Reply to comments from Reviewer 1

Montpetit et al.

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1 General Comments

The authors of the manuscript describe the capability of backscatter retrieval using snow microstructure measurements as inputs in a radiative transfer model, SRTM. The paper presents a viable case for a dedicated spaceborne snow mission and explains how the backscatter measurements can be used to characterize snowpack properties. The paper combines methodologies used

- 5 in previous studies for classification and optimization with novel snowpack measurement techniques to estimate background and snow volumetric backscatter. The paper is well thought out and constructed, with appropriate references for each step. However, the section describing the radiative transfer model itself could be modified to include more information regarding the model. Some of the methods appear in the results section for the first time, which can confuse readers. Adding a flowchart showing the complete methodology could make it easier to follow. The results are encouraging, with a low RMSE of 0.9 dB,
- 10 especially for Ku Band. The paper demonstrates publication quality in terms of conceptualization and execution of the study, but a more detailed description of some of the methodology could be provided.

The authors would like to thank the reviewer for the great feedback provided which considerably improves the manuscript. By answering the specific comments below, the methodology section has been improved with details on the radiative transfer model used and the support vector machine classifier used to classify grain types.

15 2 Specific comments

Line 12: can be "characterized" ...

Corrected.

Line 13: I believe this result is important. A sensitivity analysis of soil background roughness on backscatter for different frequencies can be provided. This implies that for a particular snow regime, this value can be used as an initial guess with hard constraints to reduce the number of parameters and simplify the optimization studies done in the future.

We agree that this is an important result of this study. Since it was conducted on a single study area, it is difficult to extrapolate this result to other areas that differ in land cover types. Also, via the optimization process, some sensitivity to background roughness was evaluated and is reflected in the standard deviation of the retrieved value. Though this study uses multi-frequency SAR, the focus of this study was to retrieve snow parameters at Ku-Band, thus adding a multi-frequency

25 sensitivity analysis to the paper would be out of scope for this study and would lengthen it. That said, this analysis will be done in the context of the Terrestrial Snow Mass Mission algorithm development and will be published in a report or possibly peer-reviewed paper/letter. To clarify, the following text was added to section 3.3:

The main objective of this study is to investigate the potential of SAR measurements to retrieve SWE. The fact that the signal intensity of lower frequencies (C- and X-band) is not sensitive to snow mass, these lower frequencies are first used to optimize

30 the soil background properties, without optimizing the snow volume scattering (i.e. polydispersity). The results from this first optimization will then be used to initialize and constrain the soil properties, and limit the number of variables to optimize in the second optimization process using the Ku-band measurements. With this second optimization, the soil backscatter and the snow volume scattering will be considered.

It was also reiterated in the conclusions:

- 35 The main objective of this study is to investigate the potential of SAR data to retrieve snow water equivalent (SWE). It is well documented that Ku-band SAR is well suited to retrieve SWE but underlying soil backscatter has to be properly estimated. This was achieved using satellite data from RADARSAT-2 and TerraSAR-X, the background soil contribution to measured backscatter was characterized. An RMSE of 0.7 dB was achieved between the simulated and measured backscatter at C- and X-Band using the retrieved background properties. Using the Geometrical Optics surface scattering model, we found that the
- 40 real part of the effective permittivity tends to increase with frequency. The retrieved parameters were then used to constrain the optimization of soil backscatter and snow volume scattering at Ku-band.

Line 25-27: Perhaps it's a case of a misplaced comma, but the statement lacks parallel structure. The first part refers to coarse resolution SWE "products," whereas the second part refers to high spatial resolution "sources."

Text has been modified to:

45 While surface snow depth observation networks support the generation and validation of coarse resolution (>25 km) snow water equivalent (SWE) products from passive microwave remote sensing (e.g., Luojus et al., 2021), higher spatial resolution (<500m) SWE products are needed to meet the needs of climate services, water resource management, and environmental prediction (Garnaud et al., 2019, 2021; Kim et al., 2021; Cho et al., 2023).

Line 32: Multiple studies demonstrate the viability of C-band for retrieving wet snow pixels. Perhaps a brief discussion could 50 be added on how Ku-band improves our retrieval capabilities compared to our previous estimates.

It is true that C-Band is a viable option to retrieve wet snow conditions. The physics behind the detection of wet snow at both C- and Ku-Band are practically the same. That said, C-Band can be sensitive to deeper liquid water content (percolation) where

the signal at Ku-Band might saturate due to its lower penetration depth within the snowpack. We agree that both frequencies are complementary to detect wet snow conditions. Text has been modified:

55 [...] (2) the ability to discriminate wet from dry snow cover (Tsang et al., 2022), as a complement to existing C-Band SAR methods (Stiles and Ulaby, 1980).

Line 158: As SMP measurements are the basis of this study a small paragraph on the working principle of the instrument can be added.

A sentence was added to describe the working principal of the instrument. The rest of the paragraph explains how the force measurements of the penetrometer are calibrated for snow microstructure measurements:

The SMP measures the necessary force to drive the penetrometer at a consistent rate vertically through the snowpack (Schneebeli et al., 1999).

Line 178: How is the stratification done using the combination of a categorical (Land Cover) and continuous variable (topography)?

65 Topographic elements (height, orientation, slope) were mapped to the same resolution as the land cover data and the stratified random sampling was done from these combined variables. Modification to text:

[...] using a stratified random sampling approach which considered land cover and topographic variables (elevation, slope, orientation) sampled at the same spatial resolution and grid as the land cover data.

Line 193: Word "ranging from" can be added for clarity.

70 Sentence was changed to:

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On average, incidence angles ranging from approximately 19.5° to 65.0° were available at each site

Line 204: For improved clarity for those unfamiliar with the model, a concise overview of SMRT along with its input parameters can be provided.

Included SMRT overview at the beginning of section 3.3 (Methods/Forward Modeling):

- 75 In this study, the Snow Microwave Radiative Transfer (SMRT, Picard et al., 2018) model was used to simulate the backscattered signal (σ^0) at C-, X-, and Ku-Band at VV polarization. SMRT is a multi-layered snow radiative transfer model where each layer is characterize by, minimally, its thickness, density, temperature, grain size (SSA, optical diameter or correlation length) and the model used to represent its microstructure. In this study, the calibrated SMP profiles provided thickness, correlation length and density and the temperature was inferred from the snowpit measurements. With these inputs, the microwave properties
- 80 such as, interface reflectivity, volume scattering, and absorption are computed using the desired physical models, frequency and incidence angle. Finally, it solves the radiative transfer equation, to calculate the surface backscatter, in the case of active microwave sensors, using the Discrete Ordinate Radiative Transfer (DORT, Picard et al., 2004, 2013). To properly simulate

 σ^0 , the following parameters need to be accurately estimated: 1. the background roughness and permittivity (Meloche et al., 2021; Montpetit et al., 2018) and 2. the snow microwave grain size (Picard et al., 2022) related to microstructure and volume

85 scattering. In this study, the Improved Born Approximation (IBA, Mätzler, 1998) was used for the volume scattering component with an exponential auto-correlation model to represent the snow microstructure, similarly to King et al. (2018); Montpetit et al. (2013).

Line 208: The constraints should be discussed along with references in a table for reproducibility.

Did the reviewer meant line 228 with regards to the boundaries of the optimized soil/snow values. The snow polydispersity 90 constraints were already presented in section 4.4 with its reference (Picard et al., 2022), but it is true that the values for the ε_{soil} and mss_{soil} were not. These latter values are now added in section 4.3 with their relevant references:

 $(2.3 \le \varepsilon_{\text{soil}} \le 5.0, \text{Meloche et al., 2021; Pulliainen et al., 1999}).$

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A table was not added since all values are already included in the text. These values are also discussed in sections 5.2 and 5.3. Finally, for reproducibility, the codes and data are all available here https://github.com/ECCCBen/TVCExp18-19, where these values are integrated within the Notebooks of Parts 7 and 8.

Line 213 and Section 4.3: The actual effect of snowpack on the high frequency backscatter should be discussed. It is not clear how the effect of snow volume backscatter and ground backscatter were separated.

Within the context of radiative transfer, unfortunately, the snow volume scattering and the ground surface backscatter cannot be decoupled since the Discrete Ordinate Radiative Transfer (DORT, Picard et al., 2004, 2013) solver requires both components

100 together, in order to simulate the backscatter at the surface of the snowpack. The effect of snow volume scattering is discussed in section 5.3 where the snow volume scattering is driven by the depth hoar layer. The fact that the two grain types are sensitive to the polydispersity values is proof of the sensitivity of the low Ku-Band signal to snow volume scattering. This is now explicitly stated in section 5.3:

The fact that the optimization process shows sensitivity to grain size via the polydispersity (K) values for both grain types

105 indicates that the lower portion of the Ku-Band spectrum is sensitive to snow volume scattering. [...] Results show that the exponential correlation length parameter, used for snow grain size, has to be reduced for rounded grain layers and boosted for depth hoar layers in order to increase and reduce the snow volume scattering for their respective layers.

Line 269: It is a clever way to identify rounded grains and depth hoar layers. A brief description of SVM classification methodology can be provided in the methods section. Additionally, a brief description of the training datasets for grain type identification is important information for various kinds of studies.

110 identification is important information for various kinds of studies.

A new section was added to the methods section to briefly describe the grain type classifier.

To represent the two-layer nature of the Arctic snowpack, the different layers of the SMP profiles were classified into rounded grains and depth hoar grains. To achieve this, the same support vector machine (SVM) classifier methodology developed in

King et al. (2020) was used. To generate the SVM classifier, only the SMP profiles acquired behind the central snowpit wall were used as training data.

SMP measurements were used as input data to the classifier. Input variables consisted of: mean depth of the SMP snow layer, its associated median force (\tilde{F}) and length scale (L). The output label for each of the SMP layers were determined by the different snow layers visually identified by the surveyors at the snowpit wall. The surveyed grain type layer closest to the mean depth of the SMP layer was used as the output label. Some layers of mixed/faceted grains were identified by the surveyors, which do not

120 directly correspond to the two dominant grain types. In order to use these layers, their labels were changed to rounded grains due to their visual similarity and consistency with what was reported by Picard et al. (2022), in terms of microwave grain size.

Line 282: Why wasn't the mean square slope calculated directly using the Lidar point cloud?

This was initially tested. Unfortunately, as mentioned in section 4.3 line 284, the LiDAR point cloud is very noisy and impacted by anthropogenic sources as well as having inconsistent point density for the different sites. This generated extreme values that were unrealistic. Nonetheless, as stated, the median value for the entire study area was used as the initial conditions. Statistically, the median value filtered out the extreme values.

Added

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Line 399: Why a distributed, statistical approach is not preferable for SWE retrievals using satellite observations? The results in the reference are not based on scatterometer data.

Line 381: Figure no. should be mentioned in the bracket, even though it is mentioned in the starting of the section.

The retrieval approach in (Pan et al., 2023; Durand et al., 2024) uses the same radar SnowSCAT scatterometer data. One uses a Bayesian approach (Pan et al., 2023) and the other uses a look up table (Durand et al., 2024) to retrieve SWE from the SnowSCAT data. In both cases, they used radiative transfer models similar to the one used in this study either directly in their retrieval or to generate their look up table.

135 The reason why the statistical approach is less desirable for satellite retrieval of SWE is due to the computation cost. This has been added in the text:

This is mainly due to the high computation cost of statistical approaches.

Figure 2: The study area figures can be improved. The fonts in the legends are small and difficult to read. Maybe the figure

Figure size has been increased to fit the full width of the page.

140 Figure 5: The histograms are slightly difficult to interpret in the overlapping areas. Therefore, if possible, the histograms can be replaced with lines for better interpretability.

Figure 5 has been modified to improve interpretability. The vertical lines of the bars have been removed, which improves the visibility of histogram overlaps.

Figure 8: I do not understand what is being shown in the figure. Does the dashed line represent the depths where the SMP measurements were made?

The dash lines represent the depths of the different measured SMP profiles and the histogram shows the spread of all snow depth measurements using the MagnaProbe for a given site. These details have been added to the figure caption. *The histogram represents the distribution of snow depth measured with the MagnaProbe. The vertical lines represent the measured snow depth of the different SMP profiles.*

150 Figure 13: The legend can be provided outside the figure and scaled up for clarity.

Legend has been put on the side and the figure has been scaled to fit the full width of the page to improve clarity.

References

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