Revisions of: A Prototype Passive Microwave Retrieval Algorithm for Tundra Snow Density
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1 General Comments

This paper tries to retrieve snow density from a two layer snowpack representation in the Canadian Arctic Tundra from passive microwave (PMW) remote sensing. To do so, they minimize a cost function between the measured brightness temperature delta (ΔTB) at 37 and 19 GHz and the simulated ΔTB using the Snow Microwave Radiative Transfer Model (SMRT). In order to simulate the ΔTB, a number of assumptions on soil background properties, snow grain size and microstructure, snow temperature, and the snow depth hoar thickness ratio are made. Finally, many of these assumptions need to be empirically calibrated in order to fit measured TBs.

The manuscript is well written and figures greatly support the text and help visualize the methodology and the results. Though I recognize and appreciate the amount of work that has been put into this study, I question some of these assumptions and would highly recommend revising the strategy used to retrieve and validate the tundra density profiles. In its current state, it is impossible to determine if the retrieval is representative of the reality or if the calibrations are simply compensating for errors coming from the assumptions made, thus providing invalid density values. Below is a list of assumptions I question and, if possible, suggest potential alternatives.

I also suggest looking at the work of Woolley et al. (2024); Meloche et al. (2022), where they present physical and statistical representations of snowpack properties for tundra snowpacks at scales similar to PMW. I would also look at the methodology of Picard et al. (2022) where they retrieved snowpack properties from passive microwave to analyze the sensitivity of PMW observations to one parameter in the snowpack (e.g. liquid water). A similar approach could be done here to test the PMW sensitivity to density.

1.1 Using weather station data to estimate TB with SMRT

Using AWS data (point scale) to estimate snow/soil conditions is not representative of the PMW scale (25 km). This can induce major errors in the retrieval process. I highly suggest looking at reanalysis datasets like ERA-5 to estimate the snow/soil properties. Its scale is much better suited for PMW data comparison. Also, it is possible to get more than one grid-cell of the reanalysis data within the PMW pixel. Using such datasets also supports further comments below.

Meloche et al. (2022) has shown that a high coefficient of variation on snow depth, i.e. using a distributed range of snow depth values, is better suited for SWE retrievals at the 25km scale. This means that using a single value for snow depth and depth hoar fraction will induce errors on the retrieved parameters since the optimization process optimizes for inaccuracies in the assumed parameters. The also showed in this study that using a static depth hoar fraction, both spatially and temporally, is not representative of what is detected by PMW at the 25 km resolution.

Another variable that could be considered while using re-analysis data is the lake fraction effect which is not considered in this study. The authors mention topography and forest cover, which needs to be minimized but they do not mention anything about lake fraction.

Using a distributed approach using: 1) a more representative source of data, and 2) comparing it with AWS data would be necessary to confirm that the retrieved densities are valid and that these retrieved values do not compensate for errors in initial assumptions.

1.2 Choice of DMRT with non-sticky spheres

Vargel et al. (2020); Royer et al. (2017); Roy et al. (2016); Liang et al. (2008) have shown that choosing the non-sticky sphere version of DMRT is not suitable to simulate TBs. The grain size need to be compensated by a scaling factor due to the stickiness of spheres (Roy et al., 2016). Vargel et al. (2020) showed that results converge towards a stickiness of τ=0.1 which confirms the work of Liang et al. (2008).

That said, more evidence has been gathered in these studies that DMRT-QCA is not the best suited theory to simulate the scattering of depth hoar layers (Vargel et al., 2020). This is why the improved born approximation is now commonly used to simulate microwave signals, both active and passive (Montpetit et al., 2024; Sandells et al., 2022; Vargel et al., 2020; King et al., 2018). Only when densities are above 400 kg·m^{-3} should the strong contrast expansion theory be considered (Meloche et al., 2024).

Keeping the validity limit of 450 $kg{\cdot}m^{-3}$ thus needs to be justified and the scattering theory for this study has to be modified accordingly. That said, with SMRT, different scattering theories can be applied to different layers of the same snowpack (Picard et al., 2018) and these theories can evolve throughout the season as the snowpack evolves.

1.3 Choosing the (Kelly et al., 2003) grain growth to simulate TBs

This model needs to be validated against observations of optical radius grain sizes. At the time of this growth model, this parameter was very difficult to quantify in the field. Since then, many instruments have been developed and should be used against field measurements. Many datasets of snow grain size were acquired and reported in the literature for the studied sites. I highly suggest comparing this grain growth model to these datasets to validate it. Otherwise, I would look at mean values and include an uncertainty to it to retrieve density, since grain size is one of the most, if not the most, important parameter to simulate PMW emissivity. In the current methodology, I would leave this parameter free and optimize it with density in order to assess the uncertainty on both parameters with a sensitivity analysis. By setting the grain size value, it is difficult to determine if the retrieval method is compensating for poor grain size estimate. This could explain higher errors in the early season.

1.4 Using 2m air temperature to estimate depth hoar layer temperature

Knowing that snow in the tundra has a high temperature gradient between the snow-air and soil-air interfaces, and that the PMW signal is sensitive to layer temperature, it is not representative to estimate the temperature of both layers with the air temperature.

I suggest using soil surface temperature as a proxy for the depth hoar layer temperature. This might be available from AWS, and is definitely available in reanalysis datasets.

1.5 Using the (Dobson et al., 1985) model to estimate the frozen ground permittivity

Zhang et al. (2010) mentions that the permittivity values calculated by the Dobson et al. (1985) model are too high and suggests a different model to estimate frozen soil permittivity. Montpetit et al. (2018) showed that both permittivity and roughness are important background properties to estimate PMW emissivity. Meloche et al. (2021) has shown that using the Wegmüller and Mätzler (1999) roughness model with the Zhang et al. (2010) permittivity model with the average root-mean-square height of 1.65 cm gave the best results.

It is highly recommended that the results of Meloche et al. (2021) be included in this study to properly simulate TBs.

1.6 Using a static depth hoar ratio to simulate seasonally evolving tundra snowpacks

See above comments from the work of Meloche et al. (2022). The depth hoar layer has a significant impact on PMW emissivity. Depth hoar fraction is highly variable both spatially and temporally. This alone could explain why the retrieved densities are closer at the end of the seasons.

Including information such as what is described in Woolley et al. (2024), i.e. a more dynamic depth hoar fraction, could improve the temporal accuracy per site and improve the inter-site comparison where different mean depth hoar fraction are most likely representative of the four sites analyzed in this study.

1.7 Not considering atmospheric contributions to the simulated TBs

Sandells et al. (2024) shows the importance of considering atmospheric conditions in TB simulations. Though the study was conducted at higher frequencies than the ones used in this study, similar conclusions were found in the following studies (Montpetit et al., 2013; Roy et al., 2013; Meloche et al., 2022). Vargel et al. (2020) also showed the importance of considering atmospheric contributions. They even showed that the contributions can be very different at 19 and 37 GHz which will have a considerable impact on the simulated ΔTB. GlobSnow products also consider atmospheric conditions to retrieve SWE (Yang et al., 2024; Zschenderlein et al., 2023).

It is thus crucial that this be considered and the methodology used by previous studies (described in Vargel et al. (2020)) is a good method to consider atmospheric contributions using reanalysis datasets.

1.8 Using a "brute-force" method to optimize the cost function

The proposed method of reducing the cost function between ΔTBs is very reliant on the above assumptions which need to be justified and validated.

There are more robust methods that have been implemented in Picard et al. (2022); Pan et al. (2017); Meloche et al. (2022) to retrieve snowpack properties from PMW. The a priori knowledge provided by the validated assumptions presented here could prove more suitable to retrieve profiled density.

1.9 Validating retrieved densities with CanSWE

The CanSWE dataset is an excellent source to compare and validate the retrieved densities from this study. That said, it is impossible to identify where the errors originate from precisely since what is compared is bulk density and the proposed assumptions are fixed. For example, a fixed depth hoar fraction does not allow to estimate the sensitivity of the retrieval method to the thickness of both layers.

In order to better assess the efficiency and accuracy of the retrieval method, a robust sensitivity analysis has to be conducted to properly identify the sources of errors and have more robust and plausible explanations on the discrepancies for certain sites and times.

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