



Supplement of

Assessment of snow depth retrievability from passive microwave observations over Arctic sea ice: a global sensitivity analysis

Ziyu Yan et al.

Correspondence to: Yufang Ye (yeyf8@mail.sysu.edu.cn)

The copyright of individual parts of the supplement might differ from the article licence.

Supplementary Material

This Supplementary Material provides additional analyses supporting the manuscript “*Assessment of Snow Depth Retrieval from Passive Microwave Observations over Arctic Sea Ice: A Global Sensitivity Analysis*.” It is intended to complement the main content by expanding on the sensitivity analysis results and the assessment of the retrievable space for snow depth.

Catalogue

1. SMRT model setup.....	2
2. Comparison between simulated TBs and satellite-measured TBs	2
3. Sensitivity test using bounded Gaussian sampling in EFAST	5
4. Sensitivity test using exponential microstructure model in EFAST	6
5. Supplementary figures for the Results section	8
6. Supplementary experiments for GR combination	9

1. SMRT model setup

Tab. S1 SMRT model setups

Topic	Snow	First year ice	
		(including saline interlayer and superimposed ice)	Multi-year ice
Scattering theory		Improved born approximation (with dense snow correction)	
Microstructure Representation		Sticky hard spheres	
Surface/interface scattering models and substrate		Default flat/Fresnel interfaces were used; A water substrate was added below the sea ice.	
Permittivity model	ice_permittivity_matzler87	ice_permittivity_matzler06 brine_permittivity_stogryn85	ice_permittivity_matzler06 polder van staten
Radiative transfer Solver		Discrete Ordinate Radiative Transfer solver	
SMRT version		1.5.1	

2. Comparison between simulated TBs and satellite-measured TBs

We perform additional TB simulation experiment using MOSAiC measurement together with collocated AMSR2 TBs. In this additional experiment, we mainly used the single-layer snow configuration corresponding to Sect. 4.1.1 of the sensitivity analysis. Because direct measurements of snow liquid water content were not available in the MOSAiC dataset used here, we restricted this comparison to the winter period, when dry snow conditions are expected to dominate. The snow depth, density, temperature and radius were taken from the MOSAiC measurements. For each snow observation site, profile measurements were averaged to obtain a representative value for the corresponding snow column.

To make the modeled TBs more comparable with AMSR2 observations, we also

included sea ice and atmospheric datasets in the forward simulation (See Tab. S2). Specifically, the SMRT model was first used to simulate the microwave emission from the snow-covered sea ice surface. The simulated surface TBs were then propagated through the atmosphere using the Wentz atmospheric radiative transfer model (Wentz and Meissner, 2000).

Overall, this SMRT configuration can reproduce the general magnitude and temporal variability of the AMSR2 observed TB, particularly at the intermediate-frequency channels from 18 to 36 GHz (See Fig. S1). At the low-frequency channels (6 and 10 GHz), the simulated TBs are systematically lower than the AMSR2 observations. This discrepancy is likely related to the stronger sensitivity to sea ice background properties. The best agreement is found at 18, 23 and 36 GHz. At 89 GHz, both the observed and simulated TBs exhibit much stronger short-term variability. The model captures part of the observed fluctuation and the late season increases. Overall, the comparison supports the use of the adopted snow and sea ice configurations as a physically plausible basis for the sensitivity analysis.

Tab. S2 Snow, sea ice and atmosphere configurations used in forward simulation

Layer	Parameter	Setting or Source
Snow	Depth	From MOSAiC measurements
	Density	
	Temperature	
	Radius	
	Stickiness	0.15
Sea ice	Thickness	Same setting as in original Manuscript Tab. 4
	Density	
	Temperature	
	Radius	
	Brine volume fraction	
	Porosity	
Atmosphere	Multi-year ice concentration	Use Dataset from University of Bremen (Ye and Heygster, 2015)
	Total water vapor	Use ERA5 reanalysis
	Total cloud liquid water	(Hersbach et al)

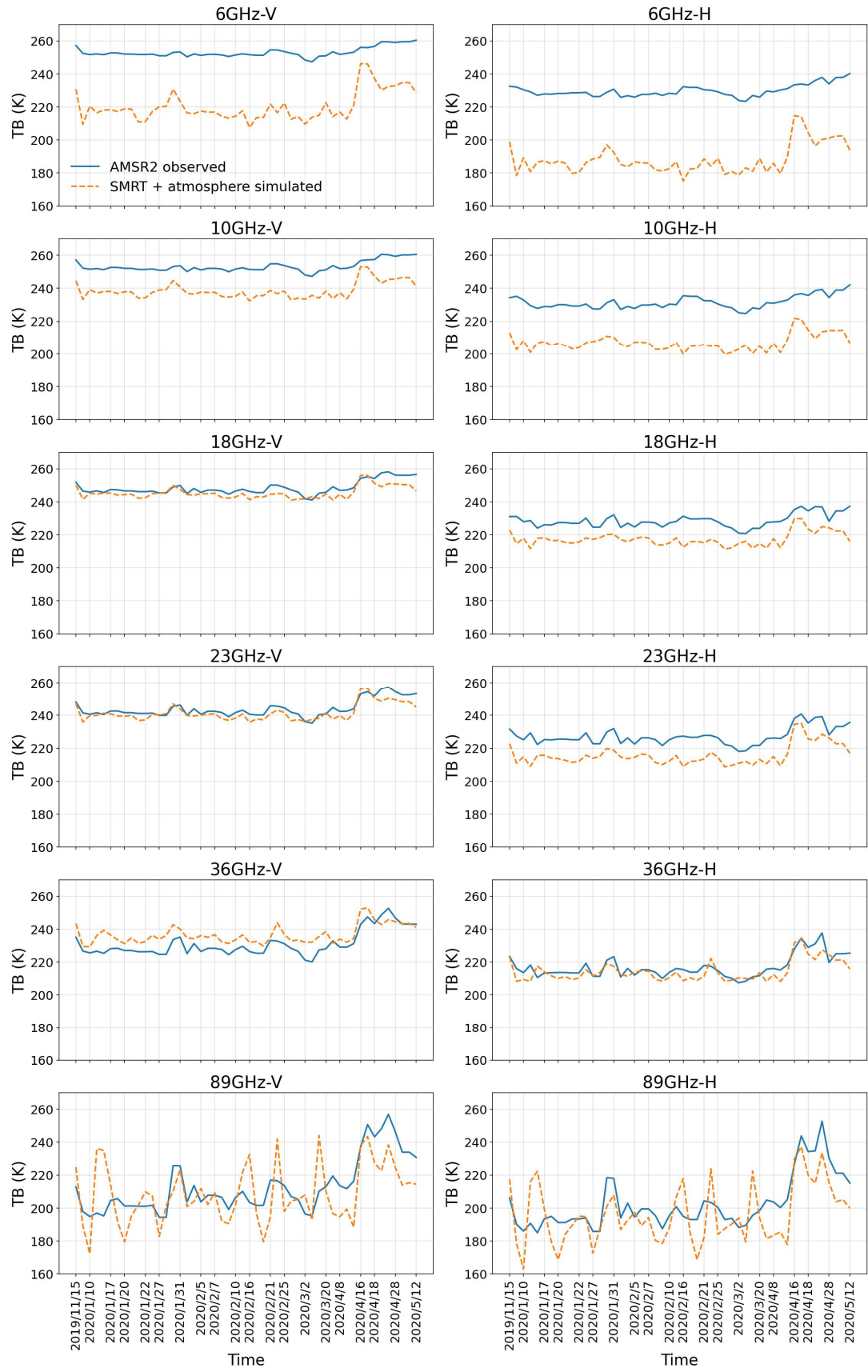


Fig.S1 Time-series comparison of SMRT-simulated TBs and AMSR2-observed TBs during the MOSAiC winter period.

3. Sensitivity test using bounded Gaussian sampling in EFAST

To evaluate whether this sampling choice affects our main conclusions, we performed an additional sensitivity test using bounded Gaussian sampling. Specifically, for parameters with available MOSAiC-derived means and standard deviations, we generated EFAST samples from bounded Gaussian distributions parameterized by these statistics (see Tab. S3), while retaining the parameter range constraints specified in the original study. This allowed the samples to be more concentrated around the MOSAiC-observed mean states while still remaining within the physically plausible intervals.

Tab. S3 Means and standard deviations (Stds) of snow parameters derived from MOSAiC measurements and used in an additional sensitivity test with bounded Gaussian sampling.

Parameter	Depth	Density	Temperature	Radius
Unit	cm	Kg/m ³	K	Mm
Mean	13.2	313.0	257.2	0.37
Std	11.7	137.7	7.2	0.38

The results of additional sensitivity test show no fundamental change in the main conclusions (Fig. S2). The most sensitive parameter in each channel remains consistent with the original uniform-sampling sensitivity test, and the frequency-dependent coupling patterns among snow depth, density and grain radius are also preserved. In particular, the dominant role of snow microstructure at higher frequencies and the strong parameter-coupling behavior identified in the original analysis remain evident under the MOSAiC-constrained Gaussian sampling.

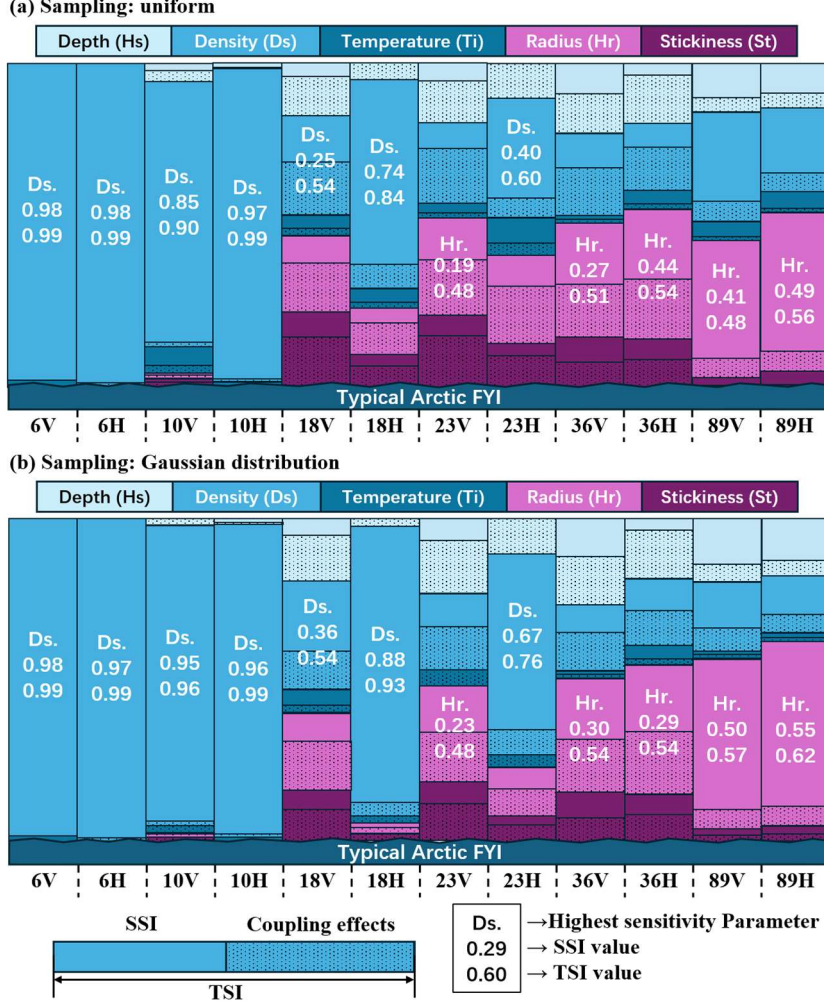


Fig. S2 EFAST sensitivity result of single-layer Arctic snow parameters under dry snow condition. Solid segments indicate the SSI of each parameter, while dotted extensions show the coupling effects captured by the TSI. For each channel (column), the strongest single sensitivity and the total sensitivity are also given numerically.

4. Sensitivity test using exponential microstructure model in EFAST

To evaluate whether our conclusions depend on the use of the sticky hard sphere (SHS) microstructure model, we repeated the sensitivity analysis using the exponential microstructure model while retaining the same SMRT configurations, parameter ranges, and sampling strategy. Because our objective was to isolate the influence of the snow microstructure model, snow depth, density, temperature, and effective grain radius were retained as the input parameters in the sensitivity analysis. For the exponential model, the correlation length (l_{ex}) was derived from the sampled radius (r) through the

corresponding conversion based on snow density (ρ_{snow}):

$$SSA = \frac{3}{\rho_{ice}r}$$

$$l_{ex} = \frac{4(1 - \rho_{snow}/\rho_{ice})}{\rho_{ice}SSA}$$

where ρ_{ice} denotes the density of pure ice (910 kg m⁻³), SSA denotes specific surface area. This conversion ensures consistency between the parameters prescribed in the two microstructure models. Because the exponential model does not use the stickiness parameter, stickiness was fixed at 0.2 in the SHS model and was not included as a variable in the sensitivity analysis.

The comparison, presented in Fig. S3, shows that the principal frequency-dependent sensitivity patterns are generally preserved between the two microstructure models. At 6 and 10 GHz, snow density remains the dominant parameter for both polarizations. At higher frequencies, particularly at 36 and 89 GHz, the snow grain radius remains dominant. Its total sensitivity indices are 0.66–0.71 at 36 GHz for both models and 0.60–0.67 and 0.53–0.59 at 89 GHz for the SHS and exponential model, respectively. Snow temperature has a consistently small influence in both models, whereas snow depth generally makes a secondary contribution. At 18 GHz V-polarization and 23 GHz H-polarization, the dominant parameter changes from density in the SHS model to the radius in the exponential model. At 18 GHz H-polarization, density remains dominant, although its total sensitivity decreases from 0.92 to 0.76. At 23 GHz V-polarization, the radius remains dominant, with total sensitivity of 0.59 and 0.66 for the SHS and exponential model, respectively.

Furthermore, the strong coupling effects associated with snow grain radius, snow depth, and snow density, which are a central focus of this study, are clearly evident under both microstructure models and exhibit highly consistent frequency- and polarization-dependent patterns (Fig. S3). In both the SHS and exponential model, the coupling contributions of these parameters become particularly pronounced at the 18 – 89 GHz. This consistency further supports our conclusion that the TB response is controlled not only by the individual snow properties but also by their nonlinear interactions, and that this key finding is robust to the choice of snow microstructure model.

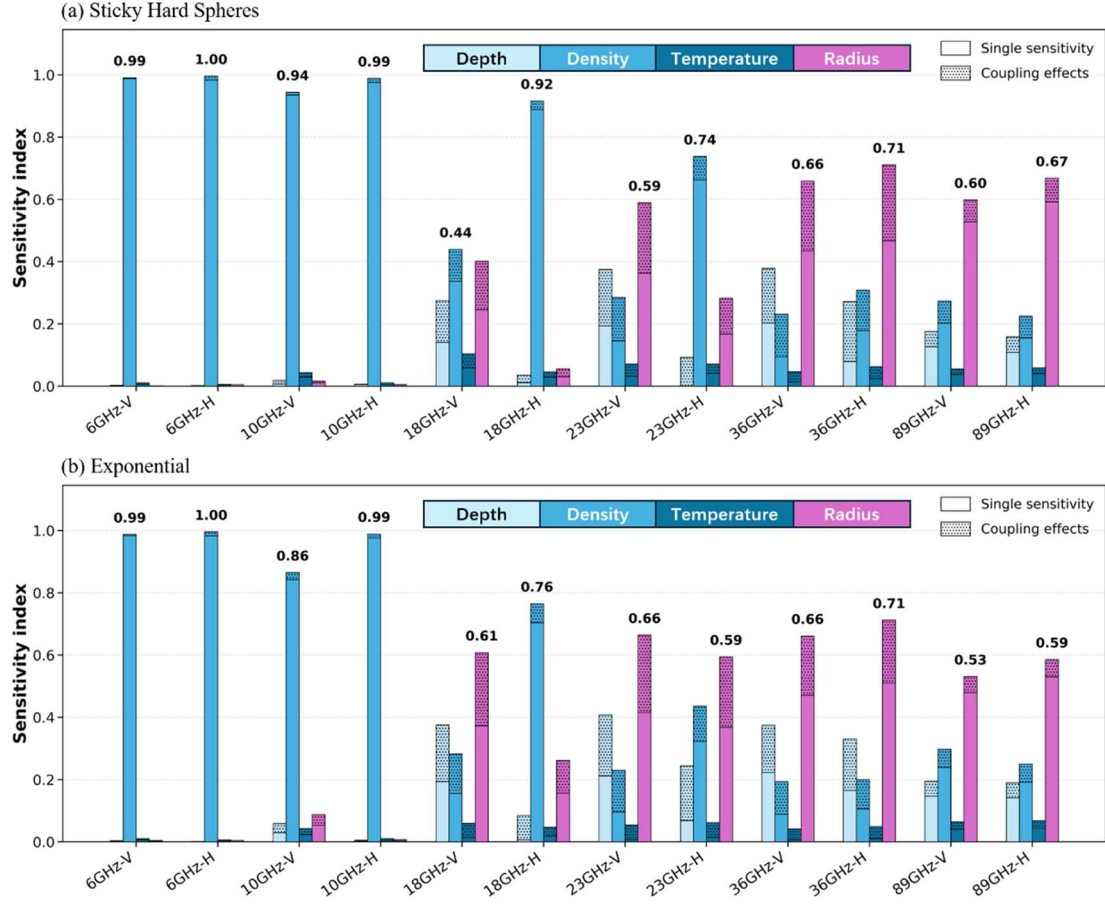


Fig. S3 Comparison of EFAST sensitivity indices obtained using (a) the SHS and (b) the exponential microstructure models. The values above each channel indicate the largest total sensitivity index among the evaluated parameters.

5. Supplementary figures for the Results section

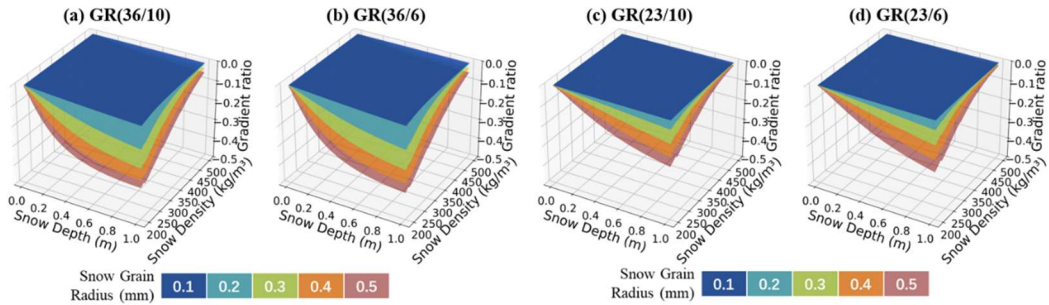


Fig. S4 TB as a function of snow depth and density for different snow grain radius. (Corresponding to Fig. 8 in the paper)

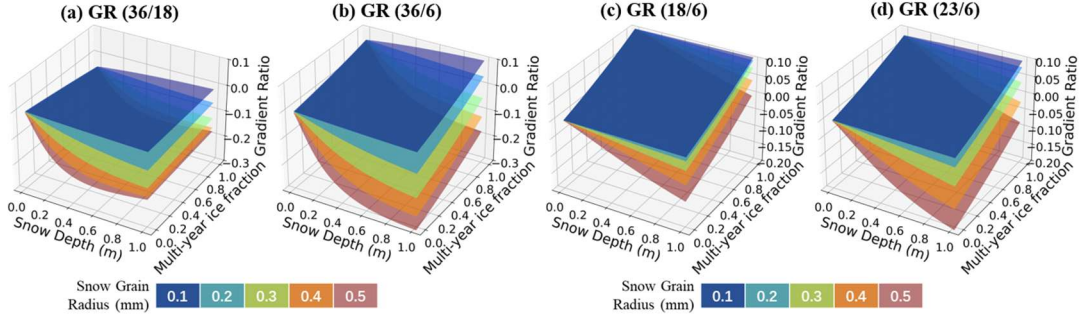


Fig. S5 TB as a function of snow depth and multi-year ice fraction for different snow grain radius. (Corresponding to Fig. 9 in the paper)

6. Supplementary experiments for GR combination

To further substantiate the key conclusions of the manuscript, we perform correlation analyses using multi-year in-situ snow depth measurements in conjunction with AMSR2 observations. These supplementary results aim to verify whether the relationships inferred from the SMRT-based simulations and EFAST sensitivity analysis are consistently reflected in observational evidence across a broader range of environmental conditions.

In addition, because the 23.8 GHz, 36.5 GHz, and 89.0 GHz channels can be substantially influenced by atmospheric variability, we apply an atmospheric radiative transfer model to estimate and reduce atmospheric contributions as much as possible. This processing step is used to better isolate snow signals in the observed TBs, thereby enabling a more defensible comparison with the atmosphere-free forward simulations presented in the main manuscript.

6.1 Atmosphere correction on AMSR2 TBs

We corrected AMSR2 observed TBs using the Wentz model (Wentz and Meissner, 2000; Lu et al. 2022). The atmosphere correction accounts for seven parameters: wind speed, atmospheric water vapor, cloud liquid water, sea surface temperature, ice surface temperature, sea ice concentration, and multi-year ice concentration. The first five parameters are taken from the ERA5 reanalysis (Hersbach et al), while sea ice concentration (Spreen et al. 2008) and multi-year ice concentration (Ye and Heygster, 2015) are obtained from the University of Bremen.

6.2 Comparison with in-situ snow depth measurements

We used in situ observations from Snow and Ice Mass Balance Array (SIMBA) buoys deployed during 2012–2016 (Locations see Fig. S6) to evaluate the different GR algorithm (Preußner et al. 2025). Specifically, the buoy-measured snow depth records were matched to AMSR2 observations (within 6.25 km, 3 hours), and the corresponding TBs were extracted both from the original AMSR2 L1R product and from the atmospherically corrected result. We further filtered the in situ snow depth measurements by selecting “pure ice” surface using a sea ice concentration threshold of SIC > 95%. All collocated observations had a MYIC greater than 20%.

Under this constraint, we evaluated four GRs:

- 1) GR(18/6)
- 2) GR(36/18)
- 3) GR(23/6)
- 4) GR(89/36)

In addition, we introduced an ERA5 snowfall dataset (Hersbach et al) to identify fresh snow conditions. If snowfall occurred on all the three days preceding a given in-suit measurement, we classified that measurement as a fresh snow measurement.

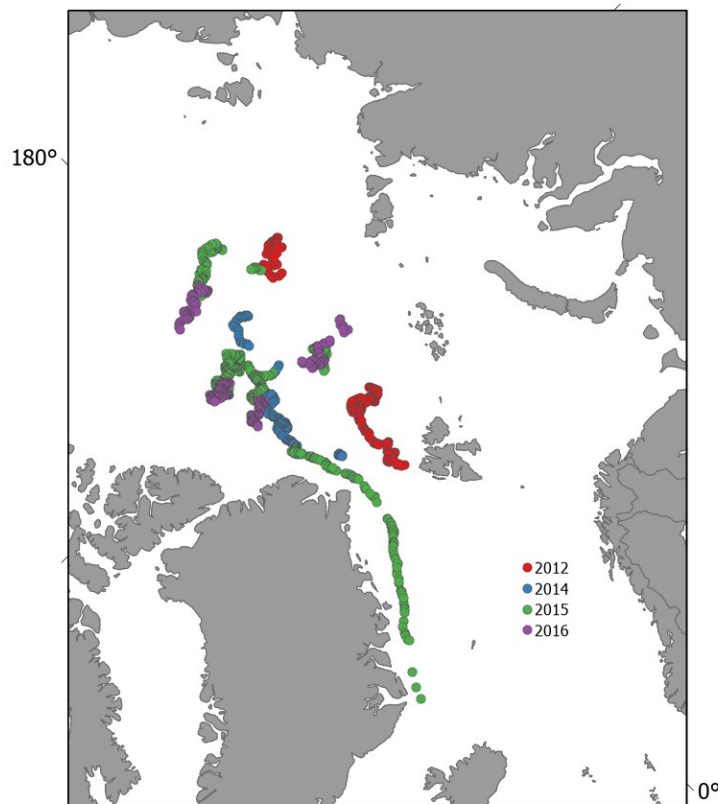


Fig. S6 SIMBA snow depth in-suit measurement locations

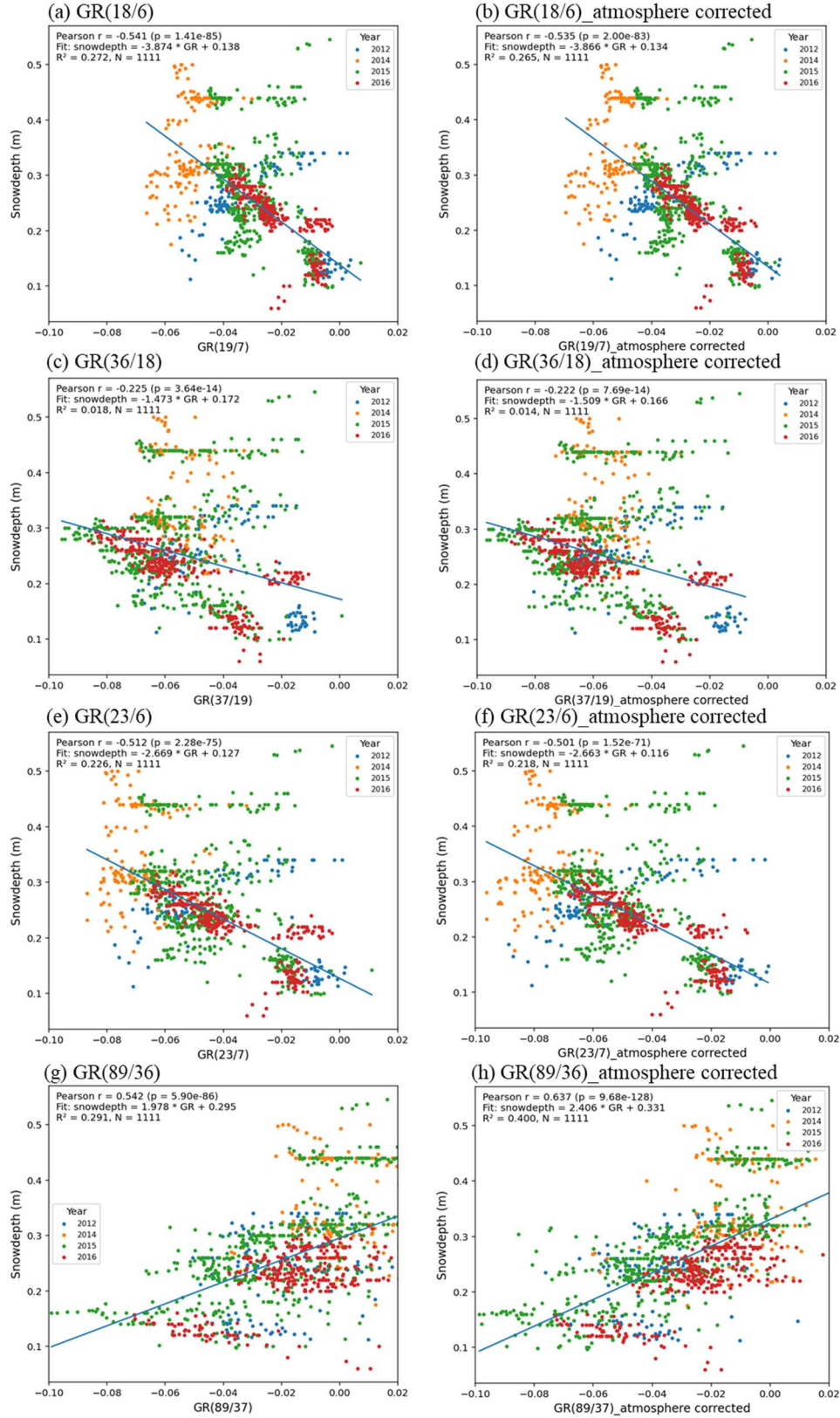


Fig. S7 Relationships between SIMBA snow depth and AMSR2 GR using original and atmospherically corrected TBs. Points are colored by year, solid lines denote linear fits (Huber Robust Regression), annotations report Pearson's r , p -value, and R^2

for each GR.

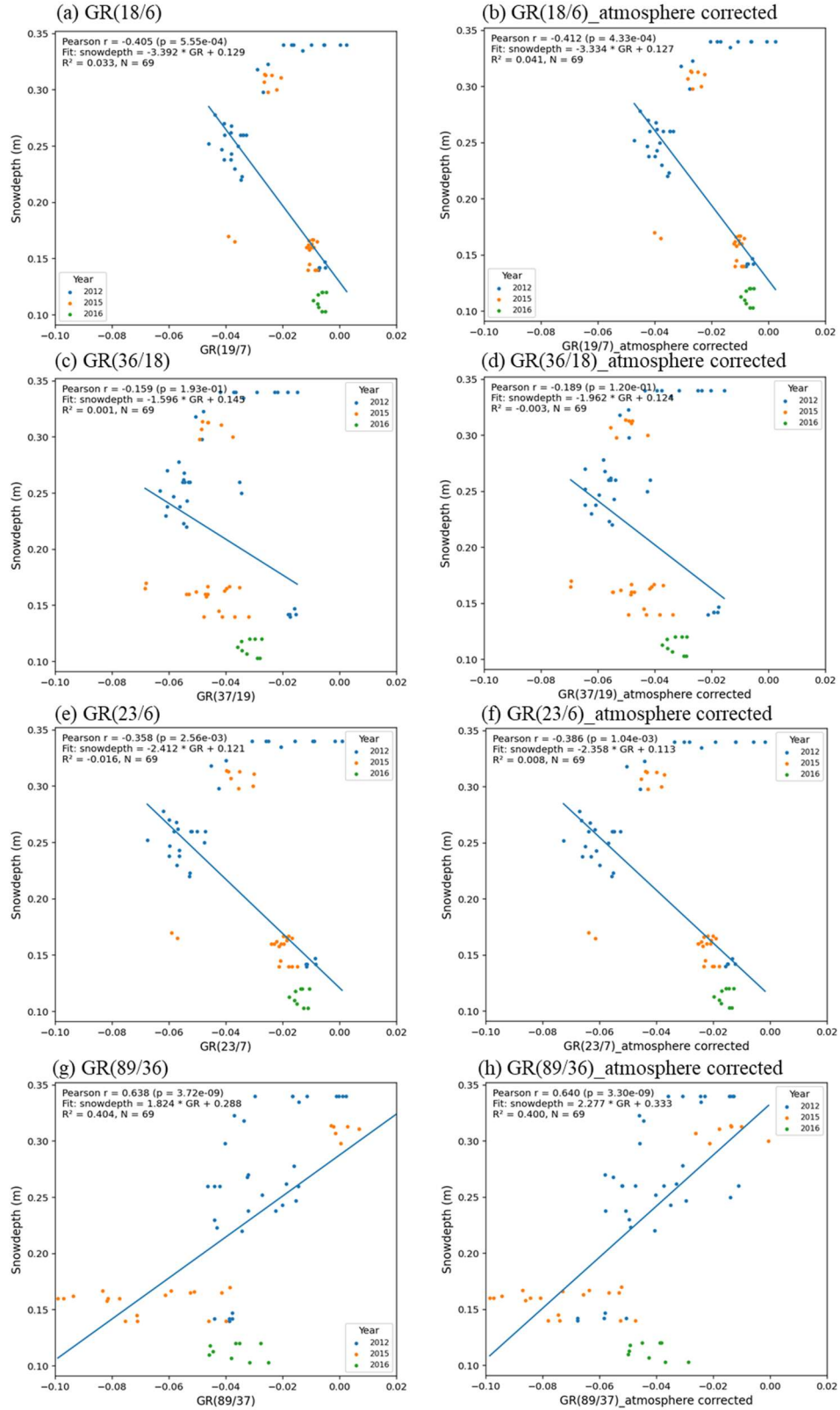


Fig. S8 Relationships between SIMBA snow depth and AMSR2 GR using original and atmospherically corrected TBs **during fresh snow measurement**. Points are colored by year, solid lines denote linear fits (Huber Robust Regression), annotations

report Pearson's r , p -value, and R^2 for each GR.

As shown in Fig. S7, GR(89/36) exhibits the strongest correlation with the buoy-measured snow depth, followed by GR(18/6) and GR(23/6). For most GRs, the correlation changes only marginally after atmospheric correction. In contrast, GR(89/36) shows a pronounced improvement after correction, with the correlation increasing by nearly 0.1, far exceeding the changes observed for the other GR combinations.

Further, Fig. S8 indicates that GR(89/36) maintains consistently high performance under fresh snow conditions, with correlation values remaining stable at approximately 0.63–0.64. By comparison, the other GR algorithms exhibit a marked decrease in correlation for fresh snow.

Ref.

Debye, P., Anderson, J., and Brumberger, H.: Scattering by an Inhomogeneous Solid, II. The Correlation Function and Its Application, *J. Appl. Phys.*, 28, 679–683, <https://doi.org/10.1063/1.1722830>, 1957.

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., and Thépaut, J.-N.: ERA5 hourly data on single levels from 1979 to present, Copernicus Climate Change Service (C3S) Climate Data Store (CDS) [data set], <https://doi.org/10.24381/cds.adbb2d47>, 2018.

Lu, J., Scarlat, R., Heygster, G., and Spreen, G.: Reducing weather influences on an 89 GHz sea ice concentration algorithm in the Arctic using retrievals from an optimal estimation method, *Journal of Geophysical Research: Oceans*, 127, e2019JC015912, <https://doi.org/10.1029/2019JC015912>, 2022.

Löwe, H. and Picard, G.: Microwave scattering coefficient of snow in MEMLS and DMRT-ML revisited: the relevance of sticky hard spheres and tomography-based estimates of stickiness, *The Cryosphere*, 9, 2101–2117, <https://doi.org/10.5194/tc-9-2101-2015>, 2015.

Mätzler, C.: Relation between grain-size and correlation length of snow, *J. Glaciol.*, 48, 461–466, <https://doi.org/10.3189/172756502781831287>, 2002.

Meloche, J., Sandells, M., Löwe, H., Rutter, N., Picard, G., Essery, R., Scharien, R. K., Langlois, A., Jaggi, M., King, J., Toose, P., Scagliola, M., Bouffard, J., Di Bella, A., and Haas, C.: Altimetric Ku-band Radar Observations of Snow on Sea Ice Simulated with SMRT, EGUsphere [preprint], <https://doi.org/10.5194/egusphere-2026-3615>, 2026.

Murfitt, J., Duguay, C., Picard, G., and Lemmetyinen, J.: Forward modelling of synthetic-aperture radar (SAR) backscatter during lake ice melt conditions using the Snow Microwave Radiative Transfer (SMRT) model, *The Cryosphere*, 18, 869–888, <https://doi.org/10.5194/tc-18-869-2024>, 2024.

Preußner, A., Nicolaus, M., and Hoppmann, M.: Snow depth, sea ice thickness and interface temperatures derived from measurements of SIMBA buoys deployed in the Arctic Ocean and Southern Ocean between 2012 and 2023, PANGAEA [data set], <https://doi.org/10.1594/PANGAEA.973193>, 2025.

Spren, G. L., Kaleschke, L., and Heygster, G.: Sea ice remote sensing using AMSR-E 89-GHz channels, *Journal of Geophysical Research: Oceans*, 113, C02S03, <https://doi.org/10.1029/2005JC003384>, 2008.

Wentz, F. J. and Meissner, T.: AMSR ocean algorithm, Algorithm Theoretical Basis Document (ATBD), Version 2, CA, USA, 2000.

Wivell, K., Fox, S., Sandells, M., Harlow, C., Essery, R., and Rutter, N.: Evaluating Snow Microwave Radiative Transfer (SMRT) model emissivities with 89 to 243 GHz observations of Arctic tundra snow, *The Cryosphere*, 17, 4325–4341, 2023, <https://doi.org/10.5194/tc-17-4325-2023>

Ye, Y. and Heygster, G.: Arctic multiyear ice concentration retrieval from SSM/I data using the NASA Team algorithm with dynamic tie points, in: *Towards an Interdisciplinary Approach in Earth System Science*, Springer, Cham, 99–108, https://doi.org/10.1007/978-3-319-13865-7_12, 2015.