# Arctic Sea Ice Thickness estimation from passive microwave satellite observations between 1.4 and 36 GHz

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#### Abstract

Arctic sea ice thickness (SIT) have been mostly retrieved from microwaved and visible altimeters since the 2000s. However, the repeatability of altimeters and their spatial coverage limit SIT estimates spatially and temporally.

On the other hand, the passive microwave (PMW) radiometer have daily basin-scale coverage of the Arctic.

In this study, we proposed a SIT retrieval from PMW observations, based on a statistical inversion technique.

It is based on the evidence of hig correlations between PMW observations and existing altimetric satellite-derived SIT, especially at 36 GHz.

Lidar ICESat-2 SIT products were used to train a neural network with multiple combinations of brightness temperatures between 1.4 and 36 GHz as inputs over the 2018-2019 time period. The PMW retrieved SIT can mimic the lidar SIT product over the full winter over the Arctic, with a correlation of 0.85, and a RMSE of 0.54 cm.

Results were also compared with the altimeter CS2SMOS and the Nucleus for European Modelling of the Ocean (NEMO) SIT products and with the Operation IceBridge QuickLook SIT measurements.

The Neural Network (NN) SIT retrieval with all frequencies from 1.4 to 36 GHz has good performance, a correlation of 0.72 and a RMSE of 57 cm when compared to OIB-QL measurements, for large sea ice thickness (mostly above 3 m), under multi-year ice environments.

The NN SIT retrieval using only 18 and 36 GHz has also shown satisfactory performances, paving the way for the creation of long time series, these two microwave channels being available since the 1980s.

## Arctic Sea Ice Thickness estimation from passive microwave satellite observations between 1.4 and 36 GHz

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#### Key Points:

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9	• High correlation is evidenced over the Arctic between passive microwave signa-
10	tures and SIT derived from lidar and radar altimeters.
11	• A Neural Network inversion is able to estimate SIT from passive microwave ob-
12	servations.
13	• The new SIT results show good performances when compared to other satellite
14	or model-derived SIT, as well as to campaign measurements.

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#### 15 Abstract

Arctic sea ice thickness (SIT) have been mostly retrieved from microwaved and visible 16 altimeters since the 2000s. However, the repeatability of altimeters and their spatial cov-17 erage limit SIT estimates spatially and temporally. On the other hand, the passive mi-18 crowave (PMW) radiometer have daily basin-scale coverage of the Arctic. In this study, 19 we proposed a SIT retrieval from PMW observations, based on a statistical inversion tech-20 nique. It is based on the evidence of hig correlations between PMW observations and 21 existing altimetric satellite-derived SIT, especially at 36 GHz. Lidar ICESat-2 SIT prod-22 ucts were used to train a neural network with multiple combinations of brightness tem-23 peratures between 1.4 and 36 GHz as inputs over the 2018-2019 time period. The PMW 24 retrieved SIT can mimic the lidar SIT product over the full winter over the Arctic, with 25 a correlation of 0.85, and a RMSE of 0.54 cm. Results were also compared with the al-26 timeter CS2SMOS and the Nucleus for European Modelling of the Ocean (NEMO) SIT 27 products and with the Operation IceBridge QuickLook SIT measurements. The Neu-28 ral Network (NN) SIT retrieval with all frequencies from 1.4 to 36 GHz has good per-29 formance, a correlation of 0.72 and a RMSE of 57 cm when compared to OIB-QL mea-30 surements, for large sea ice thickness (mostly above 3 m), under multi-year ice environ-31 ments. The NN SIT retrieval using only 18 and 36 GHz has also shown satisfactory per-32 formances, paving the way for the creation of long time series, these two microwave chan-33 nels being available since the 1980s. 34

#### <sup>35</sup> Plain Language Summary

Arctic sea ice thickness (SIT) have been retrieved from satellite radar and lidar al-36 timeters since the 2000s. However, the altimeter spatial coverage and their repeatabil-37 ity limit the SIT estimates, spatially and temporally. On the other hand, satellite pas-38 sive microwave radiometers have daily basin-scale coverage of the Arctic. In this study, 39 we proposed to estimate SIT from passive microwave observations, with a statistical in-40 version technique. It is based on the evidence of a high absolute correlation between ex-41 isting altimetric satellite-derived SIT, and passive microwave observations, especially at 42 36 GHz. Lidar SIT products are used to train a neural network with multiple combina-43 tions of brightness temperatures between 1.4 and 36 GHz as inputs, over the 2018-2019 44 time period. Results are compared with other satellite and model derived SIT, as well 45 as with in situ campaign measurements. The new passive microwave SIT retrieval with 46 all frequencies from 1.4 to 36 GHz shows good performance, even for large SIT, under 47 multi-year ice environments. The SIT retrieval using only 18 and 36 GHz also has sat-48 isfactory performances, paving the way for the development of long time series, these two 49 microwave frequencies being available from satellite since the 1980s. 50

#### 51 **1** Introduction

Over the last decades, the Arctic region has experienced climate changes at magnitudes and rates higher than most regions in the world (IPCC report, 2019) leading to a large decrease in sea ice extent (SIE) and thickness (SIT) (Pörtner et al., 2019). Sea ice regulates the energy and mass exchange between the atmosphere and the underlying ocean in the polar regions, and the observed sea ice loss over the last ~40 years contributed to the warming amplification in the boreal region (e.g., Serreze and Barry (2011); Dai et al. (2019)).

The Sea Ice Extent (SIE) has been extensively monitored from passive microwave satellite observations since the late 70's (e.g., Comiso (1986)), and its decline has been evidenced (e.g., Stroeve et al. (2012); Kwok (2018)). Large-scale satellite estimation of the Sea Ice Thickness (SIT), the other necessary parameter to estimate the sea ice volume change, is more recent, with the advent of the laser altimeter missions (Ice, Cloud and Land Elevation Satellite (ICESat and ICESat-2) (Schutz et al., 2005; Abdalati et

al., 2010)), and radar altimeter missions (e.g., ERS 1 and 2 (S. Laxon et al., 2003), or 65 CryoSat-2 (CS2) (Wingham et al., 1986; S. W. Laxon et al., 2013), see Abdalla et al. (2021) 66 for a review). Because of their nadir geometry, the repeatability of altimeters and their 67 spatial coverage limit SIT estimates spatially and temporally. Both altimetry techniques 68 (laser and radar) estimate a freeboard, i.e., the thickness of the layer protruding above 69 the water level: for the laser altimeters, this layer includes the snow cover and for the 70 low frequency radar, the signal is expected to penetrate the snow layer and reach the sea 71 ice surface. The freeboard estimate is the difference between a measurement above sea 72 ice and another one over open ocean or a lead. The estimation of the total sea ice thick-73 ness, including the submerged draft sea ice part, always assumes hydrostatic equilibrium, 74 and an estimation of the snow loading over the sea ice. As a consequence, assumptions 75 have to be made, first on the snow depth and density, often using climatologies (Warren 76 et al., 1999), but also satellite estimates or modeling, and second on the ice and water 77 densities. Long time series of publicly available sea ice thickness products include the 78 ICESat-2 monthly winter product from Petty et al. (2020) data or the CS2 winter prod-79 uct from Tilling et al. (2018). The sensitivity of the radar altimeter estimates is expected 80 to decrease for low sea ice thickness, and passive microwave observations at L-Band (1.4 GHz) 81 from the Soil Moisture Ocean Salinity (SMOS, (Font et al., 2010)) or the Soil Moisture 82 Active Passive (SMAP, (Entekhabi et al., 2010)) missions have been exploited (Kaleschke 83 et al., 2010) and merged with the CS2 estimates for an improved product (CS2SMOS) 84 covering the full range of sea ice thickness, and available on a weekly basis over the win-85 ter (Ricker et al., 2014). 86

Satellite-based SIT estimates have been evaluated and compared. Wang et al. (2016) 87 include ICESat-2, CS2, and SMOS products in their comparison against aircraft and model 88 estimates. Sallila et al. (2019) essentially concentrate on the differences between radar 89 altimeter products derived from CS2. In addition to the intrinsic limitations of the dif-90 ferent satellite sensors, estimations of SIT are based on several and different assumptions 91 on the snow loading and the geophysical parameters of the sea ice, which leads to dif-92 ferences between SIT products (Wang et al., 2016; Petty et al., 2020), even when using 93 the same instrument (Sallila et al., 2019). 94

Satellite passive microwave observations have been extensively exploited to esti-95 mate Sea Ice Concentration (SIC and the related SIE), sea ice type, as well as snow depth 96 over sea ice, mainly from 18 and 36 GHz measurements from imagers such as the Ad-97 vanced Microwave Scanning Radiometers (AMSR) or the Special Sensor Microwave / 98 Imagers (SSM/I) (Comiso, 1995; Comiso et al., 2003; Walker et al., 2006; Markus & Cav-99 alieri, 2009). Thin sea ice thickness is also now routinely estimated from passive microwaves 100 at 1.4 GHz (Kaleschke et al., 2016). However, evaluation of the potential of the passive 101 microwave observations to estimate the sea ice thickness for the full thickness range has 102 not triggered yet much efforts, as passive microwave observations are not expected to 103 penetrate the ice for more than 50 cm, and to be directly sensitive to the thicker sea ice, 104 especially at high frequency (Heygster et al., 2014). Nevertheless, we observed unexpected 105 systematic high correlation at basin-scale between passive microwave observations and 106 existing sea ice thickness, during the full winter (see sections below). Recently, Lee et 107 al. (2021) proposed an estimation of the SIT in the Arctic, from the Advanced Microwave 108 Scanning Radiometer 2 (AMSR2, Imaoka et al. (2012)) frequencies between 6 and 36 GHz, 109 based on the assumed proportionality between the scattering optical thickness at these 110 frequencies within the freeboard and the physical thickness of the freeboard, and a re-111 alistic snow depth on sea ice. The relationship between the optical thickness and the ice 112 freeboard is derived from a linear fit with ice freeboard from CS2. 113

Here, we propose to directly exploit the strong statistical relationship observed between the passive microwave observations and the existing large-scale sea ice thickness
estimates, to derive SIT using a machine-learning approach. The motivation is twofold:
first to develop a method to produce a robust long-time record of sub-monthly SIT at

basin scale, second to prepare the exploitation of the Copernicus Imaging Microwave Ra-118 diometer (CIMR) mission. CIMR (Kilic et al., 2018; Donlon, 2020) is a Copernicus High 119 Priority Expansion Mission first designed to monitor the poles. It will observe from 1.4 120 to 36 GHz, with a large 7 m antenna to reach 5 km spatial resolution at 18 and 36 GHz. 121 The Copernicus Polar Ice and Snow Topography Altimeter, CRISTAL, another Coper-122 nicus High Priority Expansion Mission, will also measure the sea ice thickness, overly-123 ing snow depth and ice sheet elevations, owing to a dual frequency altimeter operating 124 at Ku (13.5 GHz) and Ka (36.5 GHz) bands, and synergies between these two CIMR and 125 CRISTAL are encouraged. 126

A database with observations at CIMR frequencies is built, merging the SMAP ob-127 servations at 1.4 GHz and the AMSR2 ones at 6, 10, 18, and 36 GHz, to characterize sea 128 ice and snow (Soriot et al., 2022). The statistical analysis between the passive microwave 129 measurements and the SIT estimates are conducted for the ICESat-2 SIT (Petty et al., 130 2022), for the CS2SMOS SIT (Ricker et al., 2017), and for NEMO (Rousset et al., 2015) 131 modeled SIT. The data and methodology are described respectively in Sections 2 and 132 3. The machine-learning algorithm is trained on the ICESat-2 SIT. The results and their 133 evaluations are presented in Section 4. Section 5 concludes this study. 134

#### 135 **2 Data**

SMAP and AMSR2 provide brightness temperatures  $(T_B)$  from 1.4 GHz (L band) to 89.0 GHz (W band) that include the frequency range (1.4 - 36.5 GHz, from L to Ka bands) that will be observed by CIMR. The satellite-derived SIT are extracted from laser altimetry (ICESat-2) or from a combination of radar altimetry and low frequency passive microwave observations (CS2SMOS). The SIT from the NEMO model is also used (Madec & Team, 2008). Comparisons are conducted with the IceBridge-QL aircraft campaign measurements (N. Kurtz et al., 2013).

All large-scale datasets are extracted over the Arctic Ocean above 55°N, for a complete polar year from November 1, 2018, to October 31, 2019. Data are projected onto the same EaseGrid 2.0 at ~ 12.5 km resolution (Brodzik et al., 2012). The sea ice mask from Ocean and Sea Ice Satellite Application Facility (OSI-SAF) is adopted (Tonboe et al., 2017).

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#### 2.1 Passive Microwave Satellite Observations

149 **2.1.1** SMAP

Since January 2015, the NASA SMAP mission observes the Earth at 1.4 GHz at both vertical (V) and horizontal (H) polarizations, from a Sun-synchronous 6 AM/6 PM orbit (Entekhabi et al., 2014). It has a 6 m real aperture antenna that provides a spatial resolution of 40 km. The observing incidence angle is 40°, with a 1000 km swath. Its orbit inclination angle of 98° allows the full coverage of the poles.

<sup>155</sup> We directly use the daily surface  $T_B$  at 25 km spatial resolution from L2 product <sup>156</sup> (Meissner et al., 2018) provided by Remote Sensing System (https://data.remss.com/ <sup>157</sup> smap/SSS/V04.0/FINAL/L2C last access: 9 March 2022). These  $T_B$  are corrected for the <sup>158</sup> extra-terrestrial signal, and for the Faraday rotation. Within each grid cell, the SMAP <sup>159</sup>  $T_B$  are averaged on a ~ 10-day period (depending on the month, the last 10-day period <sup>160</sup> in the month can be slightly longer or shorter), for each frequency, and polarization.

#### 2.1.2 AMSR2

AMSR2 is a radiometer on board the Japanese polar orbiting satellite GCOM-W, launched in May 2012. It provides observations at 55° incidence angles at 6.9, 7.3, 10.65, 18.7, 23.8, 36.5, and 89 GHz, at both V and H polarizations, with spatial resolution from 48 km at 6.9 GHz to 4 km at 89 GHz. With an inclination angle of 88°, AMSR2 does not observe the Arctic above 88°N. Here, we analyze the frequencies common to the CIMR instrument (noted 6, 10, 18, and 36 GHz hereafter). The Level-1R daily  $T_B$  at their native spatial resolution (Maeda et al., 2016) are obtained from the JAXA website (https:// gportal.jaxa.jp, last access: 9 March 2022).

The EaseGrid 2.0 12.5 km spatial resolution is close to the 10 km spatial sampling of the AMSR2 observations, and to the spatial resolution at 36 GHz (Maeda et al., 2016). Within each grid cell, the AMSR2  $T_B$  are averaged on a ~ 10-day period (depending on the month, the last 10-day period in the month can be slightly longer or shorter), for each frequency, and polarization.

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#### 2.2 Satellite-derived Sea Ice Thickness over the Arctic

#### 2.2.1 ICESat-2 SIT

The ICESat-2 L4 monthly gridded sea ice thickness product (Petty et al., 2022) 177 is extracted (https://nsidc.org/data/IS2SITMOGR4, last access: 19 April 2022), avail-178 able during the winter from November to April at a resolution of 25 km. It is based on 179 the laser measurement of the total height of the freeboard (the thickness of the emerged 180 sea ice layer plus the snow cover layer) if sea ice concentration is > 50 %, if height sam-181 ples are at least 25 km of the coast, and under cloud-free conditions. Hydrostatic equi-182 librium is assumed for estimating the total SIT from the measured freeboard. Estimates 183 of the snow depth as well as the snow, ice, and water densities are also required. The 184 snow depth and density are simulated from the NASA Eulerian Snow on Sea Ice Model 185 (NEOSIM v1.0) (Petty et al., 2018), modified with an empirical piecewise function to 186 increase the initial model spatial resolution (Petty et al., 2020). 187

#### 2.2.2 CS2SMOS SIT

The CS2SMOS SIT product combines the CS2 radar altimeter estimates (Ricker et al., 2014; Hendricks et al., 2016) with the passive microwave SMOS observations (Tian-Kunze et al., 2014; Kaleschke et al., 2016). The data can be found at ftps://smos-diss .eo.esa.int (last access: 19 April 2022). While CS2 lacks the capability to observe thin ice, SMOS is restricted to ice regimes thinner than ~ 1 m (Ricker et al., 2017).

Unlike ICESat-2, CS2 is considered to measure the ice-only freeboard, as the radar 194 frequency (Ku-band at 13 GHz) is expected to penetrate the snow layer and reach the 195 ice surface. Calculation of the total sea ice thickness relies on the hydrostatic equilib-196 rium, with an estimate of the snow loading along with a snow, ice, and water density es-197 timation. The CS2 SIT uses the snow climatology from Warren et al. (1999), for the snow 198 depth and density. The original Warren climatological snow depth is reduced by 50~%199 over first-year sea ice N. T. Kurtz and Farrell (2011), where discrimination between first-200 year and multi-year sea ice type is provided by the satellite-derived OSI-SAF product 201 (Aaboe & Down, 2021). The method to retrieve the thin ice SIT from SMOS  $T_B$  at 1.4 GHz 202 is based on a thermodynamic sea-ice model and a one-ice-layer radiative transfer model 203 (Tian-Kunze et al., 2014). 204

An optimal interpolation scheme is developed to merge the CS2 and SMOS SIT estimates. It is applied to weekly CS2 and SMOS SIT estimates, allowing the estimation of the full SIT range. The product is available from mid-October to mid-April, on a weekly basis, with an initial 25 km spatial resolution.

#### 209 2.3 NEMO Simulations

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The NEMO model is a state-of-the-art modelling framework for research activities and forecasting services in ocean and climate sciences (Madec & Team, 2008). It uses the Louvain-La-Neuve Sea Ice Model 3.6 (LIM3.6) (Rousset et al., 2015).

In this study, the global high-resolution monitoring and forecasting system PSY4V3R1 (Gasparin et al., 2018) is adopted. It is based on version 3.1 of the NEMO ocean model, which assimilates satellite sea ice concentration from the EUMETSAT/OSI-SAF. The PSY4V3R1 NEMO model provides a daily SIT product at 2 km resolution that is averaged on the common 12.5 km EASE grid 2.0.

#### 2.4 Sea Ice Thickness Measurement Campaign

The Unified Sea Ice Thickness Climate Data Record (Lindsay & Schweiger, 2013) aggregates all types of measurements of SIT from airplane and submarines operations, from 1947 to current time. In our time window (11/2018-10/2019), only the Operation IceBridge QuickLook (OIB-QL) data are available (N. T. Kurtz et al., 2013). The measurements are provided by a nadir-looking ground penetration depth radar: the Multichannel Coherent Radar Depth Sounder (MCoRDS), operating at 193.9 MHz (Shi et al., 2010). The differences between radar echoes are directly converted to sea ice thickness.

In April 2019, 125,655 initial points have been measured and grouped to form 50km clusters (N. T. Kurtz et al., 2012). Over the resulting 88 clusters collected by the OIB-QL campaign during this period, 78 are south of 88.5° and are collocated with the previously described datasets. The mean SIT value and its associated SIT uncertainty is provided for each cluster, and the mean SIT values are located on a map (Figure 1).



**Figure 1.** Sea Ice Thickness (SIT) as estimated from the Operation IceBridge QuickLook (OIB-QL) campaign data available for this study, in April 2019.



Figure 2. From top to bottom: ICESat-2 SIT, CS2SMOS SIT, NEMO SIT, SMAP  $T_B^V$  1.4 GHz and AMSR2  $T_B^V$  36 GHz, for three 10-days winter periods (from left to right, the second 10-days periods in November 2018, January 2019, and March 2019), when SIC is above 0.8 (as provided by OSI-SAF estimates).

#### <sup>231</sup> 3 Method

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#### 3.1 Preliminary Analysis of the Data

Figure 2 shows, for the second 10-day period of November, January, and March, 233 the SIT from ICESat-2, CS2SMOS, and NEMO as well as the V-polarized brightness tem-234 perature  $T_B^V$  at 1.4 GHz (SMAP) and 36 GHz (AMSR2), when the OSI-SAF SIC is above 235 0.8. SIT products from ICESat-2, CS2SMOS, and NEMO show similar broad spatial pat-236 terns, although NEMO exhibits significantly less high SIT north of Greenland and the 237 Queen Elizabeth Islands than the satellite estimates. NEMO underestimates the large 238 SIT compared to the other products, and CS2SMOS tends to show lower SIT than ICESAT-239 2 for these large SIT values as well. The sea ice emissivity at 1.4 GHz is high, and that 240 translates in the maps into high  $T_B^V$  (>240 K), with a decrease of  $T_B^V$  in areas where sea 241 ice is likely thin and transparent enough for the underneath ocean to contribute to the 242 signal with its low emissivity. The  $T_B^V$  maps at 36 GHz exhibit spatial patterns similar 243 to the sea ice thickness derived from the satellites, with a significant decrease of the  $T_B^V$ 244 with increasing SIT. 245

To quantify theses spatial relationships, Figure 3 presents the linear correlation between the SIT from ICESat-2, CS2SMOS, and NEMO, as well as the correlation between the ICESat-2 SIT and  $T_B^V$  as a function of time during winter, for selected microwave channels. While the 1.4 GHz  $T_B^V$  shows limited correlation with the SIT and the 6 GHz  $T_B^V$  shows almost no correlation, there is a strong anti-correlation between the ICESat-2 SIT and  $T_B^V$ , at 18 and 36 GHz.

High negative correlation between  $T_B^V$  at 18 and 36 GHz and the other SIT products (CS2SMOS and NEMO) is also observed (not shown), with particularly high negative correlation between CS2SMOS and  $T_B^V$  at 18 and 36 GHz (above 0.9 in absolute value during the full winter). The spatial linear correlations have also been calculated for two SIT ranges, with a threshold at 0.7 m (not shown). For thin ice below 0.7 m, the correlation between  $T_B^V$  at 1.4 GHz and the CS2SMOS SIT is higher than with the other SIT products (ICESat-2 and NEMO). This behavior can be related to the use of  $T_B$  at 1.4 GHz in the CS2SMOS product, for its expected sensitivity to the thin ice thickness.

The physical interpretation of this anti-correlation between the  $T_B^V$  at higher fre-260 quencies and the SIT is not straightforward. These frequencies are not expected to sound 261 within the snow and sea ice. A strong decrease of  $T_B$  with increasing frequency is a sign 262 of scattering processes in the radiative transfer (Ulaby & Long, 2014; Soriot et al., 2022). 263 In these regions of low  $T_B$  at 18 and 36 GHz, the microwave signal is likely scattered, 264 within the snow pack (volume scattering due to the formation of depth hoar for instance), 265 and possibly as well at the surface (surface scattering), as these regions also correspond 266 to multi-year ice areas, where snow accumulates and where rafting and ridging occur. 267 The relationship between  $T_B$  and SIT is likely to bevery indirect, but it is still strong 268 and, as a consequence, it can be potentially exploited for SIT estimation. Given the com-269 plexities of emission and scattering processes within the sea ice and snow pack, this is 270 not an uncommon situation and these frequencies (namely 18 and 36 GHz) have already 271 been extensively used to estimate snow depth over sea ice as well as sea ice type (first-272 year of multi-year), without a robust and clear physical explanation of the direct link 273 between the observation and the snow and ice parameter of interest (see for instance (Rostosky 274 et al., 2018)). 275

#### **3.2 Statistical Inversion**

Given the statistical relationships observed between  $T_B$  and SIT, a statistical inversion is tested, based on Neural Network (NN) techniques. NNs have already been widely used in satellite remote sensing for the retrieval of a large number of geophysical parameters, including sea ice variables (Rösel et al., 2012; Braakmann-Folgmann & Donlon,



Figure 3. Spatial linear correlation among SIT and between ICESat-2 SIT and selected  $T_B$  (1.4, 6, 18, 36 GHz), as a function of time during winter in the Arctic, when SIC is above 0.8 (as provided by OSI-SAF estimates).

2019; Chi & Kim, 2021). Here we adopt a specific NN architecture called Multi Layered 281 Perceptron (MLP) (Rumelhart et al., 1985). The MLP is appropriate to approximate 282 multivariate non-linear mappings (Krasnopolsky, 2007; Cybenko, 1989; Aires et al., 2002), 283 and it will be applied here to build the statistical model reproducing the mapping be-284 tween brightness temperatures and SIT. The MLP will contain a first layer with as many 285 input neurons as microwave channels used in the retrieval, followed by a hidden layer with 286 tansig activation functions, and an output layer with a linear activation functions and 287 one node outputting the retrieved SIT. This NN architecture can be represented by a 288 function: 289

$$y_q = a_{q0} + \sum_{j=1}^k a_{qj} \cdot tanh(b_{j0} + \sum_{i=1}^n b_{ji} \cdot x_i); q = 1, 2...m$$
(1)

where  $x_i$  and  $y_q$  are components of the NN input and output vectors respectively, and 290 a and b are the matrices of the fitting parameters, i.e. the NN weights and biases. They 291 will be determined during the training phase using a database of brightness tempera-292 tures and corresponding SIT, togehter with the training algorithm of (Foresee & Hagan, 293 1997). To avoid spatial or temporal overfitting and increase the robustness of the retrieval, 294 only a random third of the database will be used for the training, as in Rodríguez-Fernández 295 et al. (2019), and an early-stop validation technique will be applied during the training 296 (Prechelt, 2012). 297

The NN is trained on the ICESat-2 SIT, to minimize the inbreeding with the pas-298 sive microwave  $T_B$  inputs. The ICESat-2 SIT is expected to be independent of passive 299 microwave observations (Petty et al., 2020) and is retrieved from a different frequency 300 domain (visible versus microwave) (Abdalati et al., 2010). Indeed, the CS2SMOS prod-301 uct is constructed with  $T_B$  at 1.4 GHz from SMOS (Ricker et al., 2017), and the NEMO 302 model assimilates OSI-SAF SIC which is based on microwave  $T_B$ . However, similar ex-303 ercise could be performed with a NN trained on CS2SMOS or NEMO. In order to min-304 imize the SIC influence, the NN is trained on pixels with SIC > 0.8, as estimated from 305 OSI-SAF. 306

Several combinations of brightness temperatures have been tested as inputs to the 307 NN and the results are compared with the SIT estimates from CS2SMOS, NEMO, and 308 OIB-QL. Among the tested  $T_B$  combinations, two are particularly interesting for further 309 studies: the combination of all CIMR frequencies (1.4, 6, 10, 18 and 36 GHz at both V310 and H polarizations) to showcase the future capability of CIMR to estimate SIT, and 311 the combination of only 18 and 36 GHz V and H channels, to facilitate the production 312 of long time series of SIT (because of the availability of long-time records of these ob-313 servations, with SSM/I, its successor SSMIS, and possibly its ancestor, the Scanning Mul-314 tichannel Microwave Radiometer (SMMR)). 315

316 4 Results and Discussion

#### 317

#### 4.1 Global Arctic Results over the Winter

First, a NN inversion is trained on a subset of the ICESat-2 SIT product, using all the frequencies from the CIMR-like database, from 1.4 to 36 GHz (named  $PMW_{CIMR}$ hereinafter). Over the Arctic winter, the linear correlation between the retrieved SIT and the ICESat-2 product is 0.85, with a Root Mean Square Error (RMSE) of 0.54 m.

Figure 4 shows some statistical analyses comparing the different SIT products, including the  $PMW_{CIMR}$  retrieval: the spatial linear correlation between the different SIT products as a function of the time (top panel), the RMSE in meter between the different products and the  $PMW_{CIMR}$  retrieval as a function of time (middle panel), or as a function of the ICESat-2 SIT (bottom panel). The normalized distribution of the ICESat-2 SIT is also shown in grey shades on the bottom panel.

The general agreement between the satellite products ICESat-2 and CS2SMOS is 328 better (both in terms of spatial correlation and RMSE) than between the satellite prod-329 ucts and the NEMO SIT estimates (Figure 4 top panels), as already expected from Fig-330 ure 2. The agreements are rather stable during the winter, with a slight degradation (de-331 creased correlation and increased RMSE) at the end of the winter season (Figure 4 two 332 top panels). The  $PMW_{CIMR}$  retrieval using all frequencies shows better spatial corre-333 lation and smaller RMSE with all SIT products at each time step (Figure 4 two top pan-334 els, symbols with solid lines), as compared to the initial correlation and RMSE between 335 the ICESat-2 original product and the other SIT products (Figure 4 two top panels, sym-336 bols without solid lines). Note that the spatial correlation between  $PMW_{CIMB}$  and CS2SMOS 337 SIT is even higher than the correlation between  $PMW_{CIMR}$  SIT and the original ICESat-338 2 SIT used to train it, meaning that the passive microwave information in the  $PMW_{CIMR}$ 339 retrieval adds to the agreement between the existing SIT estimates. 340

The RMSE between products tend to significantly increase between most products, for SIT above  $\sim 2 \text{ m}$  (Figure 4 bottom panel). The SIT population above 2 m is rather limited for all SIT products (the ICESat-2 SIT distribution is indicated in grey shades on Figure 4). For the full SIT range, and especially for the lower and higher SIT, the RMSE between the  $PMW_{CIMR}$  retrieval and the other products decreases (symbols with solid lines on Figure 4 bottom panel) as compared to the initial RMS error between ICESat-2 and the other products (symbols without solid lines on the same panel).

Figure 5 shows the maps of the  $PMW_{CIMR}$  SIT and the difference between its es-348 timates and the ICESat-2-based SIT estimates for three different 10-days winter peri-349 ods (11/2018, 01/2019, and 04/2019) not used in the NN training. The maps of the ICESat-350 2 SIT were already shown (Figure 2). The  $PMW_{CIMR}$  SIT maps show the same gen-351 eral patterns as seen in Figure 2, with high SIT north of Greenland and in the Canada 352 Basin, with an increase of the SIT over the winter in the Chukchi Sea. Noticeable dif-353 ferences between  $PMW_{CIMR}$  and ICESat-2 SIT are located along the east coast of Green-354 land, especially in January, where  $PMW_{CIMR}$  exhibits higher SIT values than ICESat-355 2. In this region, note that both CS2SMOS and NEMO have SIT larger than the ini-356



Figure 4. Statistics for inter-product differences, including the  $PMW_{CIMR}$  retrieval. Top: Spatial linear correlation (R) between  $PMW_{CIMR}$  estimates as a function of time in the winter. Middle: RMSE in m between the variables, also as a function of time in the winter. Bottom: the RMSE between the SIT estimates, as a function of the ICESat-2 SIT (with the ICESat-2 SIT distribution indicated in grey shades).

tial ICESat-2, and closer to the  $PMW_{CIMR}$  retrieval (Figure 2). North of the islands of Novaya Zemlya, especially in March, the  $PMW_{CIMR}$  predicts higher SIT than ICESAT-2, where also both CS2SMOS and NEMO have higher SIT than ICESat-2. On the contrary,  $PMW_{CIMR}$  shows thinner SIT than ICESat-2, in the Bering Strait in January.

The SIT retrieval has also been tested using less frequencies in the training of the NN. Suppressing only the 1.4 GHz channels in the NN does not change much the results (not shown): the correlation with ICESat-2 over the full winter decreases from 0.85 to 0.83, and the RMSE increases from 0.54 m to 0.57 m. It tends to degrade the retrieval of small SIT (<1 m), as compared to the original ICESAT-2 SIT, and to the CS2SMOS SIT, as expected, but only slightly.

Tests are then performed using only the 18 and 36 GHz channels (both V and H 367 polarizations), named  $PMW_{1836}$  hereinafter. With this combination, longer SIT time 368 series could be producted, using previous radiometers such as SSM/I (launched in 1987), 369 its successors SSMIS, or even SMMR (launched in 1978) that all include the 18 and 36 GHz 370 channels. The results are presented in Figure 6. The correlation between  $PMW_{1836}$  and 371 ICESat-2 SIT decreases over the full winter (from 0.85 with all channels to 0.80 using 372 only 18 and 36 GHz channels), and the RMSE increases (from 0.54 m to 0.62 m), sug-373 gesting that the retrieval using only two frequencies would slightly degrade the SIT re-374



Figure 5. From top to bottom: maps of  $PMW_{CIMR}$  SIT, and  $PMW_{CIMR}$  SIT minus ICESat-2 SIT, for the  $PMW_{CIMR}$  retrieval. For 10-days periods in November 2018 (left), January 2019 (center), and April 2019 (right).

sults compared to the use of all the frequencies available on CIMR, at least when con-sidering ICESat-2 as the reference.

However, surprisingly, compared to CS2SMOS, the correlation and the RMSE do 377 not change much when using all frequencies or 18 and 36 GHz only, with even a slight 378 increase of the correlation (from 0.85 with the CIMR frequencies to 0.88 with only the 379 18 and 36 GHz channels) and a slight decrease of the RMSE when suppressing all the 380 lower frequencies (from 0.58 m with the CIMR frequencies to 0.54 m with only the 18 381 and 36 GHz). An explanation could be related to the use of the passive microwave 18 382 and 36 GHz channels in the CS2SMOS retrieval, for the estimation of the snow depth. 383 Indeed, the CS2 altimeter data processing involves passive microwaves  $T_B$  at 18 and 36 GHz 384 to modify the original Warren (Warren et al., 1999) snow depth climatology, following 385 the N. T. Kurtz and Farrell (2011) method. To overcome the need for external snow depth 386 information, future altimeters such as CRISTAL (Kern et al., 2020) will be equipped with 387 dual-frequency radar altimeters, with the snow depth estimation being derived from the 388 difference between the signals at Ku (13 GHz) and Ka (35 GHz) frequencies. Garnier 389 et al. (2021) already tested this possibility for snow depth and SIT retrievals with en-390 couraging results, using two different altimetric missions, CS2 at 13 GHz and SARAL/AltiKa 391 at 35 GHz (Verron et al., 2015). With SARAL/AltiKa limited to 82°N (thus excluding 392 most of the multi-year ice), we did not consider this product in the current comparison. 393

394

#### 4.2 Evaluation with the IOB-QL Campaign Measurements

The  $PMW_{CIMR}$  estimates are now evaluated with the OIB-QL campaign measurements. Figure 7 shows the results of the comparison between the OIB-QL SIT measurements with the satellite and model retrievals, including the NN retrieval  $PMW_{CIMR}$  using all the frequencies from 1.4 to 36 GHz. The clusters were organized by increasing OIB-QL SIT measurement, and their location is provided for each cluster. For each OIB-QL cluster, the mean OIB-QL SIT is shown with its associated uncertainty (red crosses



Figure 6. Same as Figure 4, but using the  $PMW_{1836}$  retrieval.

and error bars). For the same clusters, the mean SIT retrieved (crosses) and their associated standard deviation (error bars) are shown for  $PMW_{CIMR}$  in black, ICESat-2 in green, CS2SMOS in orange and the NEMO model in blue. The normalized distribution of the ICESat-2 SIT is also shown in grey shades.

The range of SIT measured by the OIB-QL campaign shows that most of the sea ice observe is multi-year, with the OIB-QL cluster in the tail of the distribution of the ICESat-2 SIT. CS2SMOS and NEMO show small range of SIT, which can be explained by the fact that these products are spatially smooth (see Figure 2), with consequently few variations over a flight. The NEMO model tends to systematically underestimate the SIT, compared to the measurements campaign, as well as compared to the satellite retrievals.

Table 1 shows the bias, the RMSE, the relative RMSE (in relation to the OIB-QL 412 measurements), and the linear correlation coefficient, between the OIB-QL SIT and the 413 others SIT retrievals (including  $PMW_{1836}$ ).  $PMW_{CIMR}$  shows rather good agreement 414 with the OIB-QL measurements with linear correlations of 0.72, a bias of 16 cm, and a 415 RMSE of 57 cm. The differences between  $PMW_{CIMR}$  and  $PMW_{1836}$  results are rather 416 limited, considering that 10 channels are used in the first algorithm and only 4 in the sec-417 ond. The CS2SMOS SIT product shows the best agreements with OIB-QL measurements 418 with low mean bias of 11 cm, a RMSE of 49 cm, and a high correlation of 0.8. The  $PMW_{CIMR}$ 419 SIT performs slightly better than the ICESat-2 product. NEMO tends to underestimate 420 the OIB-QL values, with a mean bias nearly three times higher than the next worst re-421 sult  $(PMW_{1836})$ , and a RSME nearly two times more important than the other prod-422 ucts. 423



Figure 7. Comparison of SIT measurements from OIB-QL (red),  $PMW_{CIMR}$  retrieval (black), ICESat-2 (green), CS2SMOS (orange) and NEMO (blue) products. The error bars represent the mean SIT uncertainty for OIB-QL measurements and one standard deviation for the other SIT estimations. The normalized distribution of the ICESat-2 SIT is shown in grey shades on the left y-axis.

**Table 1.** Bias, root-mean-square errors, relative root-mean-square errors and Pearson correla-tion coefficient between the OIB-QL SIT and the others SIT retrievals.

	Mean Difference (m)	RMSE (m)	Relative RMSE (%)	R
PMW <sub>CIMR</sub>	0.16	0.57	17	0.72
$PMW_{1836}$	0.28	0.61	18	0.74
IS2	0.17	0.66	20	0.69
CS2SMOS	0.11	0.49	14	0.80
NEMO	0.94	1.09	28	0.69

The SIT distribution of the OIB-QL mission is heavily weighted toward very high 424 SIT values (mainly above 3 m) representing mostly multi-year ice. That does not cor-425 respond to the whole Arctic SIT distribution, where first-year ice with lower SIT are dom-426 inating (see the gray shades on Figure 4). The conclusions drawn from this evaluation 427 cannot be extended on the validity of the estimates for low SIT. Note that in the SIT 428 range measured by the OIB-QL campaign (mainly above 3 m), the NN retrieval errors 429 with respect to the other satellite products (ICESat-2 or CS2SMOS) were expected to 430 have RMSE  $\sim 0.6$  m, (see Figure 4). 431

#### 432 5 Conclusion

A simple and yet efficient statistical approach is developed to estimate the Sea Ice Thickness (SIT) from passive microwave brightness temperatures between 1.4 and 36 GHz. It is based on the evidence of high absolute correlations between the observed passive
microwave brightness temperatures (especially at 36 GHz) and existing available satellitederived SIT products. The 1.4 to 36 GHz frequency range will be covered by the future
CIMR mission to be launched by the end of the 2020's. Using a combination of SMAP
and AMSR2 observations, a neural network (NN) inversion is trained on a subset of ICESat2 SIT product derived from independent laser-altimeter measurements, and the NN SIT
is estimated over the Arctic for a full winter season.

The resulting passive microwave NN SIT using all the CIMR frequencies shows a 442 significant correlation with the ICES at-2 SIT data during the whole Arctic winter (0.85)443 and an identical spatio-temporal correlation with the CS2SMOS SIT product (0.85). The 444 NN inversion using only the 18 and 36 GHz frequencies also performs satisfactorily, over 445 the full SIT range. That would make it possible to calculate long time series of SIT from 446 former passive microwave imagers such as SMM/I and SSMIS back to the end of the 80's, 447 or even from SSMR, launched in 1978, with all these instruments being equipped with 448 radiometers at 18 and 36 GHz, at both V and H polarizations. Note that there are on-449 going efforts to inter-calibrate all these microwave imagers for climate purposes, and this 450 SIT estimation could benefit from this very long record of high quality  $T_B$  at 18 and 36 GHz. 451

The NN retrievals were compared to OIB-QL measurement campaign performed in 2019. Both NN retrievals (with all frequencies and with 18 and 36 GHz only) show encouraging performances, comparable to the results obtained with the current ICESat-2 or CS2SMOS SIT products, at least for the SIT range (mainly above 3 m) covered by the OIB-QL measurements.

Several satellite-based SIT exist, each with limitations due to their operating fre-457 quency or their algorithm assumptions. The CS2SMOS and ICESat-2 SIT products both 458 require a characterization of the snow cover (snow depth and snow density). The use of dual frequency (Ku/Ka) radar altimeters (as in Kwok et al. (2020) or Garnier et al. (2021)) 460 can help reduce the uncertainties related to the snow depth, and the future CRISTAL 461 mission, to be launched approximately at the same time as CIMR, will be equipped with 462 this dual frequency capability (Kern et al., 2020). The passive microwave SIT retrieval 463 proposed here is based on a pragmatic approach. It does not require any ancillary in-464 formation. It is easy to apply on a daily basis, on past, current, or future observations, 465 providing close-to global Arctic coverage every day over long time records. 466

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