Author responses for EGUSPHERE-2025-3610

Title: Can streamflow observations constrain snow mass reconstructions? Lessons from two synthetic numerical experiments

Authors: Pau Wiersma, Jan Magunosson, Nadav Pegel, Bettina Schaefli, Gregoire Mariethoz

The authors thank both reviewers for their constructive and useful reviews. We have responded to their comments to the best of our ability. Below is a list summarizing the changes made, along with point-by-point responses in red.

- Reinforced the literature on recurring spatial SWE patterns and emphasized their high potential in streamflow-informed SWE reconstructions in the Discussion
- Rewrote parts of the Introduction to clarify the scope of the study
- Rewrote both Results and Discussion section to make the text more concise and synthetic
- Clarified several points in the snow model section (2.2.1), and added equations explaining both snowfall and temperature threshold lapse rates
- Changed the parameter names and the formatting of variable names throughout the manuscript
- Responded to the reviewers' minor comments
- Improved wording in several instances throughout the manuscript
- Updated Fig. 2 with a map of Switerland and the location of the Dischma catchment, and Fig. 3 which contained additional data not belonging to the posterior in the original manuscript

Author response to RC1

We thank Joschka Geissler for the constructive feedback and appreciation of our work, and for taking the time to review our paper.

Summary:

The submitted manuscript investigates how streamflow observations can help reconstruct historical snow mass. Therefore, the authors formulate the problem as a Bayesian inversion (i.e. estimating the posterior distribution of SWE given streamflow observations). Two complementary numerical experiments are conducted: a fully synthetic (FS) case, in which the reference SWE is generated by the same model used in the ensemble, and a semi-synthetic (SS) case, where the reference SWE is taken from OSHD data. While the selection of the posterior ensemble was carried out using NSE between observed and modelled streamflow, the evaluation of how well the selected posterior SWE maps match with the SWEprior is performed using grid-based and catchment-aggregated snow metrics. The results demonstrate that streamflow does contain meaningful information about seasonal snow dynamics, can narrow the range of plausible SWE scenarios, and is especially useful for reconstructing catchment-aggregated melt. However, the study's results also suggest that SWE scenarios with systematic biases can still produce excellent streamflow performance. Moreover, the authors state that there is a large degree of non-uniqueness in the SWE–streamflow relationship. The semi-synthetic experiment further highlights that realistic model and forcing uncertainties amplify this equifinality. For future work, the authors recommend incorporating complementary snow observations (e.g. snow depth, SCA) to reduce equifinality and improve SWE reconstruction.

Overall Feedback:

The manuscript is of high quality in both methodology and writing and will likely be a valuable contribution to the snow-hydrology community. The authors provide a clear motivation, a well-structured experimental design, and a thoughtful discussion of relevant uncertainties (e.g., performance metric choice, model structural limitations, and forcing errors). Overall, the work is comprehensive, clearly presented, and addresses a timely question within hydrologic modeling and cryospheric science. I suggest to return the manuscript to the authors for a minor revision. I would appreciate if the authors would address my comments below during this revision.

General Comments:

In my opinion, the manuscript could benefit from a deeper methodological integration and/or theoretical discussion of recurring spatial patterns of snow accumulation, which the authors also acknowledge in the introduction (L46–56). Numerous studies show that snow distribution is controlled by (relatively static) topographic controls (elevation gradients, wind exposure, canopy effects) and tends to vary primarily in magnitude rather than in relative spatial differences. This raises an important question for the inversion framework:

Can the recurring nature of snow distribution patterns be used to reduce the effective dimensionality of the prior space or to inform the posterior selection procedure?

This is a very good point that we have indeed not given sufficient attention. Recurring snow patterns should in fact be particularly compatible with streamflow-based SWE reconstruction, since they are valid for any year in the past once they have been mapped. We have made the following adjustments to make the link with the recurring pattern literature more clearly:

- Rewrote the introduction paragraph about this topic to include more relevant literature
  - "In addition to indirect SWE observations, empirical knowledge on recurring snow patterns can help to reconstruct SWE. Numerous studies have shown that spatial snow depth distributions can be statistically linked to terrain characteristics such as elevation, slope, and sky view factor (Grünewald et al., 2013; Lehning et al., 2011; Revuelto et al., 2014) and vegetation features such as canopy structure and density (Helbig et al., 2020; Mazzotti et al., 2019; Trujillo et al., 2007). Helbig and Herwijnen (2017) derived gridded snow depth

    estimates from point-scale snow depth measurements using terrain properties of each grid cell. Pflug and Lundquist (2020) were able to extrapolate snow depth for an entire catchment from observing only 4% of its surface by leveraging recurring snow depth patterns. Similarly, Geissler et al. (2025) and Ylönen et al. (2025) used repeated UAV LiDAR surveys to define clusters of locations showing similar snow dynamics. They then used these clusters to spatially extrapolate point snow-depth measurements, producing region-wide maps of SD and SWE. Zakeri et al. (2025) downscaled low resolution SWE estimates by reusing high resolution reanalysis SWE from dates with similar low resolution SWE and climate data patterns. Finally, Michel et al. (2023) demonstrated that SWE reconstructions for poorly observed years can be constrained by applying bias corrections derived from well-observed years."

- Rewrote the discussion paragraph about this topic to account for the reviewer's comment and the above point on the high compatibility between streamflow and knowledge on recurring patterns.
    - "In this study, we isolate the constraining potential of streamflow alone. However, streamflow is likely most effective when used in combination with other sources of snow information. These can be direct observations of different snow properties (Revuelto et al., 2025) but we particularly encourage future work to explore the use of recurring spatial patterns of snow dynamics (Geissler et al., 2025; Pflug and Lundquist, 2020; Vögeli et al., 2016). Such patterns represent catchment-specific prior knowledge that, once characterized, can be reused across time, including periods predating satellite observations but overlapping streamflow observations. Prior SWE ensembles could be defined as scaled versions of observed spatial SWE patterns, thereby reducing the number of parameters to be inferred and mitigating part of the physical non-uniqueness identified in this study. These recurring patterns have so far been identified in a limited number of catchments, but recent advances in automated UAV and LiDAR technologies are likely to increase this number in the near future (Revuelto et al., 2021). Combined with long streamflow records, this opens the possibility of extending SWE reconstructions back in time by decades while maintaining realistic SWE patterns."

We highlighted specific sentences from above paragraphs to respond to the reviewer's comments below.

I would encourage the authors to reflect on *how* recurring snow patterns could be incorporated into different parts of their framework, for example:

1. Method (Sect. 2.1): Dimensionality reduction of the prior (Could be discussed for future applications..)

Currently, the prior is defined through independent parameter ranges, which leads to a large prior state space. Considering the reoccurring behaviour of snow distribution, do the authors think that this creates an unnecessarily large prior space and hence potentially amplifies non-uniqueness? One possibility would be to represent SWE as a scaled version of a known distribution pattern (Pflug & Lundquist, 2020; Vögeli et al., 2016; Ylönen et al., 2025), e.g. $H_{SWE}(x,y,t) = \alpha(t)\cdot H_{pattern}(x,y)+\epsilon(x,y,t)$

This is a great idea, we added the following sentence in the discussion: “Prior SWE ensembles could be defined as scaled versions of present-day observed spatial SWE patterns, thereby reducing the number of parameters to be inferred and mitigating part of the physical non-uniqueness identified in this study”

2. Posterior ensemble selection (Sect. 2.4): Plausibility

Posterior filtering could penalize SWE fields that violate well-known topographic dependencies (e.g., monotonic elevation gradients), thereby favoring more physically meaningful inversions. Figure 4 and especially Figure 5 show that the NSE-selected posterior contains some of the best SWE simulations of the prior – even for the SS experiment. I wonder whether a second-stage selection step, based on physically realistic spatial patterns, could further refine the posterior and help exclude SWE fields that match streamflow but are unlikely given known snow distribution processes. Such plausibility-based filtering (e.g., constraining elevation–SWE relationships or enforcing typical accumulation gradients) may help reduce non-uniqueness and improve the interpretability of the resulting posterior ensemble.

We also agree on this point and added the following sentence in the discussion directly after the previous: “Alternatively, the recurring patterns could be used to filter posterior SWE members based on physical plausibility.”

3. Discussion (Section 4.2.):

It may be worthwhile to discuss whether, in real-world applications, the existence of spatial patterns may actually help reduce non-uniqueness compared to the synthetic inversion setups presented here.

Definitely, we incorporated this in the same sentence as for point 1.

Specific Comments:

- L21: I would argue that snow patterns can also be rather consistent – I suggest writing: In addition, snowfall and snowmelt vary spatially…

  Adjusted.
- Section 2.2.3 or 2.2.4: I am missing a sentence here to what years your method is applied…

  It was mentioned in section 2.2, but we also mentioned it in section 2.2.5.
- L213: Note that this...

  Adjusted.

- L293: Space between =2500

  Adjusted.
- L319: missing space after the

  Adjusted.
- L384: missing spaces..

  Adjusted.
- L452: In your introduction you introduced data assimilation products but no real data-driven approaches. This is why I find this sentence feels a bit isolated, but still interesting. Maybe it would be worth introducing data driven approaches (e.g. Daudt et al. (2023), Zheng et al. (2018), Ylönen et al. (2025)…).

  The studies mentioned by the reviewer use ML for SWE mapping, whereas we aimed to refer to ML alternatives for the SWE-Q translation (ML hydrological models). We changed the sentence to make this clear: "The lack of evaluation data equally implies a lack of training data for data-driven methods, thereby limiting the potential of machine learning methods as an alternative link between SWE and streamflow in inverse hydrological SWE reconstruction."

- L510ff: What about catchments with lower elevation gradient, less topographic roughness, e.g. boreal catchments? Would it make sense to perform future experiments here?

  Yes it would. We added a sentence with this recommendation directly after: "While this study focuses on mountainous catchments, it would be valuable to assess the constraining potential of streamflow in lower-relief, less topographically complex environments such as boreal catchments, where different controls on snow accumulation and melt may lead to different identifiability of SWE dynamics in streamflow."

References

Daudt, R. C., Wulf, H., Hafner, E. D., Bühler, Y., Schindler, K., & Wegner, J. D. (2023). Snow depth estimation at country-scale with high spatial and temporal resolution. ISPRS Journal of Photogrammetry and Remote Sensing, 197, 105–121. https://doi.org/10.1016/j.isprsjprs.2023.01.017

Pflug, J. M., & Lundquist, J. D. (2020). Inferring Distributed Snow Depth by Leveraging Snow Pattern Repeatability: Investigation Using 47 Lidar Observations in the Tuolumne Watershed, Sierra Nevada, California. Water Resources Research, 56(9). https://doi.org/10.1029/2020WR027243

Vögeli, C., Lehning, M., Wever, N., & Bavay, M. (2016). Scaling Precipitation Input to Spatially Distributed Hydrological Models by Measured Snow Distribution. Frontiers in Earth Science, 4.https://doi.org/10.3389/feart.2016.00108

Ylönen, M., Marttila, H., Kuzmin, A., Korpelainen, P., Kumpula, T., & Ala-aho, P. (2025). UAV LiDAR surveys and machine learning improves snow depth and water equivalent estimates in the boreal landscapes.https://doi.org/10.5194/egusphere-2025-1297

Zheng, Z., Molotch, N. P., Oroza, C. A., Conklin, M. H., & Bales, R. C. (2018). Spatial snow water equivalent estimation for mountainous areas using wireless-sensor networks and remote-sensing products. Remote Sensing of Environment, 215, 44–56. https://doi.org/10.1016/j.rse.2018.05.029

Geissler, J., Mazzotti, G., Rathmann, L., Webster, C., and Weiler, M.: Forest Snow Patterns Derived Using ClustSnow Are Temporally Persistent Under Variable Environmental Conditions, Water Resour. Res., 61, https://doi.org/10.1029/2024wr038442, 2025.

Grünewald, T., Stötter, J., Pomeroy, J. W., Dadic, R., Baños, I. M., Marturià, J., Spross, M., Hopkinson, C., Burlando, P., and Lehning, M.: Statistical modelling of the snow depth distribution in open alpine terrain, Hydrol Earth Syst Sc, 17, 3005–3021, https://doi.org/10.5194/hess-17-3005-2013, 2013.

Helbig, N. and Herwijnen, A. van: Subgrid parameterization for snow depth over mountainous terrain from flat field snow depth, Water Resour Res, 53, 1444–1456, https://doi.org/10.1002/2016wr019872, 2017.

Helbig, N., Bühler, Y., Eberhard, L., Deschamps-Berger, C., Gascoin, S., Dumont, M., Revuelto, J., Deems, J. S., and Jonas, T.: Fractional snow-covered area: scale-independent peak of winter parameterization, Cryosphere, 15, 615–632, https://doi.org/10.5194/tc-15-615-2021, 2020.

Lehning, M., Grünewald, T., and Schirmer, M.: Mountain snow distribution governed by an altitudinal gradient and terrain roughness, Geophys Res Lett, 38, n/a-n/a, https://doi.org/10.1029/2011gl048927, 2011.

Mazzotti, G., Currier, W. R., Deems, J. S., Pflug, J. M., Lundquist, J. D., and Jonas, T.: Revisiting Snow Cover Variability and Canopy Structure Within Forest Stands: Insights From Airborne Lidar Data, Water Resour Res, 55, 6198–6216, https://doi.org/10.1029/2019wr024898, 2019.

Michel, A., Aschauer, J., Jonas, T., Gubler, S., Kotlarski, S., and Marty, C.: SnowQM 1.0: a fast R package for bias-correcting spatial fields of snow water equivalent using quantile mapping, Geosci. Model Dev., 17, 8969–8988, https://doi.org/10.5194/gmd-17-8969-2024, 2023.

Pflug, J. M. and Lundquist, J. D.: Inferring Distributed Snow Depth by Leveraging Snow Pattern Repeatability: Investigation Using 47 Lidar Observations in the Tuolumne Watershed, Sierra Nevada, California, Water Resour Res, 56, https://doi.org/10.1029/2020wr027243, 2020.

Revuelto, J., López-Moreno, J. I., Azorin-Molina, C., and Vicente-Serrano, S. M.: Topographic control of snowpack distribution in a small catchment in the central Spanish Pyrenees: intra- and inter-annual persistence, Cryosphere, 8, 1989–2006, https://doi.org/10.5194/tc-8-1989-2014, 2014.

Revuelto, J., López-Moreno, J. I., and Alonso-González, E.: Light and Shadow in Mapping Alpine Snowpack With Unmanned Aerial Vehicles in the Absence of Ground Control Points, Water Resour. Res., 57, https://doi.org/10.1029/2020wr028980, 2021.

Revuelto, J., Alonso-González, E., Deschamps-Berger, C., Gutmann, E. D., and López-Moreno, J. I.: Recent Advances in Snow Monitoring from Local to Global Scales, Curr. Clim. Chang. Rep., 11, 10, https://doi.org/10.1007/s40641-025-00207-0, 2025.

Trujillo, E., Ramírez, J. A., and Elder, K. J.: Topographic, meteorologic, and canopy controls on the scaling characteristics of the spatial distribution of snow depth fields, Water Resour. Res., 43, https://doi.org/10.1029/2006wr005317, 2007.

Ylönen, M., Marttila, H., Geissler, J., Kuzmin, A., Korpelainen, P., Kumpula, T., and Ala-Aho, P.: UAV LiDAR surveys and machine learning improve snow depth and water equivalent estimates in boreal landscapes, Cryosphere, 19, 4585–4610, https://doi.org/10.5194/tc-19-4585-2025, 2025.

Author response to RC2

First, I would like to apologize for the long delay in providing my review. I struggled to find time to read this manuscript due to some unforeseen academic duties.
We thank Simon Gascoin for his helpful review, we understand that things can get in the way unexpectedly so we appreciate that he still took the time. Please find our comments in red below.

I was attracted by the title. After reading the entire paper, I can see that it does not violate Betteridge's law of headlines.
That is a funny reference. I would say the answer to the title question is not a definitive no, but it is certainly not a definitive yes either.

The study is well conducted, the methodology is sound, and the results are well illustrated. However, in some parts I found the manuscript difficult to follow. In particular, the Results section is full of acronyms and symbols and would benefit from more concise and synthetic writing. The five-page Discussion is also very long; frankly, I ended up skimming parts of it. I understand that the authors wish to be very honest about the limitations of their results, but a single paper will never be sufficient to discuss all the issues related to inverse modelling in hydrology. I would suggest focusing on key issues that are specific to this study and referring to previous articles for the rest. For example, in my opinion, Section 4.5 of the Discussion is out of scope, as it deviates from the scientific objective of the study as announced in the Introduction.

Thank you for the feedback and the useful comments. We addressed them as follows:

- ○ Rewrote the results section more concisely and synthetically, which lead to a reduction of approximately one page and a good number of symbols and acronyms. We also updated figure 3, which showed additional data not corresponding to the posterior ensemble, and rewrote section 3.1 accordingly. It did not change our interpretation of the results.
- ○ Rewrote much of the discussion and left section 4.5 out, leading to a reduction of approximately two pages.

  These edits are too numerous to mention in this document, we therefore refer to the revised manuscript and the tracked changes document.

In the Introduction, the authors could better justify the motivation for their work. What is a typical use case that justifies the need to generate posterior gridded SWE from streamflow data in a gauged catchment? Doing hydrology “backward” is useful if the inferred variable has an application outside the scope of the hydrological model itself. I think that a deeper reflection on the potential applications of this approach could help to better focus the Discussion.

If the idea is to reconstruct recent SWE, then readily available remote-sensing information (or their synthetic surrogates), such as annual snow cover duration maps, could be incorporated into the model evaluation to better constrain the likelihood. This echoes Referee 1’s suggestion to consider prior knowledge on the spatial distribution of snow cover to narrow the posterior spread.

We made the following adjustments in response to this comment:

- Emphasized the potential for pre-satellite era SWE reconstruction in the 4th paragraph of the introduction:
  - ○ “However, in scarcely monitored regions and before the onset of remote sensing, the above sources of information are often lacking. In such contexts, streamflow observations offer a complementary source of information for SWE reconstruction. Streamflow gauging stations are relatively abundant due to their cost-effectiveness and importance for flood forecasting(Harrigan et al., 2022) , and their observations often predate the above-mentioned snow information sources (Do et al., 2018) .”
- Added a clarifying sentence at the end of the introduction
  - ○ “While in real-world settings streamflow observations will often exist alongside spaceborne or in-situ snow observations, the goal of this study is to isolate the constraining potential of streamflow on SWE to reveal how streamflow observations are most effectively exploited in inverse hydrological SWE reconstruction.”
- Added the following sentences in the discussion, also in response to RC1’s comments:
  - ○ “These can be direct observations of different snow properties (Revuelto et al., 2025) , but we particularly encourage future work to explore the use of recurring spatial patterns of snow dynamics (Geissler et al., 2025; Pflug and Lundquist, 2020; Vögeli et al., 2016). Such patterns represent catchment-specific prior knowledge that, once characterized, can be reused across time, including periods predating satellite observations but overlapping streamflow

> observations."

Minor comments

L27: "SCA and wet snow measurements provide only binary information." This is true at the product resolution (20 m, 100 m); however, both variables can be expressed as fractional values after spatial aggregation at the model resolution.

We removed the word binary.

L75: I feel that the Introduction should consider the work of Le Moine et al. (2015).

Their paper was on my reading list and I somehow managed to overlook it, thank you for the recommendation. We added the following sentences:

> "Also using inverse hydrological modeling, Moine et al., (2015) and Ruelland (2020) 80 derived multi-year temperature and precipitation gradients in mountainous catchments. While Moine et al. (2015) evaluated the resulting SWE estimates against station observations, Ruelland (2020) used binary snow cover maps alongside streamflow in a multi-objective inference."

L155: What is the rationale for having a different correction factor for liquid versus solid precipitation?

We added the sentence "The use of separate rainfall and snowfall correction factors has been shown to improve meteorological bias correction in snow-dominated catchments (Pulka et al., 2024) , and additionally allows us to assess whether the rainfall–snowmelt partitioning can be inferred from streamflow observations."

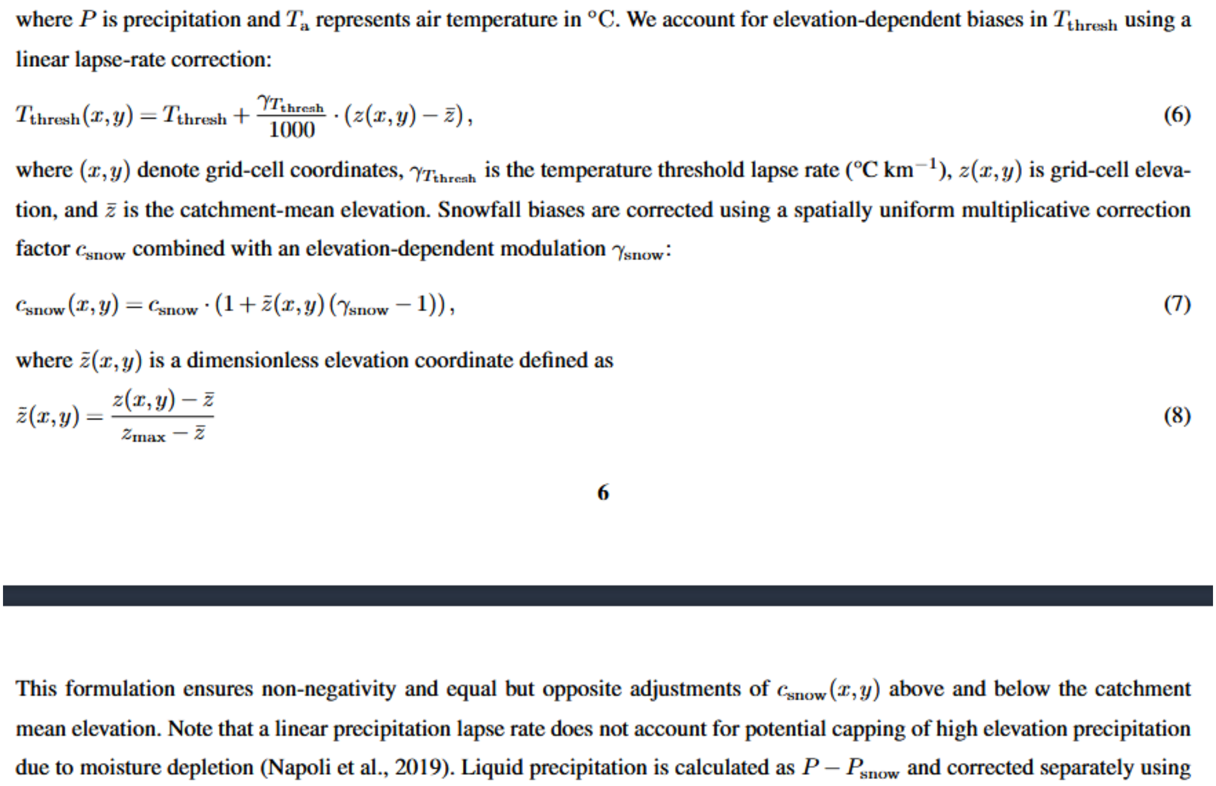
Precipitation is obtained from a 2 km grid. The authors refer to gauge undercatch to explain why catchment-scale precipitation is lower than streamflow (i.e., a runoff coefficient greater than 1). However, this discrepancy may also be due to the smoothed topography of the 2 km dataset used in the gridded precipitation interpolation scheme, which may be biased relative to the actual elevation distribution of the catchment. I did not clearly understand how precipitation was interpolated from this 2 km source to the 900 m × 700 m resolution. This processing involves two DEMs. The authors should be more specific about the source and/or resampling methods used for both DEMs. I also recommend explicitly writing the equations used for temperature and precipitation interpolation. Indeed, I do not understand why $SFCF$ is referred to as a "multiplicative correction factor," whereas $SFCF_{ELE}$ is described as "a linear elevation lapse rate." Precipitation cannot be interpolated using a temperature-like lapse rate, as this could lead to negative precipitation values. Moreover, linear scaling with elevation is not always chosen to interpolate precipitation, as it does not represent the observed capping of precipitation at high elevations due to atmospheric moisture depletion (e.g., Liston and Elder, 2006).

To clarify the regridding approach we adjusted section 2.2.1 as follows: "TabsD and RhiresD were downscaled to the 30 arcsecond model grid using area-weighted regridding with ESMValTool (Eyring et al., 2020). TabsD was first adjusted to sea level using a fixed lapse rate of 6.5 °C/km before regridding and then reprojected back to the original terrain elevation,

while precipitation was regridded directly. For both coarse and fine resolution DEM we used the MERIT digital elevation model (Yamazaki et al., 2017).”
This approach follows the standard ESMVALTOOL regridding script for ERA5 data to be used in wflow_sbm.

The elevation-dependent scaling of SFCF indeed does not follow a temperature-like lapse rate, but rather a rescaling of SFCF around the mean elevation. We added a more detailed explanation, along with the following sentence on the high elevation moisture depletion: "Note that a linear precipitation lapse rate does not account for potential capping of high elevation precipitation due to moisture depletion (Napoli et al., 2019)."

We added the following equations:



where P is precipitation and T_a represents air temperature in °C. We account for elevation-dependent biases in T_{thresh} using a linear lapse-rate correction:

$$T_{\text{thresh}}(x,y) = T_{\text{thresh}} + \frac{\gamma_{T_{\text{thresh}}}}{1000}\cdot\left(z(x,y)-\bar{z}\right), \tag{6}$$

where (x,y) denote grid-cell coordinates, $\gamma_{T_{\text{thresh}}}$ is the temperature threshold lapse rate (°C km^{-1}), $z(x,y)$ is grid-cell elevation, and $\bar{z}$ is the catchment-mean elevation. Snowfall biases are corrected using a spatially uniform multiplicative correction factor c_{snow} combined with an elevation-dependent modulation γ_{snow}:

$$c_{\text{snow}}(x,y) = c_{\text{snow}}\cdot\left(1+\tilde{z}(x,y)\left(\gamma_{\text{snow}}-1\right)\right), \tag{7}$$

where $\tilde{z}(x,y)$ is a dimensionless elevation coordinate defined as

$$\tilde{z}(x,y) = \frac{z(x,y)-\bar{z}}{z_{\max}-\bar{z}} \tag{8}$$

6

This formulation ensures non-negativity and equal but opposite adjustments of $c_{\text{snow}}(x,y)$ above and below the catchment mean elevation. Note that a linear precipitation lapse rate does not account for potential capping of high elevation precipitation due to moisture depletion (Napoli et al., 2019). Liquid precipitation is calculated as $P - P_{\text{snow}}$ and corrected separately using

L245: Why is “air temperature capped at a minimum of 0 °C”?
The air temperature is capped at 0 °C to avoid that the OSHD-derived runoff that is fed into wflow_sbm as "rainfall" would instead fall as snow. In most cases, OSHD and TabsD will agree on when melt is occuring, but there might be instances where TabsD is negative but OSHD still produces runoff. The capping is done to avoid those situations. We added the following sentence: “all snowfall events (i.e., *P* when T_{air} < 0°C) are removed, OSHD-derived snowmelt is added as precipitation, and air temperature is capped at a minimum of 0 °C to ensure this precipitation falls as rain.”
L247: The authors mention “some physical inconsistencies, such as the omission of refreezing.” What are the other inconsistencies?
In reality, negative temperatures of course do exist in the Dischma catchment so this is a physical inconsistency, but to the best of our knowledge soil refreezing is in fact the only process that is misrepresented in the model as a consequence. We replaced this sentence

with "Testing of this coupling approach showed that the secondary modeling effects of capping the temperature at 0 °C are negligible."

L450: The lack of “temporal continuity” of the ASO data is not a convincing argument for rejecting these data. ASO provides SWE maps every two weeks in several gauged catchments over multiple years. ASO catchments would actually form an ideal dataset to test the inversion of SWE using the proposed framework.

We changed the sentence to "At present, the best evaluation dataset is arguably the biweekly gridded SWE product of the Airborne Snow Observatory (Painter et al., 2016) , available for a limited number of catchments and years in the Western US."

Formatting: I think that the acronyms (“SCFCF”) or text (“snow”) in the equations should not be italicized (e.g. using \mathrm).

We adjusted all notations accordingly and replaced all parameter names to comply with the Copernicus guidelines on math symbols and variables, which certainly improved the overall appearance of the manuscript.

Do, H. X., Gudmundsson, L., Leonard, M., and Westra, S.: The Global Streamflow Indices and Metadata Archive (GSIM) – Part 1: The production of a daily streamflow archive and metadata, Earth Syst Sci Data, 10, 765–785, https://doi.org/10.5194/essd-10-765-2018, 2018.

Eyring, V., Bock, L., Lauer, A., Righi, M., Schlund, M., Andela, B., Arnone, E., Bellprat, O., Brötz, B., Caron, L.-P., Carvalhais, N., Cionni, I., Cortesi, N., Crezee, B., Davin, E. L., Davini, P., Debeire, K., Mora, L. de, Deser, C., Docquier, D., Earnshaw, P., Ehbrecht, C., Gier, B. K., Gonzalez-Reviriego, N., Goodman, P., Hagemann, S., Hardiman, S., Hassler, B., Hunter, A., Kadow, C., Kindermann, S., Koirala, S., Koldunov, N., Lejeune, Q., Lembo, V., Lovato, T., Lucarini, V., Massonnet, F., Müller, B., Pandde, A., Pérez-Zanón, N., Phillips, A., Predoi, V., Russell, J., Sellar, A., Serva, F., Stacke, T., Swaminathan, R., Torralba, V., Vegas-Regidor, J., Hardenberg, J. von, Weigel, K., and Zimmermann, K.: Earth System Model Evaluation Tool (ESMValTool) v2.0 – an extended set of large-scale diagnostics for quasi-operational and comprehensive evaluation of Earth system models in CMIP, Geosci. Model Dev., 13, 3383–3438, https://doi.org/10.5194/gmd-13-3383-2020, 2020.

Geissler, J., Mazzotti, G., Rathmann, L., Webster, C., and Weiler, M.: Forest Snow Patterns Derived Using ClustSnow Are Temporally Persistent Under Variable Environmental Conditions, Water Resour. Res., 61, https://doi.org/10.1029/2024wr038442, 2025.

Harrigan, S., Zsoter, E., Cloke, H., Salamon, P., and Prudhomme, C.: Daily ensemble river discharge reforecasts and real-time forecasts from the operational Global Flood Awareness System, Hydrol Earth Syst Sc, 27, 1–19, https://doi.org/10.5194/hess-27-1-2023, 2022.

Moine, N. L., Hendrickx, F., Gailhard, J., Garçon, R., and Gottardi, F.: Hydrologically Aided Interpolation of Daily Precipitation and Temperature Fields in a Mesoscale Alpine Catchment, J. Hydrometeorol., 16, 2595–2618, https://doi.org/10.1175/jhm-d-14-0162.1, 2015.

Napoli, A., Crespi, A., Ragone, F., Maugeri, M., and Pasquero, C.: Variability of orographic enhancement of precipitation in the Alpine region, Sci. Rep., 9, 13352, https://doi.org/10.1038/s41598-019-49974-5, 2019.

Painter, T. H., Berisford, D. F., Boardman, J. W., Bormann, K. J., Deems, J. S., Gehrke, F., Hedrick, A., Joyce, M., Laidlaw, R., Marks, D., Mattmann, C., McGurk, B., Ramirez, P., Richardson, M., Skiles, S. M., Seidel, F. C., and Winstral, A.: The Airborne Snow Observatory: Fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo, Remote Sens Environ, 184, 139–152, https://doi.org/10.1016/j.rse.2016.06.018, 2016.

Pflug, J. M. and Lundquist, J. D.: Inferring Distributed Snow Depth by Leveraging Snow Pattern Repeatability: Investigation Using 47 Lidar Observations in the Tuolumne Watershed, Sierra Nevada, California, Water Resour Res, 56, https://doi.org/10.1029/2020wr027243, 2020.

Pulka, T., Herrnegger, M., Ehrendorfer, C., Lücking, S., Avanzi, F., Formayer, H., Schulz, K., and Koch, F.: Evaluating precipitation corrections to enhance high-alpine hydrological modeling, J. Hydrol., 645, 132202, https://doi.org/10.1016/j.jhydrol.2024.132202, 2024.

Revuelto, J., Alonso-González, E., Deschamps-Berger, C., Gutmann, E. D., and López-Moreno, J. I.: Recent Advances in Snow Monitoring from Local to Global Scales, Curr. Clim. Chang. Rep., 11, 10, https://doi.org/10.1007/s40641-025-00207-0, 2025.

Ruelland, D.: Should altitudinal gradients of temperature and precipitation inputs be inferred from key parameters in snow-hydrological models?, Hydrol Earth Syst Sc, 24, 2609–2632, https://doi.org/10.5194/hess-24-2609-2020, 2020.

Vögeli, C., Lehning, M., Wever, N., and Bavay, M.: Scaling Precipitation Input to Spatially Distributed Hydrological Models by Measured Snow Distribution, Frontiers Earth Sci, 4, 108, https://doi.org/10.3389/feart.2016.00108, 2016.

Yamazaki, D., Ikeshima, D., Tawatari, R., Yamaguchi, T., O'Loughlin, F., Neal, J. C., Sampson, C. C., Kanae, S., and Bates, P. D.: A high-accuracy map of global terrain elevations, Geophys Res Lett, 44, 5844–5853, https://doi.org/10.1002/2017gl072874, 2017.