snowpack model chain (Morin et al. 2020), our tool can be applied to any simulated snow profile irrespective of its source model. Furthermore, it is possible to use our algorithm on manual profiles, but the processing of these data sets has some unique challenges (see limitation section for more details).“

2.7 Clarify capabilities in wet snow conditions

Referee Comment: *The algorithm seems to work dry snow conditions only? Can you comment on that?*

Author Response: No, it works equally well for wet snow and melting conditions in spring, see our comment 1.3 and the newly added Fig. 5.

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