Authors Response to Reviewers

Montpetit et al.

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1 Response to reviewer # 1
by: Anonymous Reviewer

1.1 General Comments

In this paper, the authors expanded an originally developed Bayesian-based SWE estimation algorithm to a new Ku-band radar sensor applied in Canada. Several important improvements were made.

The achieved SWE estimation accuracy was below 20 mm, and could be improved to 15.8 mm if three additional observation angles are provided.

The authors made great efforts to explicitly describe the influence of the prior mean and variance on the accuracy of the retrieval results and their MCMC-estimated chain uncertainties. They also described the ability of MCMC and a proper constraint setting to correctly characterize a layered snow stratigraphy. The discussions are in-depth, and most of them are correct.

I have only the following suggestions to post.

The authors would like to thank the reviewer for the great positive feedback provided which considerably improves the manuscript. By answering the major comments below, many details in the SVS-2 model data used and Section 2.3 were greatly improved. Figure 1 was also modified with the suggestions of the reviewer.

1.2 Major comments

1. In abstract, what is the physical snow RT model utilized to describe the backscattering in four incidence angles?

The following text was added in the abstract:
... coupled with the Snow Microwave Radiative Transfer model (SMRT) ...

2. It is suggested to provide a false-color image, a DEM, and a land cover in addition to the backscatter image in Figure 1.

Figure 1 was redone to include suggestions from both reviewers. Revised legend:
Figure 1. Sites sampled during the January campaign of the Trail Valley Creek (TVC) 2018/19 experiment. Squares correspond to a 100 m x 100 m around the central surveyed snowpit (see Section 2.2). Background images are two overlapped University of Massachusetts (UMASS) Ku-Band radar images corresponding to two different flight passes acquired November 14, 2018 (left, Siqueira et al., 2021), the 2 m ArcticDEM (center, Porter et al., 2023), and the vegetation classification (right, Grünberg and Boike, 2019).

3. For Section 2.3, it reads unclear whether the SVS-2 simulation dataset is a full region map or one that covers only several individual points. Additionally, the description of the forcing dataset contradicts itself between line 126 (SM in Figure 1) and line 131 (neighboring weather stations).

This has been clarified to indicate that the simulations were done at point-scale at the main weather station (SM). Sentence at L. 131 was removed and information was added to sentence at L. 126 which now reads:
These outputs were generated from point-scale simulations located at the main meteorological site of TVC (SM site in Figure 1), where most of the meteorological forcing data was acquired, and complemented by neighbouring stations when data was not available.

4. Can SVS-2 consider wind compaction and effectively model the wind slab layer for snow in Canada?

This was the objective of the study of Woolley et al. (2024), to retrieve a more realistic density and SSA profile, as seen in the Arctic. Though the density of the wind slab layer is still underestimated, the observed vertical density gradient, i.e. higher density at the surface and lower density at the bottom (depth hoar), is now better represented in the Arctic version of SVS-2. Details are now added in Section 2.3, and is further discussion in Section 5, where the underestimation of the density of the wind compacted layer by SVS-2 introduces challenges for the SWE retrieval.
Section 2.3: Both versions used in the study of Woolley et al. (2024) are tested in this study, where an Arctic version of Canadian Soil Vegetation Snow version 2 (SVS-2) was developed to improve the overall snow properties and stratigraphy of Arctic snowpacks.
Section 5: The thickness of the rounded grains (R) layer is properly estimated, i.e. Markov Chain Monte Carlo (MCMC) reduces its thickness to lower the scattering caused by the low Specific Surface Area (SSA) estimation, and does not increase its density sufficiently to properly estimate snow water equivalent (SWE). The fact the SVS-2 underestimates the R layer density, and that the MCMC model struggles to sample values that are close to measured densities, aggravates the underestimation of SWE.

5. For lines 147-153, does it mean that all sites in Figure 1 use the same single snow profile as the prior? How did you determine the variance of the prior distribution?

That is correct. Since the SVS-2 are point scale simulations centred at SM02, all sites have the same prior. We apologize for neglecting key information in section 2.3, where a 120 member ensemble of SVS-2 outputs were generated for Woolley et al. (2024), where each member had a different parameterization for wind and basal vegetation effects, and thermal conductivity. The priors are then calculate using the mean and standard deviation of all ensemble members.

A total of 120 different simulations were conducted with different combinations of wind and surface vegetation effects, and thermal conductivity parameterizations. These ensembles were used to generate the priors for the MCMC retrieval algorithm (see Section 3.5.1).

6. Line 233: What does "top 30 ensemble members" mean? Are they the first 30 members closest to the study area, or those most similar to the measured snow profile?

Similarly to previous comment, some more information on the top 30 members of the ensemble was added to section 2.3:

Test were also conducted in this study with the 30 ensemble members that had the best continuous ranked probability score (CRPS, see Woolley et al., 2024).

7. Line 253: Could you use equations to describe the idea of DEMCZ for guiding the direction of chain evolution?

The methodology is a bit more complex than some equations. It is recommended to read section 2.2 of ter Braak and Vrugt (2008) to get all the details of the DEMCZ sampler. In this section, only the reasoning as to why it was selected over the more traditional DEMC or more efficient NUTS sampler is given. Users can also refer to the PyMC library: https://www.pymc.io/projects/docs/en/v5.6.1/api/generated/pymc.DEMetropolisZ.html#pymc.

8. Lines 266-270: The methodology for implementing the constraints can be mentioned here.

Clarification on the constraint method was added:

Hard constraints were put on density, SSA and thickness between the layers. If those constraints were not met, the sampled values for these three parameters were rejected.

9. Lines 335-337: Using the Arctic version of SVS-2 simulations, the uncertainties of MCMC retrieval results are reduced when the prior s.t.d. is reduced by narrowing down from all ensembles to the top 30 ensembles. This is reasonable.

Yes, this test was to determine the impact of prior standard deviation on the retrieved SWE uncertainty. This confirms that having better land surface models improves this retrieval method but has some costs if the land surface model is heavily biased with not much variability between the ensemble members, such as what is seen with SSA.

Additionally, in Table 1, is the s.t.d. of Hsnow(R) from the top 30 members (Arctic version) 9.5 or 0.95?

Thank you for bringing this up. The value is 9.5, all other values were reviewed and the error was with the STD of the 120 members. Values for SWE were also added in table 1 as proposed by reviewer Dr. Durand.

Actually, when comparing Fig.8(b) and Fig.7(b), I did not observe a reduction in the uncertainty (i.e., the range of the error bars on the Y-axis). Could you check the values?

The values have been checked. There was not a significant change in STD between the 120 and top 30 ensembles for the Arctic version. Table 2 shows the numerical values of that uncertainty and we see only an improvement of 1 mm between the two ensembles in the retrieved SWE uncertainty. This small difference is hardly visible between Figures 9b and 8b.

10. For the low correlation of the retrieved SWE to the measured SWE in Figs. 7 and 8, could you check the correlation between SWE (or SD) and the original radar observation inputted to MCMC? Are they highly-correlated or scattered?

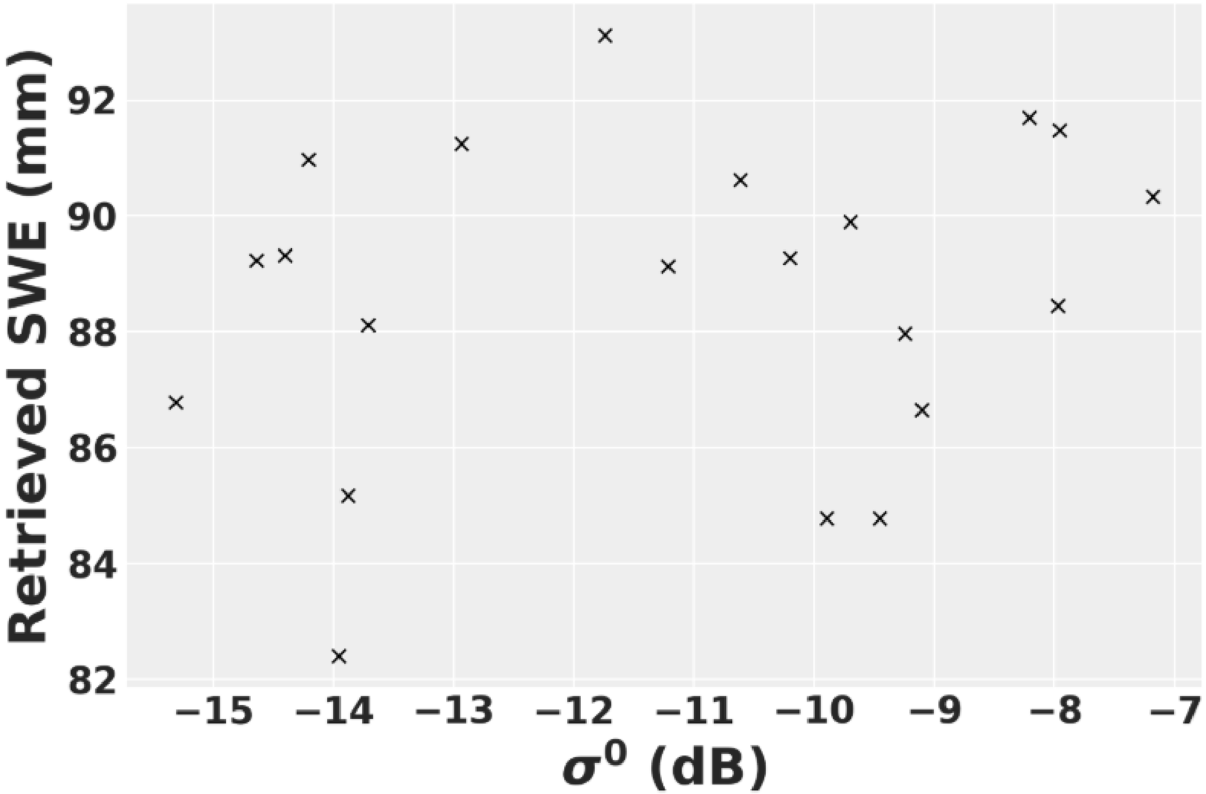
The correlation for the retrieved SWE of Figure 9a was calculated between SWE and backscatter. As seen in Figure below, the points are scattered and R^2 is highly negative. This shows the complex nature of SWE retrieval where many combinations of snow properties can result in the same backscatter coefficient, thus needing proper constraints on the MCMC priors to retrieved realistic snow profiles.

11. The corresponding content of (a) and (b) is not labeled in Figure 9.

The legend now reads:
Comparison of the retrieved SWE using the MCMC approach with priors coming from a) the top 30 ensemble members of the Arctic versions of SVS-2 (Woolley et al., 2024) and b) using the same top 30 ensemble members of the Arctic SVS-2, tripled prior uncertainty on the SSA (σ_{SSA}) and three additional radar backscatter (σ^0) observations (different incidence angles), emulating the number of observations the Terrestrial Snow Mass Mission (TSMM) would acquire. The error bars show the 1st and 3rd quartiles of the measured (x-axis) and posterior (y-axis) distributions.

12. Lines 341-346: This result indicates the considerable impact of the grain size prior on SWE retrieval—not due to the accuracy of the mean, but rather due to the tolerance that allows the MCMC retrieval system to better match the observations. Increasing the variance of grain size indirectly enhances the influence of radar observations on the retrieval.

That is correct. This point is further discussed in the discussion section. In the results section, we only mention that the retrieved SWE is closer to the observed SWE.



13. Did Figure 10 utilize a single-angle radar backscatter, as in Figures 8 and 9?

This is now explicitly mentioned in the figure legend. Figure 11a is with a single observation (same as Figure 9a), Figure 11b is with the higher SSA uncertainty and the four observations (same as Figure 10b), and the last one is the same configuration as Figure 9a without any constraints on the sampled snow properties to show that without them, it is possible to retrieve a SWE value closer to the measurement but the retrieved snow properties profile is not representative of what is truly measured in the field. Legend now reads:

Example from the SM site of prior distributions coming from the default (column a, same prior parameterization as Figure 9a) and Arctic (column b, same prior configuration as Figure 10b) versions of SVS-2 and retrieved posterior distributions from the MCMC method, for the different snow variables compared to the surveyed snow measurements. Column c) consists in the MCMC optimization using the default version of SVS-2, where no vertical constraints on snow properties were applied. σ is the free parameter corresponding to the uncertainty of the radar backscatter measurement and was not measured in the field.

14. Line 405: "other variables like thickness" -> Actually, I think what you really meant might be strategraphy, or strategraphy of layer thicknesses.

What was meant is layer thicknesses. This is also confirmed by the new experiment that was added, as suggested by the second reviewer. MCMC can easily change the thickness of each layer in order to fit the modelled backscatter to the observations. This confirms the need for good prior estimates and proper layering constraints.
These results confirm that synthetic aperture radar (SAR) σ^0 is sensitive to SWE in the Ku-Band range, since, even with a poorly estimated microstructure (Figures 11 a and c), which is an important parameter that drives snow volume scattering in that frequency range (Montpetit et al., 2024; Picard et al., 2022; King et al., 2018), other variables like thickness are tuned to fit the measured σ^0 (Figure 10 c), and can still achieve a reasonable SWE estimate compared to measurements. It should be noted that when SWE is poorly estimated by the prior, the posterior SWE estimate has a higher error (Figure 9), where SWE estimates are concentrated around the initial modelled SWE and do not diverge from that initial estimate. Also, further tests were done (not shown), where the uncertainty on the SWE was increase, by increasing uncertainty on thickness and density individually and separately. Every tests resulted in underestimation of SWE, most likely due to the underestimation of SSA in the priors, which boosted the volume scattering of both layers. The most sensitive parameter in the MCMC model being thickness, it reduced the snow thickness to reduce the volume scattering and fit the modelled σ^0 with the measured σ^0, resulting in an underestimation of SWE.

15. Lines 406-408: "It should be noted that when SWE is poorly estimated by the prior, the posterior SWE estimate has a higher error (Figure 8), where SWE estimates are concentrated around the initial modeled SWE and do not diverge from that initial." -> The accuracy of the prior SWE does influence the SWE retrieval, and this is truly reflected in the likelihood calculation. However, for the case in Figure 10(a), I think the key point is that the default SVS-2 gives a highly-underestimated bottom-layer SSA (i.e., overestimated grain size); with a small variance, the system is forced to trust this value excessively. This resulted in the underestimation of SWE. Additionally, the default SWE prior is underestimated and has a low variance. This helped to make things worse, slightly.

The key point is not to overtrust the land surface model, allowing remote sensing to correct it. Trusting a wrong prior too much is the last thing to do, especially for radar-sensitive parameters.

Excellent point. This was added in the discussion:
This is why it is important to have some knowledge of stratigraphic snow properties, e.g. number of snow layers, density and SSA gradients, to constrain the MCMC method to valid snow properties without overfitting on the most sensitive parameters, and to not over-trust the initial prior estimates, i.e. not be too restrictive on the prior uncertainties.

16. Lines 428-430: "Similarly, when comparing the outputs from both SVS-2 versions, the prior density estimates for the R layer of the default version (Figure 10a), do not allow to sample values close to the measured ρsnow, which prevents the MCMC method to properly sample other variables, such as SSA for the same layer." -> I do not fully agree that the snow density influences SSA; rather, I think SSA influences itself. Or, they both influence both. This is because, in general, the sensitivity of radar signal to snow density is low.

More discussion on this topic was added with regards to your comment and comments made by reviewer 2. Here, the grain size parameter used by Improved Born Approximation (IBA) is correlation length which is given by (see Mätzler, 2002):

$$p_c = \frac{4(1-\frac{\rho_{\text{snow}}}{\rho_{\text{ice}}})}{\rho_{\text{ice}}\,SSA} \tag{1}$$

So the scattering under IBA is driven by both SSA and density of snow. That said, the reviewer is right, the density does have a lesser impact but they do tend to influence each other in minimizing the simulated and observed backscatter.

Similarly, when comparing the outputs from both SVS-2 versions, the prior density estimates for the R layer of the default version (Figure 11 a), do not allow to sample values close to the measured snow density (ρ_{snow}), due to the lower prior uncertainty, which prevents the MCMC method to properly sample other variables, such as SSA for the same layer, since volume scattering in the IBA model depends on both SSA and density.

17. Line 500: It also indicates that remote sensing and land surface model can work together to mutually improve their accuracies. Ku-band radar is sensitive to snow depth and the SSA of the depth hoar layer, which can provide important information in regions with sparse measurements.

Absolutely, this is where the Terrestrial Snow Mass Mission aims at combining the radar measurements with the land surface model with a data assimilation scheme to keep improving both the model and the retrieved SWE from radar. This was added in the conclusion:

This work also indicates that land surface models like SVS-2 and radar measurements can work together to mutually improve their accuracies. This is part of the TSMM concept where SVS-2 and the radar measurements will work together with a data assimilation scheme to mutually improve their estimates, particularly in remote regions with little observations (Derksen et al., 2019).

1.3 Minor Comments:

1. In the abstract, uncertainty should be described more clearly to distinguish it from the RMSE compared with in-situ data. For example, use the MCMC-estimated retrieval uncertainty.

The text in the abstract as been changed to clarify the "uncertainty" in the retrieved SWE:

[...] we can retrieve SWE with an RMSE of 15.8 mm (16.4 %) and a MCMC-retrieved SWE uncertainty of 23.4 mm (25.2 %). [...]

2. In the caption of Figure 3, second line: but->by.

Changed

3. Line 489: We also show -> We would also expect?

Correct, the sentence now reads:
Given the results shown in this study, we should also expect that by allowing the priors to evolve in time and space, given the dynamic seasonal evolution of weather and snow conditions, a reduced number of iterations will be needed for the MCMC method to converge to a solution, thus improving computation efficiency.

4. Line 503: "that influence the most the radar sigma0"—maybe change to "that influence the radar sigma0 the most"?

Changed

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