## Sensitivity of short-range forecasts to sea ice thickness data assimilation parameters in a coupled ice-ocean syste

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## Abstract

Sea ice thickness (SIT) estimates derived from CryoSat-2 radar freeboard measurements are assimilated into the Met Office's global ocean-sea ice forecasting system, FOAM. We test the sensitivity of short-range forecasts to the snow depth, radar freeboard product and assumed radar penetration through the snowpack in the freeboard-to-thickness conversion. We find that modifying the snow depth has the biggest impact on the modelled SIT, changing it by up to 0.88 m (48%), compared to 0.65 m (33%) when modifying the assumed radar penetration through the snowpack and 0.55 m (30%) when modifying the freeboard product. We find a doubling in the thermodynamic volume change over the winter season when assimilating SIT data, with the largest changes seen in the congelation ice growth. Next, we determine that the method used to calculate the observation uncertainties of the assimilated data products can change the mean daily model SIT by up to 36%. Compared to measurements collected at upward-looking sonar moorings and during the Operation IceBridge campaign, we find an improvement in the SIT forecasts' variability representation when assuming partial radar penetration through the snowpack and when improving the method used to calculate the CryoSat-2 observation uncertainties. This paper highlights a concern for future SIT data assimilation and forecasting, with the chosen parameterisation of the freeboard-to-thickness conversion having a substantial impact on model results.

## Sensitivity of short-range forecasts to sea ice thickness data assimilation parameters in a coupled ice-ocean system

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## Key Points:

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12	•	We test the sensitivity of short-range forecasts to the parameters used in the
13		CryoSat-2 radar freeboard-to-sea ice thickness conversion
14	•	The snow depth, radar penetration and retracker used change the thickness by
15		up to 0.88 m (48%), 0.65 m (33%) and 0.55 m (30%), respectively
16	•	Changing the method used to characterize the observation uncertainties can
17		change the mean daily model sea ice thickness by up to $36\%$

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#### 18 Abstract

Sea ice thickness (SIT) estimates derived from CryoSat-2 radar freeboard 19 measurements are assimilated into the Met Office's global ocean-sea ice forecasting 20 system, FOAM. We test the sensitivity of short-range forecasts to the snow depth, 21 radar freeboard product and assumed radar penetration through the snowpack 22 in the freeboard-to-thickness conversion. We find that modifying the snow depth 23 has the biggest impact on the modelled SIT, changing it by up to 0.88 m (48%), 24 compared to 0.65 m (33%) when modifying the assumed radar penetration through 25 the snowpack and 0.55 m (30%) when modifying the freeboard product. We find 26 a doubling in the thermodynamic volume change over the winter season when 27 assimilating SIT data, with the largest changes seen in the congelation ice growth. 28 Next, we determine that the method used to calculate the observation uncertainties 29 of the assimilated data products can change the mean daily model SIT by up to 30 36%. Compared to measurements collected at upward-looking sonar moorings 31 and during the Operation IceBridge campaign, we find an improvement in the 32 SIT forecasts' variability representation when assuming partial radar penetration 33 through the snowpack and when improving the method used to calculate the 34 CryoSat-2 observation uncertainties. This paper highlights a concern for future 35 SIT data assimilation and forecasting, with the chosen parameterisation of the 36 37 freeboard-to-thickness conversion having a substantial impact on model results.

#### <sup>38</sup> Plain Language Summary

Satellite altimeters can be used to estimate sea ice thickness, by estimating 30 how far the sea ice sticks out above the surrounding waterline. This is done by 40 measuring the time taken for radar waves to reach the sea ice and ocean surfaces 41 and return to the altimeter. These radar waves are processed using a retracking 42 algorithm, to calculate the radar freeboard. Several assumptions are used to convert 43 this radar freeboard into sea ice thickness, including values for snow depth and 44 the ability of the altimeter's radar waves to penetrate through the snow overlying 45 the sea ice. We test the sensitivity of modelled sea ice thickness to the retracking 46 algorithm used, the snow depth and assumed radar penetration. We do this by 47 assimilating our sea ice thickness estimates, converted from radar freeboard using 48 varying values for these parameters, into the Met Office's global ocean-sea ice 49 forecasting system, FOAM. We then determine the sensitivity of modelled sea ice 50 thickness to the observation uncertainties assigned to the assimilated data. We find 51 that snow depth has the biggest influence on modelled sea ice thickness, followed by 52 the uncertainty calculation, assumed radar penetration and the retracking algorithm. 53

## 54 1 Introduction

Accurate monitoring and modelling of Arctic sea ice thickness (SIT) is integral 55 to determining its implications on regional and global climates, safe travel for 56 Arctic coastal communities, shipping routes, the marine ecosystem and wildlife 57 dependent on the ice for hunting and traveling. While the observation and modelling 58 of sea ice concentration is well developed, the same is not true for SIT. This is 59 because estimating SIT from satellite data requires knowledge about the hydrostatic 60 properties of the sea ice and its overlying snow cover. SIT can be estimated using 61 satellite radar altimeters by measuring the time taken for the radar pulse to travel 62 to the sea ice surface and return to the altimeter. The same can then be done for 63 the sea surface found in open water areas between the ice floes, with the difference between these two measurements referred to as the *radar freeboard*. By factoring in 65 assumptions on the ability of the altimeter's radar waves to penetrate the snowpack, 66 this can then be converted into the sea ice freeboard (the height of the ice above the 67

surrounding sea water). The radar range to the assumed ice surface is calculated 68 through the retracking of the radar waveform to obtain the presumed range to 69 a single scattering surface, with the choice of retracking algorithm affecting the 70 radar freeboard retrieved. Currently, two types of retracking algorithm are used 71 in SIT products. The most common is the threshold algorithm, which applies a 72 fixed percentage threshold to the waveform's first maximum power return (e.g. 73 Guerreiro et al., 2017; Laxon et al., 2013). Alternatively, a physical algorithm 74 can be used, which varies the percentage threshold used according to the physical 75 properties of the sea ice (e.g. Landy et al., 2020). Using assumptions on snow depth, 76 as well as sea ice and snow density, SIT can then be calculated assuming hydrostatic 77 equilibrium. 78

The method for converting radar freeboard estimates to SIT requires an 79 assumed value for the fractional depth of the snowpack where the retracker detects 80 the backscattered radar echo,  $\alpha$  (as per Nab et al., 2023). An assumption of  $\alpha =$ 81 1 means that the radar goes entirely through the snowpack, such that the pulse 82 path length through snow has no impact on the radar freeboard estimate.  $\alpha < 1$ 83 represents a height for the mean radar scattering intensity within the snowpack 84 (or at its surface if  $\alpha = 0$ ). As  $\alpha$  is proportional to SIT (Kwok & Cunningham, 85 2015), a reduction in the former will reduce the latter. All current SIT estimates 86 from Ku-band altimeters rely on the assumption of full radar penetration of the 87 snowpack, since it is not yet possible to measure  $\alpha$  directly from space. However, 88 studies have shown that this assumption may not be the case in reality, as snow 89 properties affect the ability of radar waves to penetrate the snowpack. During Arctic 90 field campaigns in 2006 and 2008, Willatt et al. (2010) found that the proportion of 91 radar returns appearing closer to the air-snow interface than the snow-ice interface 92 increased with temperature. Similarly, Nandan et al. (2017) predicted an upward 93 shift in the dominant scattering surface of CryoSat-2 waves with increased snow 94 salinity over first-year ice using a radiative transfer model. Nandan et al. (2023) 95 found a sensitivity of Ku-band radar waves to previous air-snow interfaces, buried 96 within the snowpack after new snowfall. On satellite footprint-scales, Nab et al. 97 (2023) showed synoptic timescale correlations between radar freeboard estimates 98 and snow accumulation, revealing radar echoes returning from within the snowpack. 99 Over Arctic sea ice, previous studies have calculated  $\alpha$  to be between 0.40 - 0.96 for 100 Ku-band radar waves (Armitage & Ridout, 2015; Kilic et al., 2019; Shen et al., 2020; 101 Nab et al., 2023). 102

The fast-changing Arctic climate means that accurate short- and long-term 103 predictions of its sea ice cover are becoming increasingly important. Data 104 assimilation of sea ice variables can be used to improve model estimates of sea ice 105 concentration, extent and thickness (e.g. Fritzner et al., 2019; Y.-F. Zhang et al., 106 2018; Williams et al., 2023; Y. Zhang et al., 2023; Gregory et al., 2023). Studies 107 have shown that SIT has a longer memory than sea ice concentration, such that 108 the change in the initial model state caused by assimilating the former will persist 109 for longer than by assimilating the latter (Guemas et al., 2016). When assimilating 110 CryoSat-2-derived SIT into the Met Office's coupled sea ice-ocean system (FOAM), 111 Fiedler et al. (2022) found an improvement in FOAM SIT results of 0.61 m mean 112 difference (0.42 m root mean square difference) relative to a control experiment 113 without SIT assimilation, when both model runs were compared to Operation 114 IceBridge (OIB) estimates. When compared to buoy SIT data in the Beaufort 115 region, no improvement was found in the modelled SIT when assimilating CryoSat-2 116 SIT data. When adding the assimilation of data from the Soil Moisture and Ocean 117 Salinity (SMOS) satellite radiometer over thin ice to this setup, Mignac et al. (2022) 118 found a reduction in SIT over first-year ice, which better matched the OIB and buoy 119 data than when only assimilating CryoSat-2-derived SIT or not assimilating any 120 thickness information. 121

Uncertainties in the snow depth, radar freeboard product and assumed radar 122 penetration all contribute to the overall error in satellite-derived SIT. To account 123 for these errors, data assimilation methods use observational error estimates to 124 determine how much weight observational data should carry in the assimilation 125 process, with observations deemed to have a lower error having a larger influence 126 on the assimilation results. The accuracy of the resulting modelled SIT estimates 127 is thus expected to improve with improved error estimates for the data assimilated. 128 The lack of error estimates provided with currently operational CryoSat-2-derived 129 radar freeboard products means that the observation uncertainty calculation 130 in CryoSat-2 freeboard and thickness assimilation research has been relatively 131 simplified so far. For example, Fritzner et al. (2019) and Chen et al. (2017) used 132 fixed uncertainties of 0.5 m and 1.5 m, respectively, for all CryoSat-2 observations 133 when assimilating CryoSat-2-derived SIT. Fiedler et al. (2022) and Mignac et al. 134 (2022) used a parameterisation method, assigning high uncertainty values (0.5 - 8)135 m) to SIT values below 1.5 m and above 4 m, with SIT values between 1.5 - 4 m136 assigned uncertainty values < 0.5 m. 137

We test the sensitivity of 1-day sea-ice forecasts in FOAM to the parameters 138 used in the freeboard-to-thickness conversion, focusing on the snow depth, radar 139 freeboard product and assumed radar penetration ( $\alpha$ ). This allows us to determine 140 how much of the sensitivity in the radar freeboard-to-thickness conversion is 141 carried through into the model forecasts. Previous studies have shown the ability 142 of CryoSat-2-derived SIT assimilation to improve modelled SIT (e.g. Fritzner et 143 al., 2019; Fiedler et al., 2022; Mignac et al., 2022; Sievers et al., 2023) but, to 144 our knowledge, there have been no studies on the sensitivity of these results to 145 the parameterisation of the freeboard-to-thickness conversion. We also test the 146 sensitivity of the 1-day SIT forecasts to the SIT observation uncertainties used in 147 the data assimilation. We do this by comparing data assimilation results obtained 148 using a simple parameterisation scheme to derive SIT observation uncertainties, as 149 described in Fiedler et al. (2022) and Mignac et al. (2022), to one using Gaussian 150 error propagation to derive SIT uncertainties from each individual radar freeboard 151 measurement, as described in Ricker et al. (2014). 152

#### 153 2 Methods

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#### 2.1 UK Met Office Forecast Ocean Assimilation Model (FOAM)

FOAM is the UK Met Office's global, coupled ocean-sea ice forecasting system. 155 It is used to produce daily analyses and short-range forecasts of ocean temperature, 156 salinity, velocities and various sea ice parameters. FOAM's operational ocean-sea 157 ice analysis is also used by the Met Office's Global Seasonal (GloSea) coupled 158 ensemble prediction system to initialise its ocean and sea ice components daily. 159 FOAM is forced at the surface using output from the Met Office Numerical Weather 160 Prediction (NWP) system. The ocean model component of FOAM, NEMO (Nucleus 161 for European Modelling of the Ocean; Madec et al., 2023) is coupled to the recently 162 developed  $SI^3$  (Sea Ice modelling Integrated Initiative; Vancoppenolle et al., 2023). 163  $SI^3$  merges the capabilities of three sea ice models formerly coupled to NEMO: 164 CICE, GELATO and LIM (Madec et al., 2023). The SI<sup>3</sup> configuration includes five 165 thickness categories (plus open water), multi-layer thermodynamics and prognostic 166 melt ponds. We run the FOAM system with a 1/4 degree tripolar grid (ORCA025) 167 for both sea ice and ocean components, with 75 vertical levels in the latter (Storkey 168 et al., 2018). 169

Data assimilation is a procedure for producing a complete estimate of the current state of the ocean and sea ice by combining information from observations with the model. A previous model forecast is compared with newly acquired

observations and the two sets of data, together with information about their 173 respective errors, are combined to produce a new, more accurate model state 174 from which to launch a forecast. The observation uncertainties are important 175 in this procedure since erroneous observations with low prescribed uncertainties 176 would unduly influence the analysis. FOAM is set up to assimilate in situ 177 and satellite-derived observational data using the three-dimensional variation 178 assimilation scheme NEMOVAR (Waters et al., 2015). A 24-hour assimilation 179 window is used to assimilate observations of sea-surface temperature (SST), 180 sea-level anomaly, sea ice concentration, and temperature and salinity profiles. 181 The in situ SST data consists of data from buoys (drifting and moored) and ships. 182 This is supplemented by satellite-derived SSTs from NOAA's Advanced Very High 183 Resolution Radiometer (AVHRR), the Advanced Microwave Scanning Radiometer 184 2 (AMSR2) and the Sea and Land Surface Temperature Radiometer (SLSTR), 185 as well as data from the Visible Infrared Imaging Radiometer Suite (VIIRS) 186 sensor data from the Suomi-NPP (National Polar-orbiting Partnership) satellite. 187 The sea-level anomaly data are in the form of along-track satellite data from the 188 Jason-2, Jason-3, Sentinel-3A and -3B, CryoSat-2 and AltiKa satellites. Sea ice 189 concentration data are provided by the Special Sensor Microwave Imager/Sounder 190 (SSMI/S) instruments from the Defense Meteorological Satellites Program 191 (DMSP) satellites. These are processed by the European Organisation for the 192 Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea-Ice Satellite 193 Application Facility (OSI-SAF). The temperature and salinity profiles are taken 194 from moored arrays, gliders, Argo floats and research Conductivity, Temperature 195 and Depth (CTD) instruments. Additional temperature profiles from Expendable 196 Bathythermographs (XBTs) and marine mammal sensors are also used. 197

NEMOVAR has previously been used to assimilate SIT observations from 198 CryoSat-2 and SMOS into FOAM (Fiedler et al., 2022; Mignac et al., 2022), 199 although this is currently not done operationally. SMOS is an L-band microwave 200 radiometer, able to estimate SIT by evaluation of the ice's surface brightness 201 temperatures (Tbs) using a radiative transfer model (Tian-Kunze et al., 2014). 202 Over thin ice (<1 m), its relative uncertainties are believed to be significantly lower 203 than altimeter-based techniques. Over thicker ice, the Tbs become insensitive to ice 204 thickness. While SMOS has a much higher temporal resolution than altimeters, 205 providing daily pan-Arctic coverage (of the thinner ice), it has coarser spatial 206 resolution, with a larger effective footprint of  $\sim 40$  km (Kaleschke et al., 2012). 207 In this study, SIT derived from both SMOS and CryoSat-2 is assimilated, alongside 208 the operationally assimilated variables mentioned previously. The SMOS data is 209 only assimilated where SIT  $\leq 1$  m (Figure 1). SMOS SIT uncertainties are provided 210 with the data and used in the assimilation of this dataset. Although SMOS SITs are 211 assimilated in all experiments performed here, our sensitivity study is purely focused 212 on the CryoSat-2 data assimilation: Only the CryoSat-2 freeboard-to-thickness 213 conversion parameters and uncertainty calculation are changed in the experiments 214 performed in this study. See Mignac et al. (2022) for a full description of the 215 methodology for assimilating CryoSat-2 and SMOS SIT estimates into FOAM. 216

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#### 2.2 Calculation of sea ice thickness with varying parameters

To derive SIT from CryoSat-2 radar freeboard estimates  $(F_r)$ , we first calculate sea ice freeboard  $(F_i)$  as follows:

$$F_i = F_r + (\alpha \frac{c}{c_s} - 1)h_s \tag{1}$$

where  $\alpha$  is the radar penetration, c is the speed of light in a vacuum,  $c_s$  is the speed of light in snow and  $h_s$  is the snow depth.



Figure 1. Day of 2016-2017 winter season until which SMOS data is assimilated into FOAM (Day 1 = 17 October 2016). Areas where SMOS is never assimilated are shown in grey.

We then use this to calculate SIT:

$$SIT = \frac{F_i \rho_w + h_s \rho_s}{\rho_w - \rho_i} \tag{2}$$

where  $\rho_w$  is the density of seawater, taken from the model density field at the surface,  $\rho_i$  is the bulk density of sea ice and  $\rho_s$  is the snow density, evolving temporally following Eq. 11 of Mallett et al. (2020):

$$\rho_s = 6.5t + 274.51 \tag{3}$$

where t is the number of months since October.

#### 227 **2.3 Description of experiments**

We start with a control experiment (CTRL), running FOAM with the 228 assimilation of its operationally assimilated ocean and sea-ice observations (see 229 subsection 2.1), which does not include SIT. We then replicate the setup of Mignac 230 et al. (2022), who assimilated CryoSat-2 and SMOS SIT into FOAM (using CICE as 231 the sea ice component). Since the publication of that paper, the sea ice component 232 of FOAM has been replaced with  $SI^3$  (see Blockley et al., 2023). We assimilate 233 CryoSat-2 and SMOS into FOAM following the methods of Mignac et al. (2022), 234 using SI<sup>3</sup> as the sea ice model. We use the AWI-derived CryoSat-2 radar freeboard 235 data for this, as this is the CryoSat-2-derived product the Met Office is currently 236 testing for operational assimilation. Mignac et al. (2022) assumed a pan-Arctic 237 fixed sea ice density (916.7  $\rm kgm^{-3}$ ), taken from CICE. We instead assume a sea ice 238 density based on ice type: Using the OSI-SAF daily ice type product (OSI-403-c; 239 Aaboe et al., 2021), we set the bulk density of sea ice  $(\rho_i)$  to 916.7 kgm<sup>-3</sup> for 240 first-year ice and 882  $\mathrm{kgm}^{-3}$  for multi-year ice (as per Ricker et al., 2014). We 241 use this second experiment, following the setup of Mignac et al. (2022) in SI<sup>3</sup>, 242 with ice type-dependent sea ice density, as our baseline experiment (BASE). We 243 perform four sets of experiments in relation to this BASE experiment: Three of 244 these are performed to test the sensitivity of modelled SIT to changing the values 245 of one parameter in the freeboard-to-thickness conversion, with the last performed 246 to test the impact of changing the CryoSat-2 SIT uncertainties. A summary of the 247 experiments is given in Table 1, with the following sub-sections describing their 248 set-up in more detail. 249

Table 1. Configuration of the experiments: Parameters for conversion of CryoSat-2 radar freeboard estimates to assimilated SIT. 252

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Experiment	Snow depth	Freeboard product	Radar penetration ( $\alpha$ )	SIT uncertainty
CTRL	N/A	N/A	N/A	N/A
BASE	FOAM	AWI	1.0	Parameterised
$\mathbf{SN}_{-}\mathbf{SMLG}$	SM-LG	AWI	1.0	Parameterised
$\mathbf{SN}_{-}\mathbf{AWI}$	AWI	AWI	1.0	Parameterised
FB_LARM	FOAM	LARM	1.0	Parameterised
FB_CPOM	FOAM	CPOM	1.0	Parameterised
α_ <b>0.9</b>	FOAM	AWI	0.9	Parameterised
α_ <b>0.6</b>	FOAM	AWI	0.6	Parameterised
UNC	FOAM	AWI	1.0	Derived

We run all experiments from 17 October 2016 to 15 April 2017. Whilst conducting the experiments for the full CryoSat-2 period would be better, the computing time required per experiment per season makes this unfeasible. We choose the 2016-17 winter season to maximise the amount of independent data available for evaluation. This means that the results found in this paper are an example of the potential impacts of the changes we are making, and should not be taken as a quantification of the impacts of CryoSat-2 assimilation in general.

#### 2.3.1 Snow depth

We test the sensitivity of short-range SIT forecasts to the choice of snow depth product  $(h_s)$ , used in Equations 1 and 2 to convert the CryoSat-2-derived radar freeboard estimates into SIT. The BASE experiment uses FOAM's model snow depths for this. We perform two experiments, replacing the FOAM snow depths used in the conversion with:

• AWI: Monthly snow depth parameterisation used by the Alfred Wegener 267 Institute (AWI), based on merging the Warren climatology with daily snow 268 depth values derived from AMSR2 over first-year ice (Hendricks et al., 2021). 269 SM-LG: Daily estimates from SnowModel-LG (SM-LG; Liston et al., 2020, 270 2021), a snow evolution model that provides daily, pan-Arctic snow property 271 distributions for snow on sea ice. These snow depths have been evaluated 272 using a range of in situ observations and were bias-corrected using OIB snow 273 depths, such that the average modeled snow depth is equal to the average 274 observed OIB snow depth over OIB observation tracks. The model is forced 275 using ERA5 reanalysis data including air temperature, precipitation and wind 276 variables. 277

The snow depth products vary noticeably, with the FOAM product showing a consistently lower snow depth than the SM-LG and AWI products (Figure 2). Regionally, the difference between the snow depth products is largest around Greenland, where the daily SM-LG snow depth is about three times as high as the AWI and FOAM snow depths, and in the Laptev region, where the AWI snow



**Figure 2.** Regional and pan-Arctic daily mean snow depth for each of the snow products used in the freeboard-to-thickness conversion.



Figure 3. Monthly average radar freeboard for the assimilated CryoSat-2 SIT products, and the difference between them: AWI (left), CPOM-AWI (middle) and LARM-AWI (right). Top row shows October 2016, bottom row shows April 2017.

#### 284 2.3.2 Freeboard product

We test the sensitivity of short-range forecasts to the use of different CryoSat-2-derived along-track radar freeboard products ( $F_r$  in equation (1)). The BASE experiment uses the AWI freeboard product, derived using the AWI threshold retracker (Hendricks et al., 2021). We perform two additional experiments, using CryoSat-2 radar freeboard data created using the physical LARM retracker (Landy et al., 2020) and the CPOM threshold retracker (e.g. Tilling et al., 2018).

The radar freeboard products vary noticeably, with the CPOM product showing a consistently higher radar freeboard than the LARM and AWI products on average, particularly in the marginal seas. In the Central Arctic, the LARM product shows consistently lower radar freeboards than the AWI and CPOM products (Figure 3).

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### 2.3.3 Assumed mean penetration of radar waves into the snowpack

In the conversion of radar freeboard to SIT in the BASE experiment, we assume the radar waves from CryoSat-2 penetrate all the way through the snowpack, reflecting off the snow-ice interface ( $\alpha = 1.0$  in Equation 1). We perform two additional experiments, assuming different mean scattering depths of the radar waves within the snowpack: •  $\alpha = 0.9$ : as for summer sea ice, following Landy et al. (2022) •  $\alpha = 0.6$ : the mean pan-Arctic value calculated by Nab et al. (2023)

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 $\alpha = 0.6$ : the mean pan-Arctic value calculated by Nab et al. (202-

Using a constant value for  $\alpha$  is a first approach: Several studies have shown that 304  $\alpha$  varies depending on wind distribution, temperature and snow properties such as 305 salinity (Nandan et al., 2023; Nab et al., 2023; Nandan et al., 2017). This means 306 that  $\alpha$  is not a constant in reality - it varies spatially and temporally. However, 307 the exact value of  $\alpha$  and its determinants is still the subject of much research. We 308 thus assign a constant pan-Arctic  $\alpha$  value to determine the sensitivity of the data 309 assimilation to this parameter, rather than trying to determine the perfect  $\alpha$  to use 310 to represent reality. 311

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## 2.3.4 Freeboard uncertainty

The current method for assimilating CryoSat-2 along-track SIT into FOAM 313 involves weighting the CryoSat-2 observations dependent on their SIT, as per 314 Figure 3 of Fiedler et al. (2022). This involves assigning high uncertainty values 315 (0.5 - 8 m) to SIT values below 1.5 m and above 4 m, such that they are weighted 316 lower in the assimilation than SIT values between 1.5 - 4 m, which are assigned 317 uncertainty values < 0.5 m. Although this works well for thick ice, Mignac et al. 318 (2022) found this method to lead to an overestimation in SIT in areas of thin ice, 319 as higher SIT estimates in these areas are given a higher weighting in the data 320 assimilation, despite not being more accurate than thinner CryoSat-2 SIT estimates 321 that are down-weighted. Instead of this parameterised uncertainty, the assimilation 322 weighting can be based on the uncertainty calculated for each freeboard observation. 323 This is currently only possible for the AWI freeboard product, as the LARM and 324 CPOM products do not include pre-calculated freeboard uncertainties, providing 325 only uncertainties on the interpolated sea surface elevation at ice floes. We run an 326 experiment (UNC) using SIT uncertainties derived from each individual freeboard 327 measurement uncertainty, by applying a Gaussian propagation of the freeboard 328 uncertainties through Equation 2 (as per Ricker et al., 2014). Uncertainties for the 329 other parameters used in the freeboard-to-thickness conversion, such as the snow 330 depth, sea-ice and snow densities, are taken from Figure 4 of Ricker et al. (2014). 331

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## 2.4 Datasets used for evaluation

The 1-day SIT forecasts are compared to SIT derived from the Beaufort Gyre 333 Exploration Project (BGEP; Krishfield et al., 2014) mooring observations, as well 334 as airborne measurements from NASA's OIB campaign (Kurtz et al., 2013). The 335 location of these data and mean SIT estimated by the airborne campaign are shown 336 in Figure 4. It is worth noting that the sea ice model used here has an approximate 337 resolution of 12 km in the Arctic, with the SIT computed as the model grid cell 338 average. Therefore, there are limitations in the model's ability to represent the 339 variability found at point measurements. 340

## 2.4.1 Mooring data

SIT measurements from the BGEP campaign were derived from 342 bottom-anchored moorings equipped with upward-looking sonars. The BGEP data 343 were collected continuously at three locations (BGEP-A, BGEP-B and BGEP-D) in 344 the Beaufort Sea between 17 October 2016 to 15 April 2017 (Krishfield et al., 2014) 345 The buoys estimate the sea ice draft at 2-second intervals, which are processed into 346 daily averages. The daily drafts are converted into SIT by dividing them by 0.89, as 347 per Rothrock (2003). We choose this simplified method for converting draft to SIT, 348 instead of per Equation 2 of Kern et al. (2015), to avoid the use of snow depth data 349

in this conversion and keep this as an independent dataset. For the evaluation, the daily model SITs are interpolated to the mooring locations.

#### 352 2.4.2 Airborne data

Total freeboard (snow depth + ice freeboard) measurements were taken during 353 the OIB campaign using an Airborne Topographic Mapper (Krabill, 2013), a 532 nm 354 wavelength conically scanning laser altimeter with a 1 m footprint. The altimeter 355 measures the elevation of the top of the snowpack and the elevation of the nearby 356 ocean surface with an accuracy of <10 cm, such that the total freeboard can be 357 estimated by taking the difference between these two (Krabill et al., 1995). At the 358 same time, the snow depth was measured using a snow radar, which is assumed 359 to reflect off the snow-ice interface. The sea ice freeboard is then estimated by 360 taking the difference between these two, and SIT calculated under the assumption 361 of hydrostatic equilibrium as per Equation 2. Multiple data products have been 362 derived from the OIB measurements. The National Snow and Ice Data Center 363 (NSIDC) Quick-Look product is used here, which is known to underestimate snow 364 depth by up to 8.8 cm (Kwok et al., 2017). In this product, SIT point measurements 365 are averaged over 50 km clusters. Point measurements with a standard deviation 366 greater than 1 m are not used in the cluster for ice thinner than 1 m, and point 367 measurements with a standard deviation greater than 2 m are not used in the 368 cluster for ice thicker than 4 m (Kurtz et al., 2013). Further processing is conducted 369 here to remove cluster observations with a standard deviation greater than 2 m, as 370 per Mignac et al. (2022). For the evaluation, the daily model SITs are interpolated 371 to the OIB cluster locations. 372

#### 373 **3 Results**

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## 3.1 Data assimilation influence on model sea ice thickness

To determine regional patterns, we use the Arctic regions defined by the 375 NSIDC (Meier et al., 2007) to plot the evolution of the regional mean SIT for the 376 different experiments (Figure 5). In the Baffin region, the CTRL experiment shows 377 significantly higher daily mean SIT than the other experiments, with this difference 378 increasing as the season progresses. By April, the mean daily SIT in the CTRL 379 experiment in this region is double the SIT found in the other experiments. In the 380 Central Arctic and East Siberian region, the CTRL experiment shows a lower daily 381 mean SIT than the other experiments, particularly between November - March. In 382 the Greenland region, the experiments with CryoSat-2 assimilation show a sudden 383 drop in daily mean SIT in February, which is not shown in the CTRL experiment. 384 Compared to the CTRL experiment, all experiments show a higher daily mean SIT 385 in all regions except for the Beaufort Sea, Baffin Bay and Barents Sea. The increase 386 in SIT after CryoSat-2 assimilation is particularly evident in the Central Arctic, 387 where the increase is largest in the SN\_SMLG and SN\_AWI experiments and occurs 388 immediately after data assimilation begins in October. In the Central Arctic, the 389  $\alpha_{-0.6}$  experiment shows the smallest difference compared to the CTRL experiment, 390 but the SIT is still 10s cm higher early in the winter season. 391



**Figure 4.** Location of bottom-anchored moorings (BGEP-A, BGEP-B, BGEP-D) and SIT derived from airborne OIB measurements.



Figure 5. Regional mean daily SIT. Note the different y-axes.



Figure 6. a-h) Mean daily difference in SIT between each experiment and the BASE experiment (experiment - BASE). Text shows the pan-arctic mean (top) and standard deviation (bottom). i) Standard deviation between the mean daily SIT for all the assimilation experiments (excluding CTRL).

Compared to the BASE experiment, the  $\alpha_0.6$  and  $\alpha_0.9$  experiments show 392 a pan-Arctic decrease in SIT on average, while the SN\_SMLG and SN\_AWI 393 experiments show a pan-Arctic increase in SIT (Figure 6). The FB\_LARM 394 experiment shows a decrease in SIT over multi-year ice and an increase in SIT 395 over first-year ice, while the FB\_CPOM experiment shows an increase in SIT in 396 almost all regions of the Arctic, except for some parts of the Central Arctic. The 397 UNC experiment shows a pan-Arctic decrease in SIT, with an increase over a 398 small part of the Central Arctic. The standard deviation (STDEV) of the SIT 399 in these experiments is higher over the Central Arctic and Russian Arctic (> 0.4400 m), where there are more CryoSat-2 observations, decreasing to <0.2 m towards 401 the Beaufort Sea and in Baffin Bay (Figure 6), where a much larger number of 402 SMOS observations dominate the SIT assimilation results (see Figure 1). The large 403 spread in the Central Arctic and Russian Arctic is supported by the large differences 404 between the assimilation experiments as the winter season progresses (Figure 5). 405

#### 406

## 3.2 Relative impact of changing each parameter

In relation to the BASE experiment, we find that changing the assumed 407 radar penetration ( $\alpha$ ), freeboard product and snow depth product used in the 408 freeboard-to-thickness conversion can change the daily regional model SIT by up 409 to 0.65 m, 0.55 m and 0.88 m, respectively, with each of these maximum values 410 found in the Central Arctic. For the  $\alpha$  experiments, the largest relative differences 411 were seen in the Central Arctic, where reducing the assumed radar penetration 412 decreased the daily mean SIT by up to 33%. Large differences were also seen in 413 East Siberian and Chukchi regions, where decreasing the assumed radar penetration 414 decreased SIT by up to 28%. When changing the freeboard product used, we find 415 the largest differences in these same three regions, with SIT changing by up to 30%. 416 When changing the snow depth product used, the largest differences where found 417 in the Central Arctic and Beaufort Sea, with SIT changing by up to 48%. When 418 considering absolute values, changing the snow depth product, freeboard product 419 and assumed radar penetration resulted in changes in modelled SIT of 0.11 m ( $\sigma$ 420 = 0.18 m), 0.07 m ( $\sigma = 0.11$  m) and 0.08 m ( $\sigma = 0.15$  m) on average, respectively 421 (Figure 7). 422



Figure 7. Difference in the daily regional SIT compared to the BASE experiment caused by changing the assumed  $\alpha$ , freeboard product and snow depth product used in the freeboard-to-thickness conversion. Top row shows value difference (m), bottom row shows percentage difference. Values are calculated as the daily difference between the BASE experiment and the experiments where the parameter of interest is changed, in each grid cell. Boxes extend from the 25th to 75th percentiles of the values, with a black line showing the median and a green dot showing the mean. Whiskers extend to the 5th and 95th percentiles. Note the different y-axes. Outliers are not shown. The radar penetration ( $\alpha$ ) set contains the  $\alpha$ \_0.9 and  $\alpha$ \_0.6 experiments. The freeboard product set contains the FB\_CPOM and FB\_LARM experiments. The snow depth set contains the SN\_SMLG and SN\_AWI experiments. The CTRL and UNC experiments are not included in this analysis.

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## 3.3 Impact of sea ice thickness data assimilation changes on the thermodynamic sea ice budget

We now investigate the impact of changing the freeboard-to-thickness conversion parameters and uncertainties on the thermodynamic sea ice budgets, in order to determine the sensitivity of the model processes to these changes.

When assimilating CryoSat-2 data, we find a decrease in thermodynamic 428 volume change in the Central Arctic and an increase in the marginal seas of the 429 BASE experiment compared to the CTRL experiment (Figure 8a). When reducing 430 the assumed radar penetration, we find a decrease in the thermodynamic volume 431 change in all regions of the Arctic, when compared to the BASE experiment. When 432 changing the snow depth product used in the freeboard-to-thickness conversion, 433 we find an increase in thermodynamic volume change in almost all regions of the 434 Arctic compared to the BASE experiment, particularly in the Beaufort Sea. The 435 spatial distribution of these changes is very similar when using SM-LG and AWI 436 snow depths. When changing the freeboard product used, we find a decrease in 437 thermodynamic volume change in the Central Arctic and an increase in the marginal 438 seas, compared to the BASE experiment. The UNC experiment shows a decrease 439 in thermodynamic volume change over most of the Central Arctic, with an increase 440 in the marginal seas and Baffin Bay. The standard deviation of the runs where 441 CryoSat-2 is assimilated is up to  $1 \ge 10^{6} \text{ m}^{3}$  in parts of the Central Arctic and East 442 Siberian regions, decreasing down to 0 m<sup>3</sup> in parts of the Canadian Archipelago 443 region (Figure 8). 444

Figure 9 shows the difference in ice volume change due to thermodynamic 445 processes when using differing parameters in the freeboard-to-thickness conversion. 446 In relation to the BASE experiment, we find that modifying the assumed radar 447 penetration, freeboard product and snow depth product used can shift the daily 448 model thermodynamic volume change by up to  $1.6 \ge 10^6 \text{ m}^3$ ,  $1.2 \ge 10^6 \text{ m}^3$  and 1.4449 x 10<sup>6</sup> m<sup>3</sup> respectively. For the  $\alpha$  experiments, the largest relative differences were 450 seen in the East Siberian and Central Arctic regions, where modifying the assumed 451 radar penetration shifted the daily ice volume change by up to 125%. When 452 modifying the freeboard product used, we also find the largest relative differences 453 in the Central Arctic, with thermodynamic volume change shifting by up to 140%. 454 Similarly, when modifying the snow depth product used, the largest differences in 455 thermodynamic volume change were found in the Central Arctic and the Beaufort 456 Sea, with differences in ice volume change of up to 150%. When considering absolute 457 values, changing the snow depth product, freeboard product and assumed radar 458 penetration used changed the model ice volume change by 0.32 x 10  $^{6}$  m<sup>3</sup> ( $\sigma = 0.93$ 459 x 10  $^{6}$  m<sup>3</sup>), 0.36 x 10  $^{6}$  m<sup>3</sup> ( $\sigma = 0.87$  x 10  $^{6}$  m<sup>3</sup>) and 0.31 x 10  $^{6}$  m<sup>3</sup> ( $\sigma = 0.80$  x 10  $^{6}$ 460  $m^3$ ) on average, respectively. 461



**Figure 8.** Difference between mean daily ice volume change due to thermodynamic processes for each experiment and the BASE experiment (experiment - BASE). Text shows the pan-Arctic mean (top) and standard deviation (bottom).



Figure 9. Difference in the daily ice volume change due to thermodynamic processes, caused by changing the assumed  $\alpha$ , freeboard product and snow depth product used in the freeboard-to-thickness conversion. Top row shows value difference (m), bottom row shows percentage difference. Values are calculated as the daily difference between the BASE experiment and the experiments where the parameter of interest is changed, in each grid cell. Boxes extend from the 25th to 75th percentiles of the values, with a black line showing the median and a green dot showing the mean. Whiskers extend to the 5th and 95th percentiles. Note the different y-axes. Outliers are not shown. The radar penetration ( $\alpha$ ) set contains the  $\alpha$ -0.9 and  $\alpha$ -0.6 experiments. The freeboard product set contains the FB\_CPOM and FB\_LARM experiments. The snow depth set contains the SN\_SMLG and SN\_AWI experiments. The CTRL and UNC experiments are not included in this analysis.



**Figure 10.** Total pan-Arctic volume of ice gained or lost through thermodynamic processes between October 2017 - April 2017 in each experiment. Top shows absolute values, bottom shows values relative to BASE experiment (experiment - BASE). Note the different y-axes.

Figure 10 decomposes the thermodynamic ice mass changes into separate 462 components that take place during ice growth (congelation growth, frazil ice 463 formation and snow ice formation) and ice melt (surface melt, bottom melt and 464 lateral melt), as per Figure 4 of Tsamados et al. (2015). On a pan-Arctic scale, 465 we find the biggest differences between the experiments come from congelation ice 466 growth, followed by bottom melt and frazil growth. This is consistent with Figure 467 5, which shows that ice generally grows much faster in the assimilation experiments 468 relative to CTRL. We find a positive total growth in all experiments over the winter 469 season, as expected, with the largest increase in sea ice volume found in the  $\alpha_{-}0.6$ 470 experiment and the smallest in the CTRL experiment. Compared to the BASE 471 experiment, we find an increase in congelation growth, and consequently total 472 growth, in the  $\alpha_{-}0.6$ ,  $\alpha_{-}0.9$  and FB\_LARM experiments, with decreases in the other 473 experiments. This means that reducing the assumed radar penetration and changing 474 the freeboard to inherently thinner products increase the rate of winter ice growth, 475 whereas changing the snow depth to inherently thicker products reduces the rate of 476 winter ice growth. 477



Figure 11. Difference between FOAM SIT and OIB SIT, between 9 March and 19 April 2017.

#### 3.4 Comparison with buoy- and airborne-derived sea ice thickness

We now compare our experiments to independent SIT datasets, to determine the impact of changing the freeboard-to-thickness conversion parameters and uncertainties on the model's ability to represent buoy- and airborne-derived SIT.

## 3.4.1 Operation IceBridge (OIB)

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The spatiotemporal patterns of modelled SIT showed noticeable differences between the CTRL experiment and the assimilation experiments. This is particularly evident to the north of Greenland, where there was a consistent increase in SIT by up to 1 m, bringing the model SIT closer to the OIB SIT (Figure 11). Despite this, all experiments still show an underestimation of SIT north of Greenland, with the SN\_SMLG and SN\_AWI experiments showing an overestimation in the Central Arctic and marginal seas.



Figure 12. Histograms of FOAM SIT and OIB SIT, between 9 March and 19 April 2017.

Between the CTRL and BASE experiments, there is an improvement in both 490 the r and RMSE values. When decreasing the assumed value for  $\alpha$ , we find an 491 improvement in FOAM's ability to represent the variability in the OIB SIT data, 492 compared to the CTRL and BASE experiments. However, we find an increase in 493 the RMSE with a decrease in assumed  $\alpha$  compared to the BASE experiment, as the 494 model SIT becomes too low. When changing the CryoSat-2 freeboard product, we 495 find a degradation in the model's ability to represent the SIT variability in the OIB 496 data, with the r value decreasing from 0.73 in the BASE experiment (r = 0.73), to 497 0.7 for the FB\_CPOM experiment and 0.65 for the FB\_LARM experiment. However, 498 we find an improvement in the magnitude of the modelled SIT in the FB\_CPOM 499 experiment (RMSE = 0.85 m) compared to the BASE (0.88 m) and FB\_LARM 500 (1.03 m) experiments. When changing the snow depth used in the SIT conversion, 501 we find a decrease in r value, from 0.77 for the BASE experiment to 0.70 for the 502 SN\_AWI experiment and 0.66 for the SN\_SMLG experiment. In terms of RMSE, 503 changing the snow depth shows an improvement, with the  $SN_AWI$  experiment (0.78) 504 m) performing better than the SN\_SMLG (0.81 m) and BASE (0.88 m) experiments. 505

We find a wider range of values in the OIB SIT data than in the FOAM data, 506 particularly in the CTRL,  $\alpha$  and freeboard product experiments, where values of 507 4 - 6 m are much more frequently found in the OIB data than in the FOAM data 508 (Figure 12). Additionally, areas of thin ice (<1 m) are present in all the FOAM 509 experiments, but not in the OIB data. In terms of variability representation, the 510  $\alpha_{-0.6}$  experiment (r = 0.77) performs the best out of all the experiments, followed 511 by the  $\alpha_0.9$  and UNC experiments (r = 0.75). In terms of RMSE, the SN\_AWI 512 experiment performs the best (0.78 m), followed by the SN\_SMLG experiment (0.81)513 m). 514

## 3.5 Beaufort Gyre Exploration Project (BGEP)

We find an overestimation in SIT in each of the experiments in the January 516 - February period at BGEP-B, with the exception of the CTRL and  $\alpha_{-0.6}$ 517 experiments (Figure 13). We find an overestimation at BGEP-A in the CTRL 518 experiment in January - February and at BGEP-D in CTRL in February, which 519 is not found in the experiments where CryoSat-2 is assimilated. We find the lowest 520 RMSE in the UNC and CTRL experiments at BGEP-A and BGEP-B, respectively. 521 At BGEP-D, we find similar RMSE values in all experiments (0.42-0.47 m), 522 523 with SN\_AWI performing the best. Overall, we find similar RMSE values in all experiments (0.35-0.37 m) except FB\_CPOM and SN\_SMLG (0.41-0.42 m). We find 524 that the FOAM experiments do not represent the daily variability measured by the 525 BGEP buoys well, finding an improvement when taking a one-week running mean of 526 the BGEP data (Figure S1). This is not surprising considering the repeat sub-cycle 527 of CryoSat-2 (30 days) and the model grid size of  $\sim$ 12 km, compared to the high 528 temporal sampling resolution of the moorings. 529

As we are only using one season of data, the linear correlation coefficient is not 530 a suitable method of assessing how well the model is able to represent the variability 531 measured at stand-alone buoys. Instead, we calculated an error by taking the 532 difference between the model and the daily mean BGEP SIT, before dividing this 533 by the daily BGEP standard deviation. This tells us how many standard deviations 534 the model prediction is away from the buoy measurement on each day. We find 535 that the UNC and CTRL experiments perform best at BGEP-A and BGEP-B, 536 respectively, with errors of 0.17. At BGEP-D, the  $\alpha_0.9$  and UNC experiments 537 perform the best with an error of 0.22. When the buoys are combined, the  $\alpha_{-}0.9$  and 538 UNC experiments perform the best with an error of 0.14. The CTRL, FB\_CPOM 539 and SN\_SM-LG experiments perform the worst at the individual buoys, with the 540 FB<sub>-</sub>CPOM experiment performing the worst when the buoys are combined. At each 541 buoy, the experiments are normally within two standard deviations of the buoy 542 measurements, decreasing to one standard deviation when the buoys are combined 543 (Figure S2). 544



Figure 13. FOAM SIT and BGEP SIT at BGEP-A, BGEP-B and BGEP-D mooring locations from 17 October 2016 to 15 April 2017. FOAM SIT is only shown on days where BGEP data is available. The grey shaded area shows the BGEP uncertainty, represented by the daily standard deviation. Coloured text shows the mean root-mean-squared error for the season for each experiment.

## <sup>545</sup> 4 Discussion and Conclusions

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## 4.1 Relative influence of each parameter

We find large differences in the modelled SIT when changing the freeboard 547 and snow product used, as well as the assumed radar penetration. However, each 548 parameter has a strongly regional impact, which differs across the experiments. 549 Our results suggest that differences in the Central Arctic are dominated by changes 550 in the snow depth, whereas the use of different freeboard products plays a more 551 dominant role in the marginal seas. The use of different observation uncertainties 552 also plays a significant role in the marginal seas, as it increases the relative 553 weighting of the assimilated CryoSat-2-derived SIT data compared to the SMOS 554 data. 555

For the snow depth product used, the largest changes occur in the Beaufort, 556 East Siberian and Central Arctic regions. Using snow depth observations from 557 SnowModel-LG or passive microwave coupled to the Warren snow climatology, 558 instead of the FOAM snow depths, increases the modelled SIT in these regions 559 by 9-25 cm (7-16%) on average. This is because both snow depth products are 560 thicker than FOAM and therefore produce thicker estimates of sea ice for a given 561 freeboard. Our snow depth experiments imply that models with a thin spring snow cover ( $\sim 20$  cm) in the Central Arctic will not produce reliable SIT after assimilating 563 CryoSat-2 freeboards. When assimilating CryoSat-2-derived SIT data, Mignac et 564 al. (2022) found a decrease in the underestimation of SIT in this region compared 565 to OIB-derived SIT, with the root-mean-squared difference decreasing from 0.95 m 566 to 0.65 m, although the underestimation bias remained to the north of Greenland, 567 where the FOAM snow depths are too low. Previous modelling studies have found 568 a large underestimation of SIT in the Central Arctic. For example, Wang et al. 569 (2016) found an underestimation of up to 2 m in February - March. Xia & Xie 570 (2018) found that CryoSat-2 freeboards increasingly underestimated those from OIB 571 as the OIB freeboard increased, up to -44 cm mean bias when the airborne laser 572 scanner freeboards were >66 cm thick. Since the thickest sea ice north of Greenland 573 is also the roughest in the Arctic, this suggests that the CryoSat-2 radar returns 574 might be biased towards smoother areas of the topography, underestimating the true 575 mean freeboard. A freeboard bias caused by the radar penetrating only a fraction 576 of the snow layer would act in the other direction, generating thinner SIT estimates 577 compared to OIB, so this appears to be a less important factor over the multi-year 578 ice region north of Greenland. 579

We find differences in SIT of up to 35% when decreasing the assumed mean 580 radar penetration of the snowpack from 100 to 90 and 60%, with the largest 581 differences seen in the Western and Russian Arctic. In comparison to the OIB 582 data, which mostly cover multi-year ice north of Greenland and Canada, the 60%583 penetration experiment led to more of an underestimation of the ice thickness 584 than other experiments. However, in comparison to thinner ice measured by the 585 Beaufort Gyre mooring ice drafts, the 60% penetration experiment was not found 586 to underestimate the in situ-measured ice thickness. Nab et al. (2023) found a 587 response in CryoSat-2-derived radar freeboard estimates to snow accumulation, wind 588 speed and air temperature, with the magnitude of the response varying between 589 tested freeboard products, which suggests that the radar penetration depth can 590 be <100% under certain conditions. Results from our bias assessment versus in 591 situ data suggest these conditions may occur more frequently over first-year than 592 593 multi-year ice; however, there could be competing biases that obscure this finding.

<sup>594</sup> CryoSat-2 measures thick ice with relatively high accuracy but struggles with <sup>595</sup> very thin ice (Ricker et al., 2014), so improvements in forecast accuracy caused by <sup>596</sup> changing the assimilation parameters are mainly found in the Central Arctic where

the observations are more accurate than the free-model run. We find a larger spread 597 in areas that have more CryoSat-2 observations, such as the Central Arctic and East 598 Siberian regions. In regions where there are fewer CryoSat-2 observations, such as 599 the Baffin and Barents regions, there is a much smaller spread in the data, as the 600 SIT assimilation is dominated by the assimilation of SMOS data. The assimilated 601 CryoSat-2 freeboard products have noticeable differences over thin ice regions, with 602 the use of the CPOM product leading to a higher SIT in these regions than the 603 LARM and AWI products. 604

605 We find that using observation errors derived from the individual freeboard measurements, rather than parameterising them based on the SIT value, leads to a 606 noticeably different SIT and thermodynamic growth distribution. The BASE and 607 UNC experiments show a 36% daily mean absolute difference in SIT, despite the use 608 of the same snow depth, assumed radar penetration and radar freeboard product 609 in the freeboard-to-thickness conversion. Compared to the BASE experiment, the 610 UNC experiment shows thinner ice on average on a pan-Arctic scale, except for 611 a small region north of the Canadian Archipelago. This is likely due to the high 612 observation errors assigned to CryoSat-2-derived SIT values below 1 m ( $\sigma = 8$  m), 613 compared to values between 1 - 4 m ( $\sigma < 0.5$  m) in the BASE experiment with an 614 empirical parameterisation of the errors. This means that measurements of thicker 615 ice have a substantially higher weighting in the data assimilation, which can lead to 616 an overestimation in SIT in areas where low-value CryoSat-2-derived SIT values are 617 removed from the assimilation despite being accurate. 618

The differences in thermodynamic volume change between the experiments 619 and the BASE run show similar spatial patterns as those for SIT, but of the 620 opposite sign. This is expected, as thin ice grows faster due to steeper temperature 621 gradients, leading to a negative feedback between SIT and thermodynamic volume 622 change (Haas, 2003). Therefore, when the assimilated CryoSat-2 observations are 623 thinner than the model (e.g. in the  $\alpha_{-}0.6$  and  $\alpha_{-}0.9$  experiments), the model reacts 624 by growing more sea ice thermodynamically. This is particularly evident in the 625 FB\_CPOM and FB\_LARM experiments, where areas that show a thinning sea 626 ice cover as a result of the data assimilation show an increase in thermodynamic 627 growth, while areas with a thickening ice cover show a decrease in thermodynamic 628 growth. We find a decrease in mean daily thermodynamic volume change in the 629 SN\_SMLG and SN\_AWI experiments. This is likely due to the increase in snow 630 depth in these runs, with the two snow depth products generally thicker than 631 modelled snow from FOAM, which leads to an increased derived SIT, insulating 632 the ice and thus reducing winter ice growth. The UNC results are slightly different 633 from the others, with a pan-Arctic thinning in SIT resulting in decreases in 634 thermodynamic growth in the marginal seas and increases over the Central Arctic. 635 We find this to be due to a seasonal change in the assimilation impact on the SIT in 636 this experiment: in October - November, the SIT in the UNC experiment increases 637 by up to 40% more than the BASE experiment in the marginal seas, while the rest 638 of the ice cover thins by more than 40% compared to the BASE experiment. As 639 the season progresses, this increase in SIT in the UNC experiment decreases, with 640 decreases in SIT seen in almost all regions by April (Figure S3). The difference 641 in thermodynamic volume growth between these experiments shows the inverse 642 pattern: the UNC experiment shows a much lower thermodynamic volume growth in 643 the marginal seas in the early winter months than the BASE experiment, with the 644 difference decreasing as the season progresses (Figure S4). 645

In this study, we have tested a variation of parameterisation combinations for
the freeboard-to-thickness conversion. We find a large spread in the model results
between these different experiments, particularly over thicker ice (e.g. the Central
Arctic), that increases as the winter season progresses. This highlights a concern

for future SIT data assimilation and forecasting, with the chosen parameterisation
of the freeboard-to-thickness conversion having a substantial impact on model SIT
results, with a difference in model SIT of up to 30-48%. Additionally, our results call
for an improved, consistent definition of CryoSat-2 radar freeboard uncertainties,
with our derived SIT uncertainties causing a change in mean model SIT of up to
36%.

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#### 4.2 Comparison with independent datasets

We find a consistent underestimation in SIT and total thickness north of 657 Greenland in all our experiments, likely due to the consistent underestimation of 658 the FOAM model snow depth in this area. When replacing this snow depth with 659 the SM-LG and AWI products, we find a significant improvement in the model SIT 660 results in this area, compared to independent datasets; however, the SIT is still 661 underestimated. These snow depth values are generally higher than those of FOAM, 662 leading to an increase in SIT on a pan-Arctic scale. The SIT is also improved 663 when using derived uncertainties from the AWI product, rather than uncertainties 664 parameterized for specific ranges of ice thickness, which suggests the uncertainties 665 for thick multi-year ice are well-constrained in the product. Over thinner ice areas, 666 the CryoSat-2 data should either be entirely discarded or the derived freeboard 667 uncertainties used, since down-weighting the assimilation of the thinnest freeboards 668 can increase the impact of erroneously thick freeboards in these areas. 669

In terms of variability, compared to the OIB estimates, each of our experiments 670 performs better than the CTRL experiment, with the  $\alpha_{-0.6}$ ,  $\alpha_{-0.9}$  and UNC 671 experiments also performing better than the BASE experiment. Compared to OIB 672 estimates, decreasing the assumed  $\alpha$  used in the freeboard-to-thickness conversion 673 leads to an increase in RMSE. As the OIB SIT estimates are calculated using an 674 assumption of full C-S-band snowradar penetration through the snowpack, this 675 is unsurprising. We find the lowest RMSE in the  $SN_AWI$  experiment (0.78 m), 676 followed by the SN\_SMLG experiment (0.81 m). Compared to the BGEP SITs, the 677 experiments perform equally well in terms of RMSE (0.35 - 0.37 m) when the buoys 678 are combined), with the exception of the FB\_CPOM and SN\_SMLG experiments 679 which perform worse (0.42 and 0.41 m, respectively). The BGEP data are limited 680 to the Beaufort Sea region, while the OIB covers large parts of the Arctic, with the 681 exception of the Russian Arctic. As a result, the BGEP datasets largely cover areas 682 of thin ice (<1.5 m), which CryoSat-2 and FOAM struggle with compared to thicker 683 ice. The UNC experiment was found to perform better than the BASE experiment 684 over areas of thin ice: when isolating areas where the OIB-derived SIT is lower 685 than 1 m, the UNC experiment was found to have a lower RMSE (0.32 m) than the BASE experiment (0.41 m), with the same r value (0.82). Similarly, compared to 687 the BGEP-derived SIT data, the UNC experiment performs better than the BASE 688 experiment at BGEP-A and BGEP-B, and when the buoys are combined. This 689 highlights the importance of assigning realistic observation errors when assimilating 690 CryoSat-2 data. This suggests that improving the observation errors used when 691 assimilating CryoSat-2 SIT data could improve model performance over areas of 692 thin ice, as the number of measurement over thin ice that are assimilated can be 693 increased by more accurately separating the inaccurate ones. 694

We repeated the above analysis with airborne estimates taken during the IceBird campaign series. However, we found these results to give very limited insight into the ability of the FOAM experiments to produce accurate SIT forecasts. We believe this is due to the large amount of pre-processing required to make this data comparable to the model data, due to the former's much higher spatial and temporal resolution. The results are shown in Supplementary Section 1.

Our results show that, while improving the representation of one parameter 701 in the freeboard-to-thickness conversion does often lead to an improved model SIT 702 result in comparison to independent observations, this is not always the case. This 703 is likely due to competing biases, which have been created by tuning the model 704 to observational data using the current parameterisation, such that changing one 705 parameter without changing the others can often bring the model results further 706 away from the observations, despite an improvement in that parameter's values. 707 This means that changing the parameters altogether is often the only way to bring 708 the model results closer to the observations, as competing biases can be corrected 709 for at the same time. The challenge is optimizing the combination of parameter 710 changes, when they have different impacts (negative or positive) in different regions 711 of the Arctic or part of the winter season. However, the purpose of this study 712 is to determine the sensitivity of the model SIT results to the parameterisation 713 of the radar freeboard-to-thickness conversion, rather than to find an optimal 714 model configuration. Optimization is complex and will likely require a trade-off 715 between accurately simulating the mean ice state characteristics and capturing 716 the inter-annual ice state variability. This is a key point, since the quality of a 717 seasonal sea ice forecasts relies on the ability to capture interannual variations in 718 the anomalies of the SIT which translate into later ice extent forecasting skill (e.g. 719 Landy et al., 2022). 720

#### 4.3 Future Work

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The sensitivity of the FOAM system's SIT forecasts to the parameterisation of 722 the freeboard-to-thickness conversion and other data assimilation parameters informs 723 us how best to configure the Met Office's operational system when implementing 724 SIT assimilation. A near-real time CryoSat-2 product is required for operational 725 assimilation of SIT into the Met Office systems. Currently, FOAM assimilates data 726 from the previous 24 hours into its systems. The AWI product is available near-real 727 time, so its SIT and snow depth values are currently being tested for operational 728 assimilation. This product also comes with freeboard uncertainties, allowing for 729 the use of derived SIT uncertainties in the operational assimilation. Additionally, 730 testing the SIT assimilation on a fully coupled ocean-sea ice-land-atmosphere system 731 would allow us to explore the impacts of SIT assimilation on land and atmosphere 732 variables, to determine how SIT uncertainties affect parameters outside of the Arctic 733 ocean. 734

Tests with other satellite-derived SIT products, such as those derived from 735 ICESat-2 and Sentinel-3, would allow us to increase the temporal and spatial 736 resolution of the assimilated SIT data. This would require a consistent definition 737 of uncertainties such that the different SIT products can be combined. Assimilation 738 of ICESat-2 SIT would remove the need for radar scattering assumptions, reducing 739 uncertainty in the SIT. However, as ICESat-2 estimates total freeboard (snow depth 740 + ice freeboard), using it to calculate SIT still requires the use of a snow product, 741 and the uncertainties coming from the snow loading for a laser altimeter product are 742 higher than for a radar altimeter product (Kaminski et al., 2018). Additionally, tests 743 with spatially and temporally varying radar penetration assumptions would improve 744 the representation of changes in radar penetration in response to meteorological 745 conditions found by previous studies. 746

### 747 Author Contribution Statement

- Carmen Nab: Conceptualization, Formal Analysis, Investigation, Writing Original
- <sup>749</sup> Draft Preparation, Writing Review & Editing. Davi Mignac: Conceptualization,
- <sup>750</sup> Methodology, Supervision, Writing Review & Editing. Jack Landy: Data Curation,
- <sup>751</sup> Writing Review & Editing. Matthew Martin: Writing Review & Editing.
- Julienne Stroeve: Writing Review & Editing. Michel Tsamados: Supervision,
- <sup>753</sup> Writing Review & Editing.

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- 762 & #NE/X004643/1).

## 763 Open Research

- The NEMO ocean model and  $SI^3$  sea ice model are available at https://forge
- .nemo-ocean.eu/nemo (Madec et al., 2023; Vancoppenolle et al., 2023). The AWI
- snow depth and radar freeboard data are available at https://doi.org/10.5281/
- zenodo.10044553 (Hendricks et al., 2021). The LARM radar freeboard data are
- <sup>768</sup> available at https://doi.org/10.5285/cbd2cf78-462a-4968-be20-05f9c125ad10
- (Landy & Stroeve, 2020). The CPOM radar freeboard data are available at http://
- www.cpom.ucl.ac.uk/csopr/seaice.php (Laxon et al., 2013). The SM-LG snow
- depth data are available at https://doi.org/10.5067/27A0P5M6LZBI (Liston et
- al., 2021). The OIB data are available at https://doi.org/10.5067/19SIM5TXKPGT
- (Krabill, 2013). The BGEP data are available at https://www2.whoi.edu/site/
- beaufortgyre/data/mooring-data/ (BGEP, 2022). The IceBird total thickness
- and snow depth data are available at https://doi.org/10.1594/PANGAEA.924848
- (Hendricks et al., 2020) and https://doi.org/10.1594/PANGAEA.932668 (Jutila et
- al., 2021) respectively. All code required to reproduce this analysis can be found at
- https://github.com/carmennab/foam\_sensitivity.

779	References
780	Aaboe, S., Down, E., Sørensen, A., Lavergne, T., & Eastwood, S. (2021).
781	Sea-ice type climate data record Oct1978-Aug2023, v2.0. Copernicus Climate
782	Change Service (C3S) Climate Data Store (CDS). ECMWF. doi: 10.24381/
783	CDS.29C46D83
784	Armitage, T. W. K., & Ridout, A. L. (2015). Arctic sea ice freeboard from AltiKa
785	and comparison with CryoSat-2 and Operation IceBridge. Geophysical Research
786	Letters, $42(16)$ , 6724–6731. doi: $10.1002/2015$ GL064823
787	BGEP. (2022). Mooring Data from the Beaufort Gyre Exploration Project
788	( <i>BGEP</i> ). Retrieved from https://www2.whoi.edu/site/beaufortgyre/data/
789	mooring-data/
790	Blockley, E., Fiedler, E., Ridley, J., Roberts, L., West, A., Copsey, D.,
791	Vancoppenolle, M. (2023). The sea ice component of GC5: coupling SI $^{\circ}$ to
792	HadGEM3 using conductive fluxes. EGUSphere. doi: 10.5194/egusphere-2023
793	-1/31
794	Chen, Z., Liu, J., Song, M., Yang, Q., & Au, S. (2017). Impacts of Assimilating
795	NCEP Climate Ecocoast System Lowrad of Climate 20(21) \$420 \$446 doi:
796	10 1175/ICLI-D-17-0093 1
709	Fiedler E K Martin M I Blockley E Mignac D Fournier N Bidout
790	A Tilling B L (2022) Assimilation of sea ice thickness derived from
800	CryoSat-2 along-track freeboard measurements into the Met Office's Forecast
801	Ocean Assimilation Model (FOAM). The Cryosphere, 16(1), 61–85. doi:
802	10.5194/tc-16-61-2022
803	Fritzner, S., Graversen, R., Christensen, K. H., Rostosky, P., & Wang, K. (2019).
804	Impact of assimilating sea ice concentration, sea ice thickness and snow depth in
805	a coupled ocean–sea ice modelling system. The Cryosphere, $13(2)$ , $491-509$ . doi:
806	10.5194/tc-13-491-2019
807	Gregory, W., Bushuk, M., Adcroft, A., Zhang, Y., & Zanna, L. (2023). Deep
808	Learning of Systematic Sea Ice Model Errors From Data Assimilation Increments.
809	Journal of Advances in Modeling Earth Systems, 15(10), e2023MS003757. doi:
810	10.1029/2023MS003757
811	Guemas, V., Blanchard-Wrigglesworth, E., Chevallier, M., Day, J. J., Déqué,
812	M., Doblas-Reyes, F. J., Hetsche, S. (2016). A review on Arctic sea-ice
813	of the Royal Meteorological Society 1/2(605) 546-561 doi: 10.1002/gi 2401
814	Cuerreiro K Floury S Zakharova F Kouraov A Bémy F & Majsongrando
815	P (2017) Comparison of CryoSat-2 and ENVISAT radar freeboard over Arctic
817	sea ice: toward an improved Envisat freeboard retrieval. The Cruosphere, 11(5).
818	2059–2073. doi: 10.5194/tc-11-2059-2017
819	Haas, C. (2003, May). Dynamics versus Thermodynamics: The Sea Ice Thickness
820	Distribution. In D. N. Thomas & G. S. Dieckmann (Eds.), Sea Ice (1st ed., pp.
821	82–111). Wiley. doi: 10.1002/9780470757161.ch3
822	Hendricks, S., Ricker, R., Haas, C., & Herber, A. (2020). Airborne sea ice plus snow
823	thickness during the PAMARCMIP 2017 aircraft campaign in the Arctic Ocean.
824	doi: 10.1594/PANGAEA.924848
825	Hendricks, S., Ricker, R., & Paul, S. (2021). Product User Guide & Algorithm
826	Specification: AWI CryoSat-2 Sea Ice Thickness (version 2.4). Retrieved from
827	https://epic.awi.de/id/eprint/54733/

- Jutila, A., King, J., Ricker, R., Hendricks, S., Helm, V., Binder, T., & Herber, A. 828 (2021). Airborne snow depth on sea ice during the PAMARCMIP2017 campaign in 829 the Arctic Ocean, Version 1. doi: 10.1594/PANGAEA.932668 830
- Kaleschke, L., Tian-Kunze, X., Maaß, N., Mäkynen, M., & Drusch, M. (2012).831 Sea ice thickness retrieval from SMOS brightness temperatures during the 832

833 834	Arctic freeze-up period. Geophysical Research Letters, 39(5), L05501. doi: 10.1029/2012GL050916
835	Kaminski, T., Kauker, F., Toudal Pedersen, L., Voßbeck, M., Haak, H., Niederdrenk,
836	L., Gråbak, O. (2018). Arctic Mission Benefit Analysis: impact of sea ice
837	thickness, freeboard, and snow depth products on sea ice forecast performance.
838	The Cryosphere, $12(8)$ , $2569-2594$ . doi: $10.5194/tc-12-2569-2018$
839	Kern, S., Khvorostovsky, K., Skourup, H., Rinne, E., Parsakhoo, Z. S., Djepa, V.,
840	Sandven, S. (2015). The impact of snow depth, snow density and ice density on
841	sea ice thickness retrieval from satellite radar altimetry: results from the ESA-CCI
842 843	Sea Ice ECV Project Round Robin Exercise. The Cryosphere, 9(1), 37–52. doi: 10.5194/tc-9-37-2015
844	Kilic, L., Tonboe, R. T., Prigent, C., & Heygster, G. (2019). Estimating the snow
845	depth, the snow-ice interface temperature, and the effective temperature of Arctic
846	sea ice using Advanced Microwave Scanning Radiometer 2 and ice mass balance
847	buoy data. The Cryosphere, 13(4), 1283–1296. doi: 10.5194/tc-13-1283-2019
848	Krabill, W. B. (2013). IceBridge ATM L1B Elevation and Return Strength,
849	Version 2. NASA National Snow and Ice Data Center DAAC. doi: 10.5067/
850	19SIM5TXKPGT
851	Krabill, W. B., Thomas, R. H., Martin, C. F., Swift, R. N., & Frederick, E. B.
852	(1995). Accuracy of airborne laser altimetry over the Greenland ice sheet.
853	International Journal of Remote Sensing, 16(7), 1211–1222. doi: 10.1080/
854	01431169508954472
855	Krishfield, R. A., Proshutinsky, A., Tateyama, K., Williams, W. J., Carmack, E. C.,
856	McLaughlin, F. A., & Timmermans, ML. (2014). Deterioration of perennial
857	sea ice in the Beaufort Gyre from 2003 to 2012 and its impact on the oceanic
858	freshwater cycle: SEA ICE IN THE BG FROM 2003 TO 2012. Journal of
859	Geophysical Research: Oceans, 119(2), 1271–1305. doi: 10.1002/2013JC008999
860	Kurtz, N. T., Farrell, S. L., Studinger, M., Galin, N., Harbeck, J. P., Lindsay, R.,
861	Sonntag, J. G. (2013). Sea ice thickness, freeboard, and snow depth products
862	from Operation IceBridge airborne data. The Cryosphere, 7(4), 1035–1056. doi:
863	10.5194/tc-7-1035-2013
864	Kwok, R., & Cunningham, G. F. (2015). Variability of Arctic sea ice thickness
865	and volume from CryoSat-2. Philosophical Transactions of the Royal Society A:
866	Mathematical, Physical and Engineering Sciences, 373 (2045), 20140157. doi: 10
867	.1090/ISta.2014.0157 Kwelt D. Kuntz N.T. Duncken I. Ivenoff A. Neuman T. Fennell S. I.
868	Tachudi M (2017) Intercomparison of snow donth ratriovals over Aratia son
869	ice from reder data acquired by Operation IceBridge The Crucenberg 11(6)
870	2571-2593 doi: 10.5194/tc-11-2571-2017
071	Landy I C Dawson G I Tsamados M Bushuk M Stroeve I C Howell
972	S E L Aksenov V (2022) A year-round satellite sea-ice thickness record
874	from CryoSat-2. Nature, 609(7927), 517–522. doi: 10.1038/s41586-022-05058-5
875	Landy J C Petty A A Tsamados M & Stroeve J C (2020) Sea
876	Ice Roughness Overlooked as a Key Source of Uncertainty in CryoSat-2 Ice
877	Freeboard Retrievals. Journal of Geophysical Research: Oceans, 125(5). doi:
878	10.1029/2019JC015820
879	Landy, J. C., & Stroeve, J. (2020). Arctic sea ice and physical oceanography derived
880	from CryoSat-2 Baseline-C Level 1b waveform observations, Oct-Apr 2010-2018.
881	UK Polar Data Centre, Natural Environment Research Council, UK Research &
882	Innovation. doi: 10.5285/CBD2CF78-462A-4968-BE20-05F9C125AD10
883	Laxon, S. W., Giles, K. A., Ridout, A. L., Wingham, D. J., Willatt, R., Cullen, R.,
884	Davidson, M. (2013). CryoSat-2 estimates of Arctic sea ice thickness and
885	volume. Geophysical Research Letters, $40(4)$ , 732–737. doi: 10.1002/grl.50193
886	Liston, G., Itkin, P., Stroeve, J., Tschudi, M., Stewart, J. S., Pedersen, S. H.,

Elder, K. (2020). A Lagrangian Snow-Evolution System for Sea-Ice Applications 887 (SnowModel-LG): Part I—Model Description. Journal of Geophysical Research: 888 Oceans, 125(10). doi: 10.1029/2019JC015913 889 Liston, G., Stroeve, J., & Itkin, P. (2021).Lagrangian Snow Distributions for 890 Sea-Ice Applications, Version 1. ERA5 subset. NASA National Snow and Ice Data 891 Center DAAC. doi: 10.5067/27A0P5M6LZBI 892 Madec, G., Bell, M., Blaker, A., Bricaud, C., Bruciaferri, D., Castrillo, M., ... 893 Wilson, C. (2023). NEMO Ocean Engine Reference Manual (Tech. Rep.). (Version 894 Number: v4.2.1) doi: 10.5281/ZENODO.8167700 895 Mallett, R. D. C., Lawrence, I. R., Stroeve, J. C., Landy, J. C., & Tsamados, M. 896 (2020).Brief communication: Conventional assumptions involving the speed of 897 radar waves in snow introduce systematic underestimates to sea ice thickness 898 and seasonal growth rate estimates. The Cryosphere, 14(1), 251-260. doi: 899 10.5194/tc-14-251-2020 900 Meier, W. N., Stroeve, J., & Fetterer, F. (2007).Whither Arctic sea ice? A clear 901 signal of decline regionally, seasonally and extending beyond the satellite record. 902 Annals of Glaciology, 46, 428-434. doi: 10.3189/172756407782871170 903 Mignac, D., Martin, M., Fiedler, E., Blockley, E., & Fournier, N. (2022).904 Improving the Met Office's Forecast Ocean Assimilation Model (FOAM) with the 905 assimilation of satellite-derived sea-ice thickness data from CryoSat-2 and SMOS 906 in the Arctic. Quarterly Journal of the Royal Meteorological Society, qj.4252. doi: 907 10.1002/qj.4252 908 Nab, C., Mallett, R., Gregory, W., Landy, J., Lawrence, I. R., Willatt, R., ... 909 Tsamados, M. (2023).Synoptic Variability in Satellite Altimeter-Derived 910 Radar Freeboard of Arctic Sea Ice. Geophysical Research Letters. doi: 911 10.1029/2022GL100696 912 Nandan, V., Geldsetzer, T., Yackel, J., Mahmud, M., Scharien, R., Howell, S., ... 913 Else. B. Effect of Snow Salinity on CryoSat-2 Arctic First-Year Sea Ice (2017).914 Freeboard Measurements: Sea Ice Brine-Snow Effect on CryoSat-2. Geophysical 915 Research Letters, 44(20), 10,419–10,426. doi: 10.1002/2017GL074506 916 Nandan, V., Willatt, R., Mallett, R., Stroeve, J., Geldsetzer, T., Scharien, R., 917 (2023).Wind redistribution of snow impacts the Ka- and ... Hoppmann, M. 918 Ku-band radar signatures of Arctic sea ice. The Cryosphere, 17(6), 2211–2229. 919 doi: 10.5194/tc-17-2211-2023 920 Ricker, R., Hendricks, S., Helm, V., Skourup, H., & Davidson, M. (2014).921 Sensitivity of CryoSat-2 Arctic sea-ice freeboard and thickness on radar-waveform 922 interpretation. The Cryosphere, 8(4), 1607–1622. doi: 10.5194/tc-8-1607-2014 923 Rothrock, D. A. (2003). The arctic ice thickness anomaly of the 1990s: A consistent 924 view from observations and models. Journal of Geophysical Research, 108(C3), 925 3083. doi: 10.1029/2001JC001208 926 Shen, X., Ke, C.-Q., Xie, H., Li, M., & Xia, W. (2020).A comparison of Arctic 927 sea ice freeboard products from Sentinel-3A and CryoSat-2 data. International 928 Journal of Remote Sensing, 41(7), 2789–2806. doi: 10.1080/01431161.2019 929 .1698078930 (2023).Sievers, I., Rasmussen, T. A. S., & Stenseng, L. Assimilating CryoSat-2 931 freeboard to improve Arctic sea ice thickness estimates. The Cryosphere, 17(9), 932 3721-3738. doi: 10.5194/tc-17-3721-2023 933 Storkey, D., Blaker, A. T., Mathiot, P., Megann, A., Aksenov, Y., Blockley, E. W., 934 ... Sinha, B. (2018).UK Global Ocean GO6 and GO7: a traceable hierarchy 935 of model resolutions. Geoscientific Model Development, 11(8), 3187–3213. doi: 936 10.5194/gmd-11-3187-2018 937 Tian-Kunze, X., Kaleschke, L., Maaß, N., Mäkynen, M., Serra, N., Drusch, M., & 938 Krumpen, T. (2014).SMOS-derived thin sea ice thickness: algorithm baseline, 030 product specifications and initial verification. The Cryosphere, 8(3), 997–1018. 940

941	doi: 10.5194/tc-8-997-2014
942	Tilling, R. L., Ridout, A., & Shepherd, A. (2018). Estimating Arctic sea ice
943	thickness and volume using CryoSat-2 radar altimeter data. Advances in Space
944	Research, 62(6), 1203–1225. doi: 10.1016/j.asr.2017.10.051
945	Tsamados, M., Feltham, D., Petty, A., Schroeder, D., & Flocco, D. (2015, October).
946	Processes controlling surface, bottom and lateral melt of Arctic sea ice in a state
947	of the art sea ice model. Philosophical Transactions of the Royal Society A:
948	Mathematical, Physical and Engineering Sciences, 373(2052), 20140167. doi:
949	10.1098/rsta.2014.0167
950	Vancoppenolle, M., Rousset, C., Blockley, E., Aksenov, Y., Feltham, D., Fichefet,
951	T., Tietsche, S. (2023, January). S13, the NEMO Sea Ice Engine. doi:
952	10.5281/ZENODO.7534900
953	Wang, Q., Ilicak, M., Gerdes, R., Drange, H., Aksenov, Y., Bailey, D. A., Yeager,
954	S. G. (2016). An assessment of the Arctic Ocean in a suite of interannual
955	CORE-II simulations. Part I: Sea ice and solid freshwater. Ocean Modelling,
956	99, 110–132. doi: 10.1016/j.ocemod.2015.12.008
957	Waters, J., Lea, D. J., Martin, M. J., Mirouze, I., Weaver, A., & While, J. (2015).
958	Implementing a variational data assimilation system in an operational 1/4 degree
959	global ocean model. Quarterly Journal of the Royal Meteorological Society,
960	141(687), 333–349. doi: 10.1002/qj.2388
961	Willatt, R., Giles, K., Laxon, S. W., Stone-Drake, L., & Worby, A. (2010). Field
962	Investigations of Ku-Band Radar Penetration Into Snow Cover on Antarctic Sea
963	Ice. IEEE Transactions on Geoscience and Remote Sensing, $48(1)$ , $365-372$ . doi:
964	10.1109/TGRS.2009.2028237
965	Williams, N., Byrne, N., Feltham, D., Van Leeuwen, P. J., Bannister, R., Schroeder,
966	D., Nerger, L. (2023). The effects of assimilating a sub-grid-scale sea ice
967	thickness distribution in a new Arctic sea ice data assimilation system. Inc $C_{\text{maxwell}} = 17/(6) = 2500 = 2522$ , doi: 10.5104/to.17.2500.2022
968	Cryosphere, 17(0), 2509-2552. doi: 10.5194/tc-17-2509-2025
969	Ala, W., & Ale, H. (2018). Assessing three wavelorin retrackers on sea ice freeboard
970	Remote Sensing of Environment 20/ 456-471 doi: 10.1016/j.rsp.2017.10.010
971	Zhang V Bushuk M Winton M Hurlin B Crogory W Landy I & Jia I
972	(2023). Improvements in September Arctic Sea Ice Predictions Via Assimilation of
974	Summer CryoSat-2 Sea Ice Thickness Observations. <i>Geophysical Research Letters</i> .
975	50(24), e2023GL105672. doi: 10.1029/2023GL105672
976	Zhang, YF., Bitz, C. M., Anderson, J. L., Collins, N., Hendricks, J., Hoar, T.,
977	Massonnet, F. (2018). Insights on Sea Ice Data Assimilation from Perfect

- Model Observing System Simulation Experiments. 5911–5926. doi: 10.1175/JCLI-D-17-0904.1 Journal of Climate, 31(15), 978
- 979

## Supporting Information for: Sensitivity of short-range forecasts to sea ice thickness data assimilation parameters in a coupled ice-ocean system

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**Figure S1.** FOAM SIT and one-week running mean of BGEP SIT at BGEP-A, BGEP-B and BGEP-D mooring locations from 25 November 2016 to 15 April 2017. The grey shaded area shows the BGEP uncertainty, represented by the daily standard deviation. Coloured text shows the mean root-mean-squared error for the season for each experiment.



**Figure S2.** Daily difference between FOAM SIT and BGEP SIT at BGEP-A, BGEP-B and BGEP-D mooring locations, normalised by the BGEP standard deviation. Coloured text shows the mean absolute value for each experiment. Note the different y-axes.

α\_0.9

\_

FB\_LARM

SN\_SMLG

UNC

CTRL

:



Figure S3. a-g) Monthly difference between mean daily sea ice thickness in the UNC experiment and the BASE experiment (UNC-BASE) h) standard deviation of the monthly differences.

Oct



100 -50 50 0



Jan

50 100 -100 -50 0 Thermodynamic Volume Growth Difference (%)

-100 -50 50 0 Thermodynamic Volume Growth Difference (%) -100 Thermodynamic Volume Growth Difference (%)





Figure S4. a-g) Monthly difference between mean daily thermodynamic volume change in the UNC experiment and the BASE experiment (UNC-BASE) h) standard deviation of the monthly differences.

## 1. IceBird

As part of the IceBird campaign series, total thickness (snow depth + sea ice thickness) measurements were collected during the PAMARCMIP campaign in March and April 2017 (Hendricks et al., 2020). The data was gathered using the AWI EM-Bird, a helicopter-borne electromagnetic (EM) induction system on flights in the Beaufort Sea and the Chukchi Sea. The system works by sending a low-frequency EM field through the sea ice, generating eddy currents in the water below. This induces a secondary EM field that propagates back upwards through the sea ice, the strength of which is directly related to the distance between the EM system and the underside of the sea ice. Using a laser, the distance between the EM system and the snow surface is then measured, such that the total thickness can be derived as the difference between the laser-determined snow surface and the EM-determined underlying water surface. See Haas et al. (2009) for a full description of this method. On the same flights, snow depth measurements were taken using the AWI Snow Radar (Jutila et al., 2021), an ultrawideband microwave radar able to estimate snow depth on sea ice with a mean bias of 0.86 cm. See Jutila et al. (2022) for a full description of this method. The high-frequency IceBird snow depth and total thickness data are binned into 12 km grid cells (equivalent to the FOAM grid size in the Arctic), with the median taken to avoid the impact of outliers. To determine the sea ice thickness, we take the difference between the coincident total thickness and snow depth measurements. Only points where data for both the total thickness and snow depth are available are used. For the evaluation, the model SITs are then interpolated to these observation locations.

With the exception of the  $\alpha_0.6$  and UNC experiments, we find a consistent overestimation in the model SIT compared to the IceBird SIT everywhere except at the ice edge (Figure S5). Similarly to the OIB comparison, we find a wider range of values in the IceBird data than in the model results, particularly at SIT values below 1 m and above 3 m (Figure S6). We find a negative correlation between the IceBird data and each of the experiments (Figure S6). Each of the assimilation experiments performs worse than the CTRL experiment in terms of the magnitude of the r value. The experiments perform similarly in terms of RMSE (0.80 - 0.85 m), with the exception of the SN\_SMLG and SN\_AWI experiments (0.91 and 0.96 m, respectively).

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Figure S5. Difference between FOAM SIT and IceBird SIT, between 9 March and 19 April 2017.



Figure S6. Histograms of FOAM SIT and IceBird SIT in the Beaufort and Chukchi Seas, between 30 March and 8 April 2017.

## References

- Haas, C., Lobach, J., Hendricks, S., Rabenstein, L., & Pfaffling, A. (2009). Helicopter-borne measurements of sea ice thickness, using a small and lightweight, digital EM system. *Journal* of Applied Geophysics, 67(3), 234–241. doi: 10.1016/j.jappgeo.2008.05.005
- Hendricks, S., Ricker, R., Haas, C., & Herber, A. (2020). Airborne sea ice plus snow thickness during the PAMARCMIP 2017 aircraft campaign in the Arctic Ocean. doi: 10.1594/PANGAEA .924848
- Jutila, A., King, J., Paden, J., Ricker, R., Hendricks, S., Polashenski, C., ... Haas, C. (2022).
  High-Resolution Snow Depth on Arctic Sea Ice From Low-Altitude Airborne Microwave Radar
  Data. *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1–16. doi: 10.1109/TGRS
  .2021.3063756
- Jutila, A., King, J., Ricker, R., Hendricks, S., Helm, V., Binder, T., & Herber, A. (2021). Airborne snow depth on sea ice during the PAMARCMIP2017 campaign in the Arctic Ocean, Version 1. doi: 10.1594/PANGAEA.932668