Response to Reviewer 1 Comments:

This manuscript presents a machine-learning framework for snow-depth estimation in mountainous regions using Sentinel-1 C-band SAR backscatter variables, change-detection-based backscatter indices, and several auxiliary predictors. The method is applied to the Colorado Rocky Mountains, European Alps, and Indian Western Himalayas. The authors report improved performance relative to the existing C-Snow and C-RISE products, and use SHAP-based explainable AI to interpret regional and condition-dependent model behaviour. The manuscript explicitly states two main objectives: developing an improved scalable SAR-based snow-depth estimation method and gaining better understanding of the physical mechanisms underlying C-band backscatter-based snow-depth estimation.

The authors sincerely thank the reviewer for evaluating the manuscript and for the comments, which have been valuable in improving the clarity of the work. Upon reviewing the comments, the authors recognize that certain wording in the manuscript has led to the study's claims being interpreted more strongly than intended. These have now been revised so that the contribution is presented accurately. The authors also appreciate the concerns raised regarding the contribution of the Sentinel-1 backscatter variables relative to the auxiliary variables. These have been examined in detail, and additional analyses have been conducted to more clearly quantify this contribution. Detailed responses to the comments are given below, and the corresponding changes have been made in the manuscript. The authors hope that these responses answer the concerns raised.

Kindly note that the reviewer's comments are in black font, while the authors' responses are in blue font.

While the empirical prediction results are promising in some regions, I do not think the manuscript provides a sufficiently significant scientific contribution for publication in The Cryosphere.

The authors appreciate the concern regarding the manuscript's scientific contribution. While respecting this assessment, the authors believe that the contribution extends beyond the prediction results themselves and also note that improvements obtained with the proposed framework are observed across all three study regions and all the evaluated scenarios, rather than only in some of them.

The framework differs from existing ML-based Sentinel-1 studies (Daudt et al., 2023; Dunmire et al., 2024; Ni et al., 2024; Zhu et al., 2022) by incorporating change-detection-based backscatter indices alongside direct backscatter variables. The results show that these derived indices provide additional snow depth information beyond the direct backscatter variables, which demonstrates the importance of how the Sentinel-1 signal is represented within the retrieval framework.

The study also provides a harmonized implementation of the framework across the Colorado Rocky Mountains, European Alps, and Indian Western Himalayas, enabling a systematic comparison of the Sentinel-1 backscatter–snow depth relationship under substantially different snow, vegetation, terrain, and climatic conditions. The explainable AI analysis quantifies the relative contributions of Sentinel-1 backscatter and auxiliary variables, thereby identifying the conditions under which the radar observations contribute more strongly to the retrieval and those under which the prediction relies more heavily on auxiliary information. This is important for assessing the transferability and limitations of Sentinel-1-based snow depth retrievals, particularly where ground observations are unavailable to indicate how far the estimates can be relied upon. The generalization of the models is also assessed directly by validating them on stations withheld from training and, separately, on water years withheld from training, so that spatial and temporal performance are established independently. All variables are derived and processed on the cloud-based Google Earth Engine platform using preprocessed Sentinel-1 data, thereby reducing computational requirements and making the approach feasible for large-scale, long-term snow monitoring.

Overall, the study provides an improved and scalable method for Sentinel-1-based SD estimation, along with insights into how the backscatter–SD relationship varies across contrasting snow regimes. The authors believe that this work is well aligned with the aims of The Cryosphere, particularly in advancing seasonal snow monitoring in mountainous regions.

In particular, the second stated objective is not achieved. The explainable AI analysis describes the behaviour of the trained ML model, but it does not establish physical mechanisms linking snow depth and C-band backscatter.

The authors agree that the word "mechanisms" claims more than the study can deliver, and the second objective has been reframed as

"ii) to gain physical insight into C-band backscatter-based SD estimation under contrasting conditions"

SHAP only quantifies how a trained model distributes its output among the input variables, thereby describing the contribution of each variable to the model predictions. It contains no representation of the scattering process and therefore cannot, by itself, establish a causal link between snow depth and C-band backscatter. It can, however, provide insight into Sentinel-1 C-band backscatter-based snow depth retrieval by quantifying how, where, and when backscatter variables contribute to the retrieval; how their contributions vary with snow depth, vegetation cover, snow class, and season; and how these patterns differ across three contrasting snow regimes.

The patterns observed in this study are consistent with independent physical expectations, although no physical constraint was imposed during model training. The limited sensitivity of C-band to shallow snowpacks and its reduced sensitivity during the melt period, due to increasing liquid water content and dielectric losses, are both consistent with the current understanding of C-band scattering physics. The fact that these relationships emerge consistently across three regions with contrasting snow climates, terrain, vegetation, and observation networks suggests that they reflect the behaviour of the backscatter–SD relationship itself rather than the particular model fitted in any one region.

However, these observations cannot be interpreted as evidence of the underlying scattering mechanism. Demonstrating the physical scattering mechanisms requires controlled radar experiments with concurrent snowpit characterization, supported by radiative transfer modelling. Such a mechanism-level interpretation cannot be established from spaceborne backscatter and ground-based snow depth observations alone, and the need for dedicated radar experiments has already been acknowledged in the manuscript:

P22, L461: "further radar-based experiments are needed to better understand the underlying scattering mechanisms"

P23, L469: "detailed radar experiments are required to corroborate these observations"

P24, L505: "more detailed tower-based radar and field experiments across different snow and terrain types are essential to characterize these processes more accurately and inform the radiative transfer models"

The need for such experiments is particularly relevant given the current understanding of the C-band backscatter–snow depth relationship. Although the sensitivity of Sentinel-1 C-band backscatter to snow depth has been reported in previous studies (Lievens et al., 2019, 2022), the underlying scattering physics remains poorly understood. To the best of the authors' knowledge, the study of Brangers et al. (2024) is the only C-band tower experiment specifically designed to investigate this relationship, and it is limited to a single alpine site. The observations reported in the present study do not identify the scattering mechanism, but they help characterize the observed backscatter–SD relationship, constrain the conditions under which it is observed, and provide hypotheses that can be tested through future radar experiments. Given the limited understanding of the C-band backscatter–snow depth relationship, insights of this kind are valuable both for guiding future experimental studies and for implementing Sentinel-1-based snow depth retrievals over large regions or operationalizing the approach.

The authors agree that the wording of the objective and a few statements in Sections 4.3 and 5 did not consistently convey this. The manuscript has been revised accordingly so that the contribution is presented as providing physical insight into Sentinel-1-based SD retrieval, rather than as identifying the underlying scattering mechanisms.

Moreover, the model appears to rely strongly on auxiliary variables such as snow cover duration, elevation, day of water year, snow class, and altitude group. The authors’ own SHAP analysis shows that SCD is the most influential variable across all regions, with DEM also highly important, whereas the backscatter variables are secondary and condition dependent.

The authors thank the referee for this comment and agree that snow cover duration (SCD), elevation (DEM), and day of water year (DOW) contribute substantially to model performance, and that the influence of the Sentinel-1 backscatter variables is condition-dependent. However, it cannot be concluded from the reported SHAP values that the backscatter variables are of secondary importance to the retrieval. Therefore, additional analysis has been conducted to examine this directly.

The SHAP values in the manuscript are reported at the level of individual features. The Sentinel-1 information is represented by six variables (γ°_{vv}, γ°_{vh}, $\gamma^\circ_{vh/vv}$, I_{vv}, I_{vh}, I_{cr}), whereas SCD is represented by one. The importance of the Sentinel-1 observations is therefore divided among six correlated features. Grouping the six together over the entire dataset gives the values shown in Table 1.

Table 1. Grouped SHAP importance of each variable group in the three study regions.

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

Grouped in this way, the Sentinel-1 backscatter variables account for about 15%, 18%, and 20% of the total importance in CRM, EA, and IWH, respectively. In EA and IWH, these values are comparable to those of SCD (29 % and 25 %), DEM (20 % and 17 %), and DOW (14 % and 22 %), indicating that the model relies on a combination of satellite observations and auxiliary variables rather than being dominated by a single predictor. Only in CRM is SCD the largest contributor, consistent with previous studies showing that C-band Sentinel-1 backscatter has limited sensitivity to the relatively shallow snowpacks typical of this region (Hoppinen et al., 2024).

To further investigate the contribution of Sentinel-1 backscatter and SCD to snow depth estimation accuracy, additional experiments were conducted using four models: static variables only (M1), static variables with SCD (M2), static variables with Sentinel-1 backscatter (M3), and the full model (M4). Here, the static variables are DEM, DOW, PTC, snow class, and altitude group. All four models use the same preprocessing, station split, temporal folds, sample weighting, hyperparameter ranges, and random seeds, so that they differ only in the input variables. The results are shown in Table 2:

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

Model	Temporally Independent Cross-Validation MAE(r)			Spatially Independent Testing MAE(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)

The results show that adding the Sentinel-1 backscatter variables yields performance improvements comparable to those from adding SCD. In both EA and IWH, the improvements from Sentinel-1 backscatter (M3) are similar to, or slightly greater than, those from SCD (M2) relative to the baseline model (M1), indicating that the combined contribution of the six backscatter variables is comparable to that of SCD and does not indicate that the backscatter variables play a secondary role in the retrieval. In CRM, SCD contributes more strongly than Sentinel-1 backscatter, which is expected given the known limitations of C-band backscatter over shallow snowpacks. Furthermore, comparing M2 with the full model (M4) shows that adding the Sentinel-1 backscatter variables to a model already containing all auxiliary variables further reduces the test MAE by 1.8 cm (CRM), 1.4 cm (EA), and 2.4 cm (IWH), while also reducing the standard deviation of the prediction errors. All three improvements are statistically significant ($p < 0.002$), which shows that Sentinel-1 provides complementary snow depth information beyond that contained in the auxiliary variables.

It is also important to consider the characteristics of the study dataset. The Sentinel-1 C-band signal is known to be most sensitive to snow depths of approximately 1–3 m (Hoppinen et al., 2024), whereas a large proportion of the observations in the dataset correspond to shallower snow conditions. The SD distribution of the available stations is therefore directly relevant: 64% of CRM, 46% of EA, and 31% of IWH observations are below 50 cm, and only 17% of CRM observations exceed 100 cm. Under these conditions, auxiliary variables are expected to contribute more strongly to the prediction.

The use of backscatter together with auxiliary variables follows the approach in the existing Sentinel-1-based snow depth studies, although those studies use only the direct backscatter variables as inputs (Daudt et al., 2023; Dunmire et al., 2024; Ni et al., 2024; Zhu et al., 2022), whereas the change detection-based indices are also used here. The aim of the present study is not to establish that Sentinel-1 backscatter alone can accurately estimate snow depth, but to examine how the method behaves under different snowpack, vegetation, and seasonal conditions, which is particularly useful when the approach is operationalized. To the best of the authors' knowledge, no previous Sentinel-1-based study has quantified how much of the model skill comes from the backscatter variables versus the auxiliary variables, under which conditions, and in which snowpack regimes.

Accordingly, the revised manuscript reports both the individual and the grouped SHAP importance, and the ablation experiments described above have been included in the appendix.

Therefore, the manuscript reads mainly as an applied machine-learning retrieval exercise rather than a contribution to radar snow physics or cryospheric process understanding. The current framing overstates the physical insight provided by the analysis. I recommend rejection. A substantially reframed and redesigned study might be suitable elsewhere as an applied ML paper, but in its current form I do not think it meets the scientific standard expected for The Cryosphere.

As noted above, the wording that gave an impression of claiming more than the study delivers has been revised. The authors would, however, politely disagree with the view that the manuscript reads primarily as an applied machine-learning retrieval exercise. The manuscript concerns estimating snow depth from Sentinel-1 C-band backscatter and how that backscatter relates to snow depth under different snowpack, vegetation, and seasonal conditions. Machine learning is the means by which these are carried out rather than the subject of the study, and the conclusions drawn in the manuscript do not concern the modelling itself. The subject matter is therefore cryospheric rather than methodological, and the work follows the line of studies reported in The Cryosphere (Lievens et al., 2022; Brangers et al., 2024; Hoppinen et al., 2024; Boeykens et al., 2026; Lemos and Riihelä, 2025) concerned with the development and evaluation of Sentinel-1 backscatter-based snow depth retrievals in mountainous regions, including machine-learning approaches, and is therefore relevant to the snow and radar remote-sensing community.

As stated, the study developed an improved and scalable Sentinel-1-based snow depth estimation framework, tested across three contrasting snow regimes, and identified the conditions under which the C-band signal contributes to the estimate and vice versa, as well as identified which backscatter variables contribute under each condition. Together, these indicate the range over which C-band retrieval can be applied and how the existing Sentinel-1-based products should be interpreted. While the scattering physics at C-band remains an open question, these observations narrow it, indicating the conditions that would be most informative to target in future radar experiments, and are of practical use where such retrievals are applied at large scales.

Reframing was therefore necessary and has been carried out. Redesign, however, does not appear to be necessary, as the data, experiments, and analyses support the revised claims. With the framing corrected and the additional analyses included, the authors consider the study to fall within the scope and standards of The Cryosphere and would be glad to make any further revisions that the editor and the referee consider necessary.

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