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Interactive comment on "Estimating Snow Depth on Arctic Sea Ice using Satellite Microwave Radiometry and a Neural Network" *by* Anne Braakmann-Folgmann and Craig Donlon

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We thank the anonymous reviewer for his assessment and valuable ideas to improve and clarify the manuscript.

This is a well written paper that introduces a novel approach to estimating snow-on-sea-ice thickness using multi-frequency passive microwave data. The authors go on to show how better snow thickness estimates impact the further calculation of sea ice thickness. The paper is well organized, the references complete, and the figures generally clear. The authors discuss several previous snow thickness algorithms in some detail. They compare results against OIB data to test RMSE and correlation. I

think it would be useful to add additional description about the physical basis for the different algorithms. In most cases at least in so far as I recall, the algorithms are largely empirical and validated against in situ data.

We added more details about the physical basis of the algorithms in Section 2.1 (p.4 ll. 23-25): "[Markus and Cavalieri (1998) developed the first algorithm to retrieve snow depth h_s on sea ice from passive microwave measurements in 1998.] **The physical basis of their algorithm is the fact that brightness temperature is sensitive to volume scattering. The brightness temperature over snow on sea ice decreases, when snow depth increases or when frequency decreases. They found the highest correlation to Antarctic snow depth observations with** [the gradient ratio between 19 GHz and 37 GHz brightness temperatures Tb at vertical polarization V:]"

True, all algorithms presented in the paper are based on empirical fits to observation data (OIB, buoys or ship and ground observations). This is already discussed in the paper.

However the authors seek to use this analysis as a guide for the CIMR mission. Without more detail on the physical basis, it is hard to say how well the algorithm will perform or serve to continue as a long term record given differences between the CIMR instrument parameters and earlier sensors. See for example Zabel and Jezek, 1994, Consistency in Long Term Observations of Oceans and Ice From Space, JGR Oceans, Vol 99, p. 10109.

We added a more details describing the CIMR sensor in Section 3.2 (p.11 ll.7-9): "[Since CIMR would provide the same frequencies that we are using] **(6.9, 18.7 and 36.5 GHz) at the same incidence angle (55°)** [and a similar L1R product, our neural networks could directly be applied to CIMR data and would provide snow depth at a higher spatial resolution]."

Both AMSR2 and CIMR are measuring brightness temperature at 55° incidence

angle and 6.9 GHz, 18.7 GHz and 36.5 GHz as used in the algorithms. The same holds for the former AMSR-E sensor. The slightly different incidence angle of SSMI (53.1°) and frequency (19.35 and 37.0 GHz, no C-band channel) were taken into account by using regression coefficients of the Markus and Cavalieri approach that were adapted for the AMSR instrument parameters by Comiso et al. (mentioned in Section 2.1). Both our neural networks and the algorithms by Rostosky et al. and Kilic et al. are designed for the instrument parameters of AMSR-E, AMSR2 or CIMR. To extend the long term record beyond 2001, when AMSR-E was launched, data from SMMR could be used, but the different incidence angle (50.2°) and slightly different frequencies (6.6, 18.0 and 37.0 GHz) might degrade their performance. Zabel and Jezek (1994) state that snow on sea ice is not too sensitive to small differences in instrument parameters, since surface roughness dominates. Evaluating this could be subject to future work.

The AMSR2+SMOS NN takes additional brightness temperature measurements at 1.4GHz from SMOS. CIMR will cover the same frequency, but at a constant incidence angle of 55°, while SMOS is measuring at varying incidence angles between 0 and 65°. To simulate brightness temperatures as they will be measures by CIMR we only took measurements from SMOS between 50 and 60° incidence angle and averaged them. This is described in Section 3.3. Therefore we are confident that the instrument parameters of AMSR2 and SMOS are close enough to CIMR.

In several of the tables, the authors quote precision to the mm level. Given that the OIB data are at best accurate to 1 cm for snow thickness and maybe 5 cm for ice thickness, the precision in the table should be changed to reflect that.

The precision in the tables and the text has been changed. For the SIT we kept cm precision, but point to the lower accuracy of the OIB data in the text: "[In terms of RMSE our AMSR2-only neural network performs as good as the OIB snow product and both the algorithm by Rostosky et al. and the AMSR2+SMOS neural network are

only 1 cm worse,] **which is not significant considering that the accuracy of the OIB SIT is at best 5 cm. Therefore the last digit of the bias and the RMSE should not be overrated." And** "[When using our two neural networks' snow depth in the SIT calculation, the difference between them becomes marginal] **and is smaller than the accuracy of the OIB SIT."**

It might also be interesting to think about the accuracy of the algorithm derived snow thickness and SIT. There is uncertainty in the accuracy of the OIB data but there is also algorithmic uncertainty the arises from the assumptions in the algorithm. What might be the later and what might be the total uncertainty in the results presented here? I recommend publication after the authors have reviewed my comments.

We divided the former chapter 4.1. into two subsections and added a third subsection on uncertainty estimation at the end of chapter 4.1 (as 4.1.3.) (p.18, l.10): "Finally we assess the uncertainty of our neural networks to enable usage of this snow product in models or for SIT calculation. The very complex and highly nonlinear relationship between the input and snow depth output hinders a stringent variance propagation. Instead, to assess the uncertainty of our neural network approaches, we employ the Monte Carlo method and generate an ensemble of 50 samples for each input brightness temperature. We draw these samples from a normal distribution using the observed brightness temperature as mean and 0.5 K as standard deviation for AMSR2.

For SMOS we take the standard deviation provided in the L3 files for each observation and propagate them through our averaging process to obtain a standard deviation for each SMOS measurement used as input to the polarization ratio. The mean of these standard deviations is 0.76 K for V polarization and 0.79 K for H polarization. Further uncertainty arises from the tie points used both in the Nasa Team algorithm for SIC and to correct the open water part of the footprint (Eq. 2). Therefore we also create an ensemble of 50 samples for each tie point using the values from Ivanova et al. as mean and 3 K as standard deviation. The

resulting mean uncertainty in SIC from the Nasa Team algorithm is 4 %.

We then estimate snow depth using each ensemble member as input to our neural networks. This yields an ensemble of snow depth estimates. The standard deviation of this ensemble is used as an uncertainty measure for the estimated snow depth value. Across all OIB data the resulting final uncertainty (mean standard deviation) is 0.05 m for the AMSR2-only NN and 0.02 m for the AMSR2+SMOS NN, indicating that the AMSR2+SMOS NN is less sensitive to noise in the input data. The error (repeatability) of the Monte Carlo simulation is 0.0005 m and 0.0001 m respectively. This approach however only assesses how robust the neural networks are to uncertainty in the input data and auxiliary parameters such as the tie points. Further uncertainty arises from training the neural networks with OIB data, which has its own uncertainty and limitations unlike a real ground truth dataset. "

In the conclusion we added a sentence (p.22, l.11): "From a Monte Carlo simulation we derive an uncertainty of 5 cm for the AMSR2-only and 2 cm for the AMSR2+SMOS NN."

We also updated the sample code provided on github (mentioned under code availability) to include a standard deviation for each snow depth estimate (p.23, ll.18-19).

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