# Response to Reviewer 2 Comments:

## General comments

The manuscript presents the development and validation of a Machine Learning (ML) model used to estimate snow depth (SD) from Sentinel-1 backscatter data and auxiliary variables. The modeling framework is applied over three different mountain ranges: The European Alps, Colorado Rocky Mountains and Indian West Himalayas. Overall, the reported results are comparable and even appear as improvement over previous Sentinel-1 based SD estimates. The ML model conception, training and evaluation strategies seem standard and quite robust.

The authors sincerely thank the reviewer for the positive remarks on the model development and evaluation strategies and for the constructive comments provided, which have been valuable in improving the clarity and scope of the work.

The comments raised by the reviewer have been carefully considered, and the manuscript has been revised to improve the clarity of the methodological description, interpretation of the results, and scope of the conclusions. In particular, the authors have revised the interpretation of the results and discussion related to explainable AI analysis to ensure that the statements and conclusions are consistent with the actual SHAP-based attribution and the evidence reported in this study. Additional analyses and corresponding revisions have also been implemented to address the specific concerns raised by the reviewer.

Detailed point-by-point responses to each of the comments, along with the changes made in the revised manuscript are given below.

Kindly note that the reviewer's comments are in black font, the authors' responses are in blue font, and *the revisions made to the manuscript are in green italic font.*

My main comments are related to the explainable AI (SHAP values) analysis, and the conclusions that can stem from it. I think this analysis is useful in determining where and when can backscatter related variables be more informative about snow depth. However, these insights appear as more statistical rather than physical as stated in the objectives, because the latter cannot be assessed without observed or at least estimated snowpack conditions (e.g. Marin et al., 2020). I suggest rewording across the whole manuscript to reflect this.

The authors acknowledge this suggestion from the reviewer, and reviewer-1 also raised similar concerns. The authors agree with both the reviewers that SHAP analysis provides statistical insights regarding the contribution of individual predictor variables to the model predictions, rather than direct evidence of the physical mechanisms governing C-band backscatter from snow. In the absence of independent information on snowpack properties, these SHAP patterns cannot be directly linked to specific microwave scattering mechanisms.

SHAP analysis in this study is used for examining how the contribution of C-band backscatter variables to snow-depth predictions varies based on several conditions i.e., different snow-depth ranges, snow classes, vegetation conditions, and stages of the snow season. The current study does not involve in-situ or modelled snowpack characteristics data as in Marin et al. (2020), and the conditioning variables do not directly characterise the snowpack's internal properties. However, they provide indirect indicators of snowpack and environmental conditions and can offer useful context for interpreting model behaviour, particularly in the absence of measured or modelled snowpack properties. These results describe the behaviour of the trained model under different conditions and should be interpreted as statistical attribution patterns rather than direct explanations of the underlying snowpack physics.

The second objective has already been reframed in response to the first referee. Additionally, the wording in the abstract, Sect. 4.3 and the conclusions have been revised to present the physical insight in this sense, and the statistical nature of the attribution is now explicitly stated where the SHAP results are introduced.

I think that the relatively low SHAP values of the backscatter variables compared to auxiliary snow cover duration (SCD), elevation (DEM) and day of water year (DOW) are concerning. I suggest directly addressing this mismatch, because it works against the manuscript's goal. It could be interpreted as a potential "conflict" between maximizing model performance and gaining insights from backscatter variables. I'd recommend either limiting the relevance of these variables in the model output, or reporting the performance when excluding each of these auxiliary datasets.

The authors understand the concern regarding the low SHAP values of the backscatter variables. However, the SHAP values are reported per feature, so the Sentinel-1 information is divided among six correlated variables, while SCD, DEM, and DOW are each single variables. The combined contribution of the backscatter variables is comparable to that of the dominant and independent auxiliary variables in EA and IWH as shown in Table 1. A substantial contribution from the auxiliary variables is expected, as SD is strongly related to the elevation, the stage of the season, and the duration of snow cover, and these variables therefore carry SD information directly, in addition to providing proxy information on the snowpack and site conditions under which the backscatter is observed. The low share of the backscatter variables is also consistent with the characteristics of the datasets used, as the C-band signal is most sensitive to SD in the range of about 1 to 3 m, whereas 64 % of the CRM, 46 % of the EA, and 31 % of the IWH SD observations are below 50 cm. Backscatter alone, therefore, does not adequately capture SD variability across all conditions, which is why existing Sentinel-1-based studies, including ML-based ones, use backscatter alongside auxiliary variables (Daudt et al., 2023; Dunmire et al., 2024; Zhu et al., 2022).

Table 1. Grouped SHAP importance of each variable group in the three study regions. The values are dimensionless.

| Variables | CRM | EA | IWH |
|---|---|---|---|
| S1 backscatter | 0.15 | 0.18 | 0.20 |
| SCD | 0.46 | 0.29 | 0.25 |
| DEM | 0.22 | 0.20 | 0.17 |
| DOW | 0.09 | 0.14 | 0.22 |
| PTC | 0.06 | 0.10 | 0.08 |
| Snow Class | 0.02 | 0.09 | 0.03 |
| Altitude Group | 0.00 | 0.00 | 0.04 |

The authors acknowledge the reviewer's concern that including auxiliary variables may reduce the relative SHAP importance of the backscatter variables. SHAP values represent the contribution of individual predictors to the model predictions, and these contributions depend on the other variables included in the model. The insights reported in Sect. 4.3 are concerned with the conditions under which the backscatter variables contribute to the SD estimate and which of them contributes in each condition. The auxiliary variables are what make these conditions explicit in the model, and the contribution of the backscatter variables is examined with respect to them. The analysis also requires a model that estimates SD reasonably well, as the SHAP values of a model with poor accuracy would reflect that it mostly fails to reproduce SD. Improving estimation accuracy is, in this sense, necessary for obtaining these insights rather than being achieved at their expense. Following the reviewer’s recommendation, additional model experiments are carried out, in which the configurations differ only in the input variables used; their results are presented in Table 2. These results can be used to assess the contribution of Sentinel-1 data by comparing model performance with and without the backscatter variables, including when auxiliary variables are already present. Unlike SHAP values, this comparison directly evaluates the effect of including the backscatter variables on model performance. The static variables here are DEM, DOW, percent tree cover (PTC), snow class, and altitude group. M1 uses the static variables alone; M2 adds SCD to them; M3 adds the six backscatter variables instead; and M4 contains all of them.

Table 2. Performance of the four model configurations used to test the importance of input variables.

| Model | Temporally Independent Cross-Validation MAE in cm (r) | | | Spatially Independent Testing MAE in cm (r) | | |
|---|---|---|---|---|---|---|
| | CRM | EA | IWH | CRM | EA | IWH |
| M1(Static) | 19.21(0.89) | 34.74(0.82) | 116.79(0.62) | 23.74(0.75) | 37.92(0.71) | 68.25(0.61) |
| M2 (Static+SCD) | 15.81(0.91) | 33.44(0.82) | 115.85(0.63) | 17.35(0.87) | 35.80(0.74) | 66.35(0.62) |
| M3(Static+S1) | 16.7(0.91) | 30.75(0.84) | 113.78(0.61) | 18.75(0.85) | 35.02(0.76) | 65.76(0.65) |
| M4(Full) | 14.65(0.92) | 30.47(0.84) | 115.41(0.6) | 15.60(0.9) | 34.38(0.76) | 63.92(0.65) |

Adding SCD to the static model, from M1 to M2, reduces the test MAE by 6.4 cm in CRM, 2.1 cm in EA, and 1.9 cm in IWH, whereas adding the backscatter variables instead of SCD, from M1 to M3, reduces it by 5.0 cm, 2.9 cm, and 2.5 cm, respectively. The backscatter variables, therefore, account for an improvement comparable to that of SCD, the most influential auxiliary variable. In EA and IWH, where snowpacks are deeper, the backscatter variables contribute more than SCD, whereas in CRM, SCD contributes more, consistent with the reduced sensitivity of C-band backscatter to the shallow snowpacks in that region. Adding the backscatter variables to the model that already contains all the auxiliary variables, from M2 to M4, further reduces the MAE by 1.8 cm, 1.4 cm and 2.4 cm in CRM, EA and IWH respectively. The backscatter variables therefore provide SD information that the auxiliary variables do not, which the low per-feature SHAP values alone would not indicate.

Accordingly, the revised manuscript reports the grouped SHAP importance along with the per-feature values and includes the experiments of Table 2 in the appendix.

Given the hydrological relevance, I found that metrics about annual peak SD and peak SD timing were missing. It represents an important benchmark for the model and the information it can deliver, although the analysis may be limited to certain sites/regions due to data scarcity. Additionally, model evaluation in distinct hydrological conditions (e.g. drought and wet years) can give further insight into model applicability and usefulness.

The authors agree that the annual peak SD and its timing are the quantities of most interest for hydrological applications and that these were not reported. These have now been evaluated and are presented in a new subsection.

*"4.1.3, Model Performance for the Annual Peak SD and Its Timing*

*The annual peak SD and the date on which it occurs are of interest in hydrological applications, and the model's performance for these is therefore assessed separately. For each station and water year, the annual peak is taken as the maximum of the estimated SD series and its timing as the date on which that maximum occurs, and these are compared with the maximum of the daily in-situ record and its date. The daily record is used as the reference so that the peak and its date are those of the snowpack itself rather than of a series restricted to the S1 acquisitions, and both maxima are taken within the period covered by the two records in common.*

*Performance for the annual peak and for its timing is given in Table 3, the timing difference being positive when the estimated peak occurs later than the observed one. The peak was underestimated in all three regions, while its timing was close to the observed value on average, and both followed the observed pattern. In the CRM region, the peak was underestimated by 11.1% of the mean observed peak, with a mean absolute error of 15.4%. The underestimation was confined to the deeper snowpacks, with the bias remaining close to zero for the shallower peaks and increasing with peak depth. The timing showed a median difference of 6 days, with a median absolute deviation of 6 days, the lowest among the three regions. For 65.0% of the station water years, the estimated peak occurred within 12 days of the observed one, which is one S1 repeat cycle.*

*Table 3. Performance of the ML model for the annual peak SD and its timing in the three study regions.*

| **Region** | **Mean observed peak (cm)** | **Bias (cm)** | **MAE (cm)** | **RMSE (cm)** | **r** | **Median timing difference (d)** | **Median absolute deviation (d)** |
|---|---|---|---|---|---|---|---|
| CRM | 144.9 | −16.1 | 22.3 | 32.3 | 0.91 | 6 | 6 |
| EA | 176.2 | −12.2 | 34.3 | 48.8 | 0.86 | 3 | 15 |
| IWH | 287.2 | −59.8 | 107.6 | 157.9 | 0.60 | 1 | 15 |

*In the EA region, the peak was underestimated by 6.9%, with a mean absolute error of 19.5%. The bias here changed sign with peak depth: shallower peaks were overestimated, and deeper ones underestimated. The median timing difference was 3 days, with a median absolute deviation of 15 days, and 45.8% of the station water years had their estimated peak within 12 days of the observed one.*

*In the IWH region, where the number of station water years is limited by the availability of continuous daily records, the peak was underestimated by 20.8%, with a mean absolute error of 37.5%. The bias showed the same dependence on peak depth, with the deepest snowpacks accounting for the largest share of the underestimation. The timing differed by a median of 1 day, with a median absolute deviation of 15 days, and in 47.6% of station water years, the estimated peak fell within 12 days of the observed peak.*

*Since the estimated SD values are available only on the S1 acquisition dates, part of the underestimation is due to sampling rather than the model itself, and the results for the IWH are based on a smaller sample than those for the other two regions. The underestimation of the deeper peaks is consistent with the behaviour reported in Sect. 4.1.2, where the stations with very deep snowpacks also show underestimation. For hydrological applications, these results show that the estimates capture both the magnitude and the timing of the seasonal maximum well. In CRM and EA, the magnitude is reproduced with comparatively low error and high correlation, while the timing is resolved within one repeat interval for most of the deeper snowpacks, which is useful for tracking the progression of the accumulation season and the onset of melt. The deeper peaks are, however, underestimated, which may be due to the larger proportion of shallower observations in the training datasets, and this dependence should be taken into account where the absolute values matter, particularly in catchments with deeper snowpacks."*

Regarding the evaluation under distinct hydrological conditions, the authors agree that it would enhance understanding of the applicability of the estimates, and this possibility was examined. However, identifying such conditions is itself not straightforward. A snow drought or an abundant snow year has to be identified with respect to a climatological normal of at least a few decades, and the type of year has also to be distinguished. A record of this kind is not consistently available across the three regions, as in situ SWE observations are sparse and discontinuous, making reanalyses such as ERA5 the only continuous long-term source. But the reliability of these reanalyses is not uniform across the three regions, and for regions like the IWH, the performance of these products has not yet been established. A proper evaluation would need a longer record, a classification that is dependable in all three regions, and a separation of the types of years. This makes it a separate study in itself, and it is accordingly noted as a scope for future work. The models are, however, evaluated through the temporally independent cross-validation described in Sect. 3.3.1, in which each water year is held out in turn, so the reported performance already covers water years of differing snow conditions. The conditions characterising such years at the station level are also covered by the performance for the annual peak across the range of peak depths in Sect. 4.1.3 and by the performance across SD ranges, across the months of the season, and under dry and wet snow conditions in Sect. 4.2.

In general, the results appear to confirm the prior knowledge about the relationship between backscatter and canopy, and shallow, deep or wet snow. Regarding the latter, I think the manuscript could be enriched by including either wet snow or runoff onset information (Gagliano et al., 2026) to quantify what kind of performance the ML model can deliver under these conditions (e.g. is it

able to compensate through other variables like DOW?). A drop-off in the SHAP value for the backscatter variables would be a nice verification.

The authors thank the reviewer for this recommendation, which has helped strengthen the manuscript's claims.

The authors agree that some of the contributions presented in Sect. 4.3 confirm the prior knowledge reported in recent studies on the relationships between the backscatter and the canopy, the snow depth, and the wetness. These relationships, however, have been reported in individual study regions, and SHAP-based analyses of Sentinel-1 SD estimation have so far been confined to a single region and to direct backscatter variables, without utilising change-detection-based indices (Dunmire et al., 2024; Boeykens et al., 2026). The present study instead applies a single framework that includes both direct backscatter variables and change-detection-based indices, consistently across three regions with contrasting snow regimes. This multi-region framework allows us to examine which patterns in the contributions of backscatter variables are consistent across the three study regions and which vary between regions; these insights are difficult to capture in a single-region study. The contribution of the backscatter variables increased with the station-average SD across all three regions and was generally larger at lower PTC, indicating that these patterns held across the contrasting conditions represented by the three study regions. Other contributions are region-specific or are not anticipated from the existing knowledge. Although Icr is the backscatter variable most commonly used for Sentinel-1 backscatter-based SD estimation, Ivh was found to be more important, particularly in IWH where the deeper snowpacks enhance volume scattering. The contributions also differ between snow classes, being lower in the ephemeral class and higher in the tundra class, particularly for Ivh and Icr, and the altitude group was influential only in IWH.

Following the reviewer's recommendation, two additional analyses are carried out and reported in the revised manuscript: (i) SD estimation accuracy under dry and wet snow conditions, and (ii) examination of changes in the SHAP contributions of backscatter variables around the snowmelt runoff onset.

For the first analysis, observations were classified as dry or wet snow using the wet-snow flag provided with the C-Snow product (Lievens et al., 2022). The bias of the ML model, C-Snow, and C-RISE estimates was then compared under the two conditions, i.e., dry and wet.

For the second analysis, the runoff-onset information from Gagliano et al. (2026), as suggested by the reviewer, was used, which provides complete coverage of the study period. The runoff onset dataset is used for examining the contributions of variables under wet snow conditions. Since the snowpack becomes wet during the moistening and ripening phases that occur before the runoff onset, and the duration of these conditions varies between locations, the analysis has been carried out at temporal offsets from the runoff onset day, which shows how the contribution changes as the snowpack moistens, ripens, and begins to release water. The results of these analyses have been incorporated into the revised manuscript. The main revisions are as follows:

A new section 2.2.9 is included:

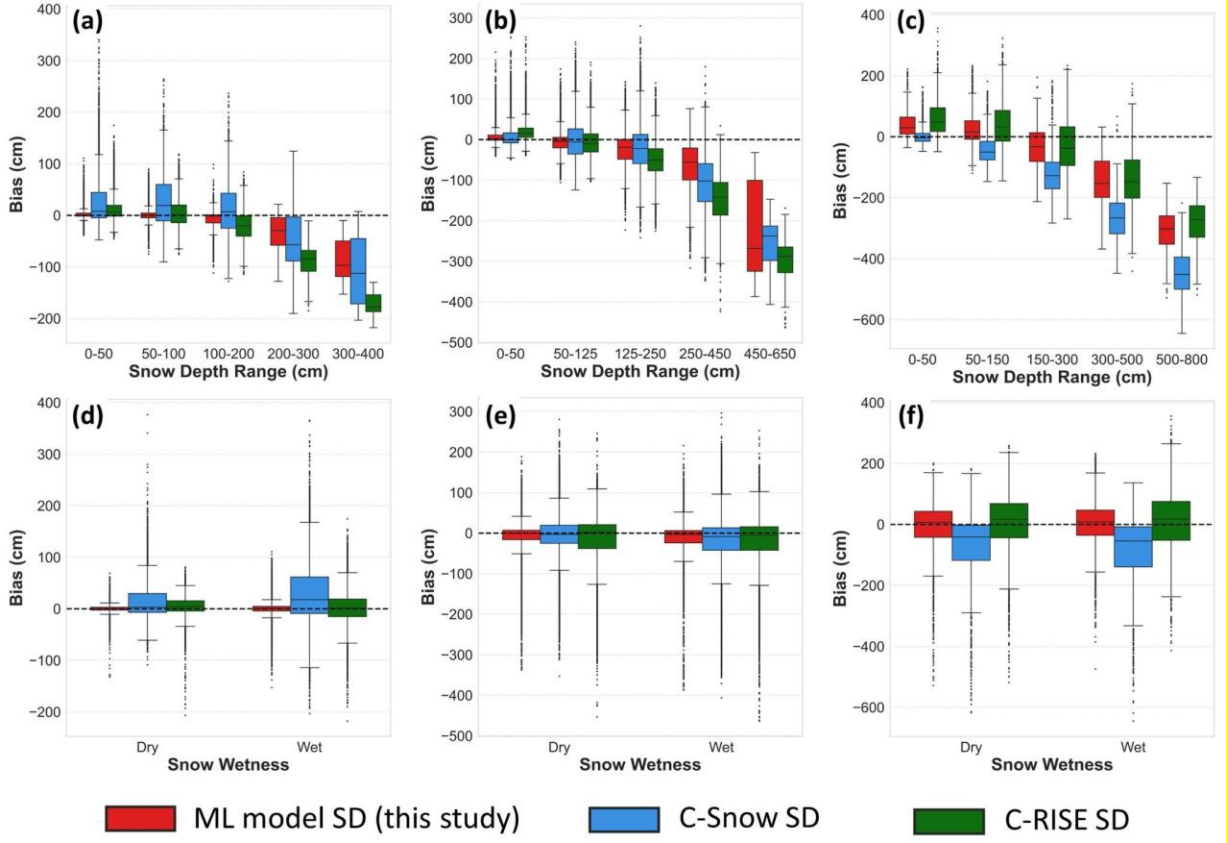
*“2.2.9 Snowmelt Runoff Onset*

*The timing of snowmelt can influence the S1 backscatter and, consequently, the estimation of the SD. The influence of snowmelt on backscatter contributions is examined using the global Sentinel-1-based runoff onset dataset developed by Gagliano et al. (2026). The dataset provides runoff onset dates as day-of-water-year values at 80 m spatial resolution for 2015–2024, covering the study period of all three regions. The onset is defined as the date of the minimum in the S1 backscatter time series, corresponding to the transition from the ripening phase to the runoff phase of the melt sequence (Marin et al., 2020), and is reported with a median absolute deviation of 10 days relative to snow pillow observations. For each station, the onset of the corresponding water year is taken as the median of the 80 m values within the 500 m cell, and the station water years for which the onset is not reliably determined or falls outside the observed period are excluded.”*

In section 3.4, the statement is modified as follows:

*“SHAP values are analysed across different stages of the winter season, within snow classes and altitude zones, and with respect to the snow wetness indicated by the timing of the snowmelt runoff onset, for all three study regions."*

In section 4.2, the following is included at the end:



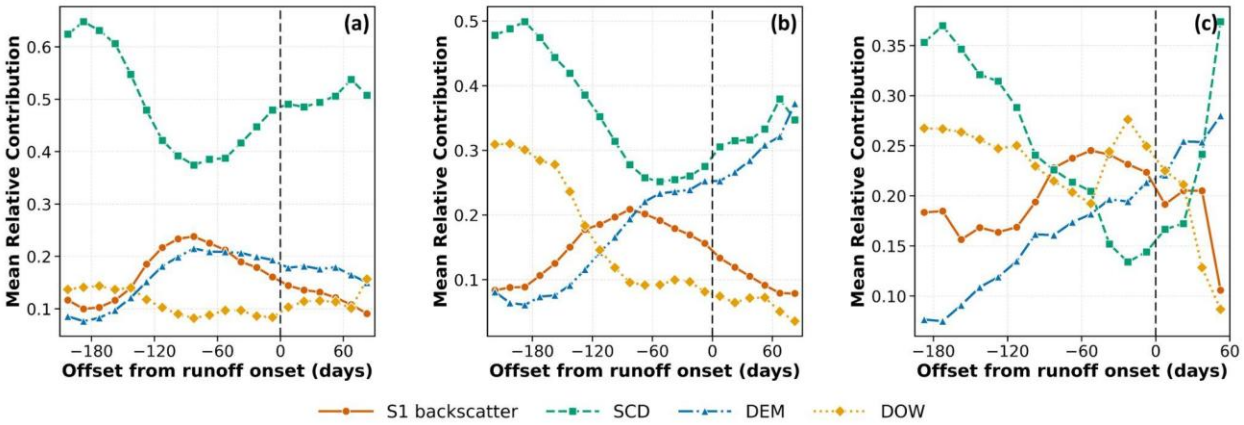

*"Figure 9. Bias comparison of ML model, C-Snow, and C-RISE estimates across SD ranges (a–c) and dry and wet snow conditions (d–f) in CRM, EA, and IWH, respectively. Wet snow is identified using the wet snow flag provided with the C-Snow product."*

*"The estimates were also compared between dry and wet snow conditions, identified using the wet snow flag provided with C-Snow (Fig. 9d–f). In CRM (Fig. 9d), the bias of the ML model remains close to zero in both conditions, whereas the overestimation by C-Snow nearly doubles in wet snow, and its bias range also widens, while the bias of C-RISE, although close to zero in both conditions, has a wider range than that of the ML model. In EA (Fig. 9e), all three estimates are underestimating wet snow, with the ML model showing the smallest underestimation. In IWH (Fig. 9f), the bias range of the ML model is comparable in both conditions and is less than that of C-RISE, while the underestimation by C-Snow is considerably larger in wet snow. Overall, these results indicate that the ML model performs relatively better and is comparatively less affected under wet snow conditions than the C-Snow and C-RISE estimates."*

In section 4.3.2 the statement is modified as follows:

*"To facilitate interpretation, relative SHAP values (the absolute SHAP value of each variable divided by the sum for all variables) were analysed across five scenarios: (i) across the season at 15-day intervals (Fig. 11a, c, e), (ii) across stations grouped by average SD (Fig. 11b, d, f), (iii) across different ranges of PTC (Fig. 12a, c, e), (iv) across different snow classes (Fig. 12b, d, f), and (v) across temporal offsets from the snowmelt runoff onset (Fig. 13), for the three study regions CRM, EA, and IWH."*

In section 4.3.2, the following is included at the end:




*"Relative contribution of the S1 backscatter, SCD, DEM and DOW to the SD estimates, obtained from the SHAP values, in (a) CRM, (b) EA and (c) IWH. The values are averaged and shown against the offset from the onset of snowmelt runoff (Gagliano et al., 2026) in 15-day intervals before and after the onset. The dashed vertical line marks the runoff onset."*

*"Fig. 13 illustrates the temporal variation in the relative contributions of backscatter-based variables with respect to snowmelt runoff onset. The offset denotes the number of days between each observation and the corresponding runoff onset date for a given station and water year. Across all three study regions, the relative contribution of backscatter-based variables increased through the accumulation period, peaked well before the onset, and then declined as the onset approached. This declining trend persisted beyond the runoff onset date, indicating a sustained reduction in the relative contribution of backscatter-based variables during the later stages of snowmelt. Notably, the runoff onset date represents the minimum of the Sentinel-1 backscatter time series, whereas the decline in SHAP contributions begins earlier. This earlier reduction in relative contributions may be associated with snowpack wetting during the preceding moistening and ripening phases, before runoff begins (Marin et al., 2020). Over the same period, the contributions of the auxiliary variables increased, indicating a shift in the model's reliance towards them as the backscatter-based variables became less informative. These changes also help in understanding the rationale behind the comparatively less change in ML model's performance between dry and wet snow conditions as presented in Section 4.2."*

Overall, I think the manuscript needs to address the points raised above in order to reach an originality level fit for publication in The Cryosphere. In its current form, too much emphasis is given to the ML model and its performance. The actual knowledge gap that this study can explore is the information content and predictability of SD within the backscatter variables, rather than developing a perfect model which relies mostly on auxiliary data.

The points raised above have been addressed through the additional analyses carried out. The study is built on two objectives: (i) developing an improved and scalable Sentinel-1-based SD estimation method and (ii) investigating the contribution of C-band backscatter to SD estimation under contrasting conditions. The improved SD estimation is one of the contributions, and it is also what makes the second objective addressable, as the contributions of the variables can be interpreted only for a model that estimates SD reasonably well. The additional analyses conducted in response to the reviewer's comments primarily address the second objective and expand the investigation of the contribution of backscatter variables across different snow and environmental conditions.

The predictability of SD from the backscatter variables is demonstrated through additional model experiments that separate the contribution of the backscatter variables from that of the auxiliary variables. This contribution is comparable to that of SCD in EA and greater in IWH, so the estimates do not rely primarily on the auxiliary data, and it increases with the observed SD. The SHAP-based analyses then show where and when this information is carried, including under dry and wet snow conditions and near the onset of snowmelt runoff. Carried out within a single framework across three regions with contrasting snow regimes, these analyses also distinguish the patterns that hold across all three from those specific to a region. Together, they indicate where the Sentinel-1 backscatter contributes to the SD estimate and where it does not, thereby adding to the understanding of backscatter-based SD estimation.

The authors hope that with these additions the revised manuscript meets the originality expected for publication in The Cryosphere.

Specific comments

The final sentence (Line 22) on the abstract reads as if an interannual SHAP analysis was conducted ("...across seasons,"). I'd recommend changing it to "within seasons" or something similar to represent the 15 day-of year window SHAP analysis.

Thanks for pointing this out. The sentence now reads as follows:

*"The analysis reveals distinct patterns across different stages of the season, snow types, vegetation conditions, and regions...."*

On figure 1 (a), I'd suggest either increasing the resolution of the global map or use a simpler map. The satellite image with national and state/provinces borders and names looks too busy and blurry.

Figure 1 has been reorganised, and the global map in Fig. 1a has been replaced with a simpler, higher-resolution map, as shown below.

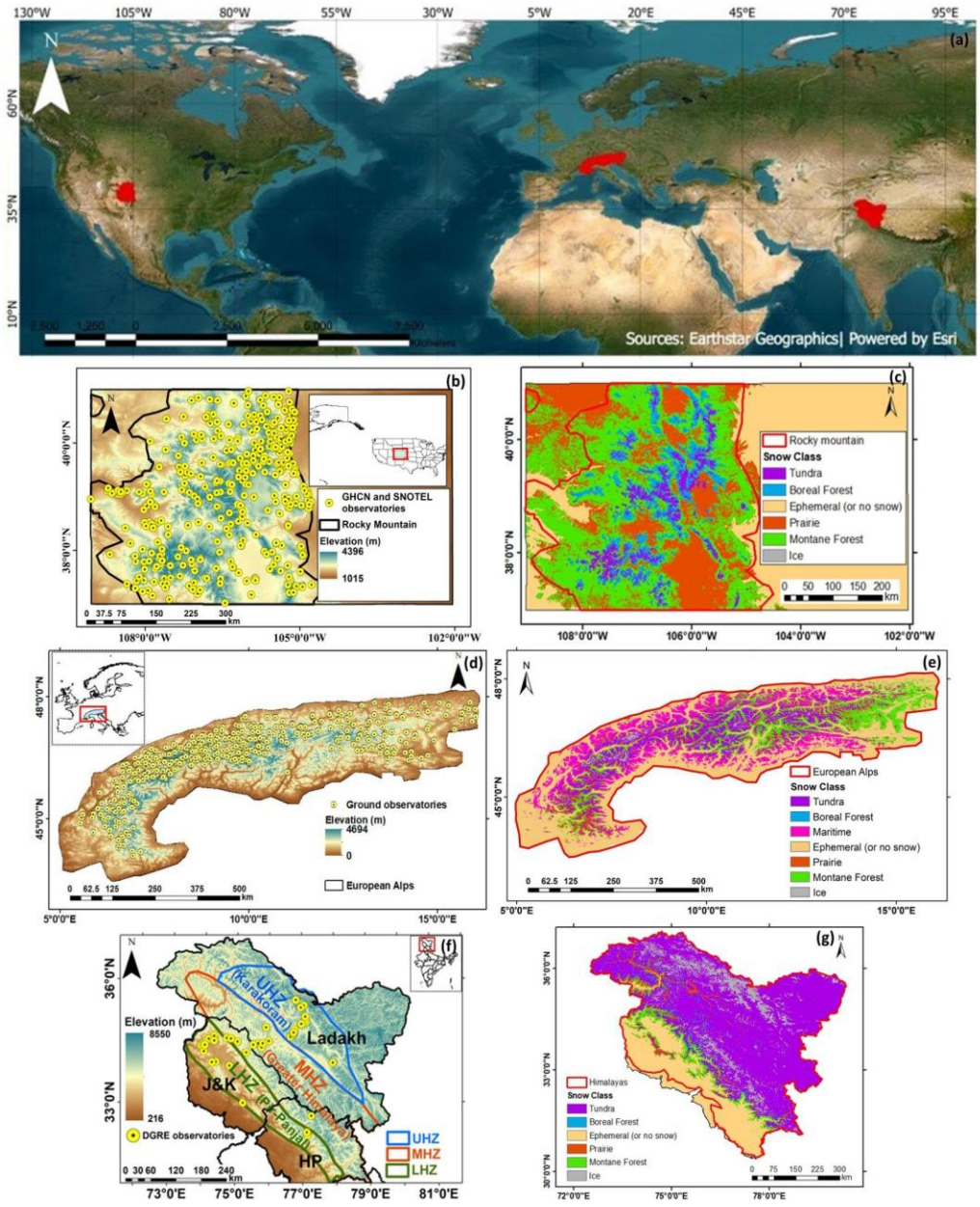



*Figure 1. Global map showing the three study regions (a), with regional maps illustrating elevation characteristics and ground observation stations (b, d, f; f is reproduced from Singh et al. (2024)), and snow classes (c, e, g) for CRM, EA, and IWH. Basemap sources: Earthstar Geographics | Powered by Esri. Elevation data are from SRTM Plus (Version 3.0, NASA JPL), and snow class data are from Sturm and Liston (2021).*

In figure 5, the correlation colorbar could be unique for all the plots related to that metric, given that all 3 cover the same -1 to 1 range of values. Similarly for the bias metric, the colormaps are graded to show intra-region bias variability. Maybe showing a single color grade for all stations across the three ranges could be more effective at communicating performance disparities across these mountain ranges. This could also free up some room, allowing for larger font sizes on the colorbars and legend.

Thanks for this suggestion. A single common color bar is now used for the correlation panels (Fig. 5a, 5b, 5c), and the freed-up space has been used to increase the font sizes of the color bars and the legend, as shown below.

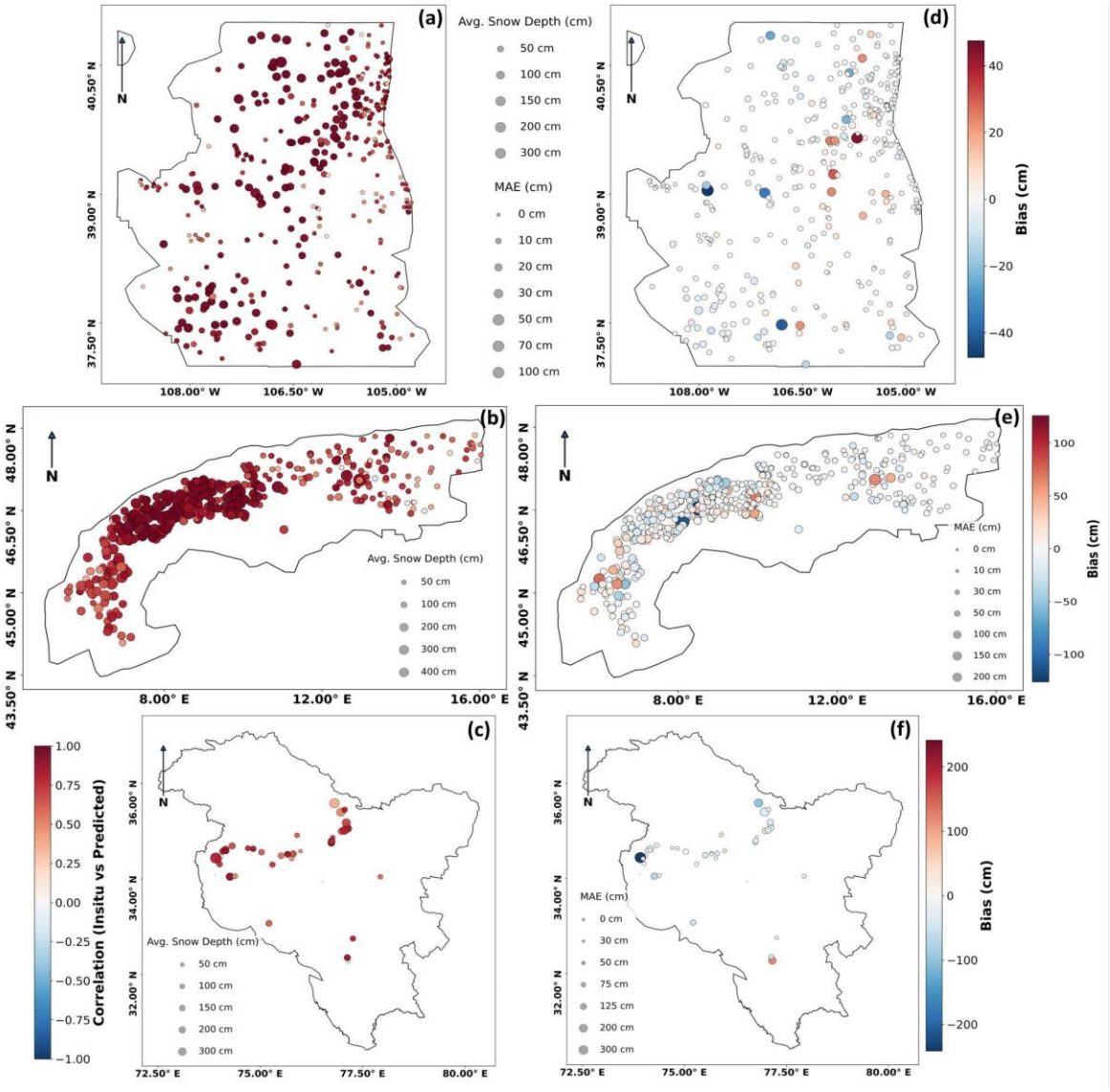



*Figure 5. Spatial distribution of stations with model performance: (a-c) correlation and average SD, and (d-f) MAE and bias for CRM, EA, and IWH, respectively.*

For MAE and bias, a common scale would not be informative, since these are absolute errors in cm and their magnitudes follow the regions' SD ranges. On a common scale, the CRM and EA stations would appear nearly uniform, and the stations with locally higher errors could not be identified. The per-region grading has therefore been retained.

References

Boeykens, L., Dunmire, D., Jans, J. F., Waegeman, W., De Lannoy, G., Beernaert, E., Verhoest, N. E. C., & Lievens, H. (2026). Machine learning for snow depth estimation over the European Alps, using Sentinel-1 observations, meteorological forcing data and process-based model simulations. The Cryosphere, 20(5), 3187–3216. https://doi.org/10.5194/TC-20-3187-2026

Daudt, R. C., Wulf, H., Hafner, E. D., Bühler, Y., Schindler, K., & Wegner, J. D. (2023). Snow depth estimation at countryscale 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

Dunmire, D., Lievens, H., Boeykens, L., & De Lannoy, G. J. M. (2024). A machine learning approach for estimating snow depth across the European Alps from Sentinel-1 imagery. Remote Sensing of Environment, 314, 114369. https://doi.org/10.1016/J.RSE.2024.114369

Gagliano, E., Shean, D., & Henderson, S. (2026). A global high-resolution dataset of snowmelt runoff onset timing from Sentinel-1 SAR, 2015–2024. Earth System Science Data, 18, 5871–5894. https://doi.org/10.5194/ESSD-18-5871-2026

Lievens, H., Brangers, I., Marshall, H. P., Jonas, T., Olefs, M., & De Lannoy, G. (2022). Sentinel-1 snow depth retrieval at sub-kilometer resolution over the European Alps. The Cryosphere, 16(1), 159–177. https://doi.org/10.5194/TC-16-159-2022

Marin, C., Bertoldi, G., Premier, V., Callegari, M., Brida, C., Hürkamp, K., Tschiersch, J., Zebisch, M., & Notarnicola, C. (2020). Use of Sentinel-1 radar observations to evaluate snowmelt dynamics in alpine regions. The Cryosphere, 14, 935–956. https://doi.org/10.5194/TC-14-935-2020

Zhu, X., Gu, L., Li, X., & Jiang, T. (2022). Snow Depth Estimation Based on Parameter Combinations Selection and Machine Learning Algorithm Using C-Band SAR Data in Northeast China. IEEE Geoscience and Remote Sensing Letters, 19. https://doi.org/10.1109/LGRS.2021.3129998