Revisions of: A random forest derived 35-year snow phenology record reveals climate trends in the Yukon River Basin
By: Pan et al.

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1 General Comments

This paper calibrates a RF model on dynamic and static variables to identify snow phenology. Among the dynamic variables, they used the MEaSUREs passive microwave (PMW) brightness temperatures (TB) and modelled snow cover (IMS/SnowModel). They then use the RF classifications over a 35-year period to identify phenology trends. The methodology is sound and the manuscript well written overall. Some clarifications would be needed in order to improve the manuscript and some details still need to be discussed and analyzed. That said, this study provides quality insights and will benefit the cryosphere community.

Though RF is a great tool for multi-variate predictions, there has been a lot of work with Neural Networks (NN), which are very accessible today and have proven to be more robust to link snow properties to PMW measurements (Forman and Xue, 2017). Not that this study needs to be reprocessed, simply something to keep in mind for future implementations of this work. NN are also stronger at identifying simultaneously both spatial and temporal links within the datasets, which would greatly benefit this study. That said, Xiao et al. (2021) did show that RF outperformed ANN to retrieve FSC using the MEaSUREs TB. This latter reference is relevant to be cited in this work.

Also, some questions still remain about the accuracies of the calibrated MEaSUREs TB. Since this study does not use radiative transfer modelling, this TB dataset is still relevant and the calibration uncertainty should be dealt with in the RF model, and compensated by other input variables.

2 Major Comments

The first comment I have is in the processing of TBs. Most studies using TBs at those frequencies will apply an atmospheric correction to remove the impact of the atmospheric water vapour. Dolant et al. (2016) mentions that at 37 GHz, the atmospheric contribution to the measured TB can be up to 10 K. This is ~ 10 % of the signal which is not to be neglected. It will also have a significant impact on the RF model predictions since no atmospheric information is included in the predictor variables. I strongly suggest correcting TBs with the methodology of Liebe (1989), or at the very least include atmospheric water vapour from a reanalysis dataset as an input variable to the model to account for atmospheric conditions.

Another concern I have about this study is that, it was shown by Meloche et al. (2022), using an RF model, that snow depth is strongly linked to topographic features. In this study, it seems it has little importance. I would suggest including similar topographic features from high-resolution DEMs to ensure that topographic information is well captured by the RF model. There are also known issues with TB measurements in high-topography areas (Xiong et al., 2022), and this could help improve the predictions in this study.

This leads to another concern, using TB data in high-topography areas. TB measurements in those areas show high errors due to many factors, one being local incidence angle variation. As mentioned above, adding more topographic information could reduce the uncertainty and could improve the RF model reliability in these areas.

3 Minor Comments

L.50: It is not true that PMWs are insensitive to cloud cover. Please modify this part with regards to major comment above. PMWs can see through clouds but are still impacted by them and the total atmospheric water column. Atmospheric corrections should be applied.

L.66-68: This sentence is a bit confusing to me. This paragraph is about active microwaves, and I feel this sentence should be in the previous paragraph.

L.71: Please justify why only SSM/I and SSMIS were considered for the study. Why not include AMSR, AMSR2 and SMMR to expand the time series and add more data.

L.79-80: This line also seems misplaced since it is the only sentence in the paragraph that talks about active microwaves (backscatter), where the rest is about PMW (brightness temperature/emissivity). Also, with passive microwaves, the emissivity of the snow layers increases and that relationship is stronger with higher frequencies (see Dolant et al., 2016). At lower frequencies, the resulting TB can decrease since you lose the emission from the soil, but with a thick enough snowpack, at K-Ka bands, you will get an increase in TB. In the case of active microwaves, you lose the volume scattering component for the backscatter and only have surface scattering and all (or at least most of) the signal is scattered away from the radar sensor, thus decreasing the measured backscatter (see Tedesco et al., 2015).

L.89-91: I suggest including the review of Meloche et al. (2022) in this section. They used a RF model to retrieve snow depth as well, and their conclusions are relevant to this study.

L.311-312: Please add details on how the 80/20 split was done. Was it randomized? If not, data is most likely correlated and this will affect model performances.

L.323-325: Please discuss the potential errors coming from the different spatial scales of the datasets. The RF model outputs are at the km scale while the GHCNd data is very localized and does not capture spatial variability at the km scale.

L.383-384: It would be good to include a quick paragraph here to confirm the variability of the model outputs. Since these two models are applied at different time frames, it is possible that snow cover is more stable during the IMS period than the SnowModel period. Are the histograms of both models similar or is the SnowModel histogram more spread? This could influence the interpretation of the results and also affect the RF model precision.

L.389: 7-10 days not categorized? Is it because there is no data within that range?

L.398-400: Why are the scales (number of days) for each category different for the two different predictions?

L.403-405: See comment above on TB uncertainty in high topography areas.

Section 5.4: It is not clear to me why the time series was split in 2006? Please clarify.

L.505-506: This could also be due to higher errors in the TB measurements at high-altitudes.

Equations are not numbered, please revise.

References

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