RESEARCH ARTICLE

Improving the Met Office’s Forecast Ocean Assimilation Model (FOAM) with the assimilation of satellite-derived sea-ice thickness data from CryoSat-2 and SMOS in the Arctic

Davi Mignac | Matthew Martin | Emma Fiedler | Ed Blockley | Nicolas Fournier

Met Office, Exeter, UK

Correspondence
D. Mignac, Met Office, FitzRoy Road, Exeter, EX1 3PB, UK.
Email: davi.carneiro@metoffice.gov.uk

Funding information
Horizon 2020 Framework Programme, Grant/Award Numbers: 723526, 727862

Abstract
Derived from two complementary satellites, CryoSat-2 and Soil Moisture and Ocean Salinity (SMOS), sea ice thickness (SIT) data are assimilated into the Met Office’s global ocean–sea ice forecasting system, FOAM, using a 3D-Var assimilation scheme, NEMOVAR. CryoSat-2 along-track SITs, which are converted from freeboard measurements using the model snow depth, and a daily, gridded SMOS SIT product are used in the assimilation to constrain the Arctic sea ice thickness. When using only CryoSat-2 assimilation, SIT forecast fields within the ice pack are greatly improved with respect to independent airborne measurements. However, the positive impacts of CryoSat-2 assimilation in thick ice regions are counteracted by an SIT overestimation in areas of thin ice, due to biased freeboard measurements there. Adding the SMOS assimilation results in much thinner SITs in those regions, which performs better than the control when compared to SIT objective analyses and mooring measurements in the Beaufort and Barents Seas. Furthermore, SMOS assimilation enhances the short-term predictive skill of the marginal sea-ice concentration relative to the control. This is translated into a consistent retreat of the sea-ice covered areas in the 5-day forecasts during March 2017, which is in better agreement with independent ice edge products. This work successfully demonstrates improvements in FOAM sea ice when SIT observations from both CryoSat-2 and SMOS are assimilated, representing an important step towards the operational implementation of SIT assimilation within Met Office forecasting systems.

KEYWORDS
1. Tools and methods: data assimilation, general circulation model experiments, observations, remote sensing, 2. Scale: global, 3. Physical phenomenon: ice/icing

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.
© 2022 Crown Copyright, Met Office. Quarterly Journal of the Royal Meteorological Society published by John Wiley & Sons Ltd on behalf of Royal Meteorological Society. This article is published with the permission of the Controller of HMSO and the Queen’s Printer for Scotland.
1 | INTRODUCTION

In the face of substantial reductions in both Arctic sea ice extent (Stroeve and Notz, 2018; Gulev et al., 2021) and thickness (Kwok and Rothrock, 2009; Mallett et al., 2021) in the past few decades, there is an increasing need for accurate sea ice predictions covering the time-scales of days, seasons and beyond. This decline in Arctic sea ice cover may have implications for the weather and climate at lower latitudes (Koenigk et al., 2016; Pedersen et al., 2016), the polar ecosystem (Meier et al., 2014), and Arctic shipping by opening new sea routes (Smith and Stephenson, 2013; Wei et al., 2020), which are under the influence of more variable and mobile Arctic sea ice (Eicken, 2013).

Although global analysis and forecasting systems have successfully been used for mid- and low-latitude ocean prediction for some time, their application to Arctic sea ice is less mature, since observations are much less abundant and data assimilation techniques less advanced in the polar regions than at lower latitudes (e.g. Bauer et al., 2016; Uotila et al., 2019). Due to satellite observations dating back to 1979, the sea ice concentration (SIC) is one of the few sea ice variables that have been well exploited by data assimilation studies into standalone sea-ice models (Thomas et al., 1996), coupled ocean–sea ice models (Lisæter et al., 2003; Peterson et al., 2015; Posey et al., 2015; Yang et al., 2015; 2016) and coupled ocean–atmosphere–sea ice models (Lea et al., 2015; Guaivarch et al., 2019; Mu et al., 2020; Barton et al., 2021). Therefore, SIC assimilation is well established and routine at many operational centres (e.g. Bertino and Lisaeter, 2008; Blockley et al., 2014; Posey et al., 2015; Lemieux et al., 2016). Conversely, the developments of sea ice thickness (SIT) assimilation are much more incipient in operational sea-ice forecasting systems when compared to SIC, even though SIT is particularly relevant for quantifying changes in crucial climate indicators, such as the total Arctic sea-ice volume (Kwok and Rothrock, 2009). It is also well known that winter SIT provides important preconditioning for the evolution of Arctic sea ice through the summer melt season (Kauker et al., 2009; Holland et al., 2011; Blockley and Peterson, 2018).

Despite its control over Arctic sea ice evolution, SIT observations from satellites are relatively recent, with CryoSat-2 being the first dedicated satellite mission to observe sea ice freeboard, launched in 2010. Assuming hydrostatic equilibrium, freeboard measurements, which are defined as the height of the ice above the water level, can be converted into SIT (Tilling et al., 2016). The CryoSat-2 mission was primarily designed to measure the thickness of perennial, thick ice, since the retrieval method can have large uncertainties over thin ice regions (Ricker et al., 2014). Due to its complementarity to CryoSat-2, the Soil Moisture and Ocean Salinity (SMOS) mission, launched in 2009, plays a relevant role in the SIT observation network (Xie et al., 2016; Ricker et al., 2017). SMOS provides measurements of brightness temperatures at microwave frequencies, which can be used to infer SITs over areas of thin ice with relatively low uncertainties (Tian-Kunze et al., 2014; Kaleschke et al., 2016).

The complementarity between CryoSat-2 and SMOS SIT datasets is also reflected in the assimilation impacts demonstrated by previous studies (Ricker et al., 2017; Mu et al., 2018a; 2018b). The SMOS assimilation alone improves the representation of both SIT and SIC over areas of thin ice in coupled ocean–sea ice models, although its impact is very small far from the ice edge (Yang et al., 2014; Xie et al., 2016; Gupta et al., 2021). Conversely, when only CryoSat-2 observations are assimilated, the thickness of the ice pack is well constrained, but their assimilation also produces mixed results over thin-ice regions (Fritzner et al., 2019; Fiedler et al., 2022). Therefore, the SIT assimilation of both satellites is required to consistently improve the sea ice in distinct Arctic regions (e.g. Chen et al., 2017; Mu et al., 2018a; 2018b).

The assimilation of CryoSat-2 SITs described in the literature often uses gridded, temporally-averaged products (e.g. weekly, monthly) instead of the original along-track data, due to noise in the freeboard retrievals (Laxon et al., 2013; Ricker et al., 2014). The feasibility of SIT assimilation, derived from CryoSat-2 along-track freeboard data, has been recently demonstrated by Fiedler et al. (2022) using the Met Office’s FOAM global ocean–sea ice forecasting system. This is aligned with the nature of the operational systems at the Met Office, which use observations within short time assimilation windows to initialise forecasts close to real time. In addition to the assimilation of derived SITs from CryoSat-2 along-track data, here we investigate improvements in FOAM by also assimilating SMOS SIT retrievals in the Arctic. An evaluation of the SIT and SIC 1-day and 5-day forecasts is presented against independent observations, considering: a control run assimilating all the standard observation types in FOAM which does not include SIT (Blockley et al., 2014); a run with the additional SIT assimilation of CryoSat-2 along-track data; and a further SIT assimilation run, using the SIT observations from both SMOS and CryoSat-2.

The article is outlined as follows. Section 2 describes the Met Office ocean–sea ice forecasting system, the assimilated and independent observations used in the validation, as well as the assimilation configurations. Section 3 shows the results of the SIT assimilation experiments, including the impacts on the mean sea-ice state, the validation against independent observations, and the assessment of the SIT and SIC short-range forecasts. Finally, discussions and conclusions are presented in Section 4.
2 | METHODS

2.1 | The FOAM system and the experiment set-up

The Forecast Ocean Assimilation Model (FOAM: Blockley et al., 2014) is the Met Office’s operational, coupled ocean–sea ice system. FOAM produces global analyses and 5-day forecasts of ocean and sea-ice variables each day. FOAM analyses are used operationally to initialise the Met Office’s seasonal prediction system, GloSea (MacLachlan et al., 2015), and FOAM sea-ice and ocean components are also employed in a coupled ocean–sea-ice–land–atmosphere short-range forecasting system (Guiavarch et al., 2019). The latter Met Office system provides 10-day ocean forecasts to the Copernicus Marine Environment Monitoring Service (CMEMS; marine.copernicus.eu). Therefore, the implementation of any developments in FOAM will also be beneficial to these coupled short-range and seasonal prediction systems.

The FOAM version used in this work employs the NEMO ocean model version 3.6 (Nucleus for European Modelling of the Ocean: Madec, 2017), coupled to version 5.1.2 of the Los Alamos Sea Ice Model (CICE: Hunke et al., 2015). The operational FOAM system has recently been upgraded from 1/4° to 1/12° horizontal resolution (Barbosa Aguiar et al., 2022), but the 1/4° version is used here. Both the ocean and sea-ice components employ a quasi-isotropic tripolar ORCA grid (Madec and Imbard, 1996). NEMO is configured with a nonlinear free surface and 75 vertical levels, with 1 m vertical resolution at the surface and decreasing resolution with increasing depth (Storkey et al., 2018). The CICE configuration includes five thickness categories (plus open water), multi-layer thermodynamics and prognostic melt ponds (Ridley et al., 2018). FOAM is forced at the surface using hourly wind fields and 3-hourly air temperature and humidity at 10 m, as well as precipitation and radiative fluxes from the operational Met Office Unified Model (MetUM: Walters et al., 2011) global numerical weather prediction (NWP) system. The spatial resolution of the atmospheric forcing used here is ~17 km.

The NEMOVAR data assimilation scheme is used in all configurations of the operational Met Office ocean analysis and forecasting systems. This is an incremental, multi-variate, multi-length-scale assimilation method, configured in FOAM as a three-dimensional variation (3D-Var) FGAT (First Guess at Appropriate Time: Waters et al., 2015; Mirouze et al., 2016) scheme. An assimilation window of 24 hr is used to assimilate observation types from a variety of platforms, including sea-surface temperature (SST), sea-level anomaly (SLA), temperature and salinity profiles, and SIC. SST in situ observations are gathered from ships, and moored and drifting buoys, whereas satellite SST data are obtained from Advanced Very High Resolution Radiometer (AVHRR) sensors on board National Oceanic and Atmospheric Administration (NOAA) and MetOp satellites, and Visible Infrared Imaging Radiometer Suite (VIIRS) sensors on board the Suomi-NPP (National Polar-orbiting Partnership) satellite. Temperature and salinity profiles are provided by Argo floats, moored buoy arrays, gliders, and research CTD (Conductivity, Temperature and Depth) instruments. Additionally, temperature profiles from XBTs (Expendable Bathythermographs) and marine mammal sensors are also used. Along-track satellite SLA data are provided by the Jason-2, Jason-3, Sentinel-3A, CryoSat-2 and AltiKa satellites. Finally, SIC observations are assimilated from Special Sensor Microwave Imager/Sounder (SSMI/S) instruments on board the series of satellites within the Defense Meteorological Satellites Program (DMSP), which are processed by the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea-Ice Satellite Application Facility (OSI SAF). No SIT observations are currently assimilated operationally, although Fiedler et al. (2022) have already verified the impact of assimilating SITs derived from along-track CryoSat-2 freeboard measurements on FOAM analyses and forecasts.

In this study, a control FOAM system (CTL) assimilating SST, SLA, profiles of temperature and salinity, and SIC observations is run alongside two other experiments with the additional assimilation of SIT observations: one assimilating SIT observations derived from CryoSat-2 freeboard measurements (A-CS2), along the lines of that described by Fiedler et al. (2022); and another one assimilating both SIT observations from CryoSat-2 and SMOS (A-CS2SMOS) to show the impacts relative to CTL and A-CS2 when SIT from SMOS is also assimilated. The CTL and A-CS2 are initialised from a previous FOAM run with the same configurations as the CTL (Fiedler et al., 2022), whereas A-CS2SMOS is initialised from A-CS2 (see Table 1).

Daily analysis and 1-day forecast fields were generated from each experiment. The common period between the experiments, from 25 November 2016 to 15 April 2017, is used to assess the model results and evaluate the impact of the additional SMOS SIT assimilation. Additionally, the analysis fields from each experiment were also used to initialise 5-day forecasts in March 2017. It is worth noting that CryoSat-2 and SMOS SIT measurements are only available between mid-October and mid-April every year, due to the detrimental impact of summertime melting on the satellite retrievals (Kaleschke et al., 2016; Tilling et al., 2016).
### Table 1. Configuration of the FOAM experiments

| Assimilated observations | Initial condition | Run period               |
|--------------------------|-------------------|--------------------------|
| CTL                      | SST, SLA, T, S and SIC | From a previous FOAM run | 15 October 2014–15 April 2017 |
| A-CS2                    | Same as CTL + CS2 SIT | From a previous FOAM run | 15 October 2014–15 April 2017 |
| A-CS2SMOS                | Same as CTL + CS2 SIT + SMOS SIT | From A-CS2 | 25 November 2016–15 April 2017 |

#### 2.2 Assimilated SIT observations

Brightness temperatures at 1.4 GHz (L-band) measured by SMOS have been used to derive sea ice thickness in the Arctic since 2010 (Kaleschke et al., 2016). The measurements of brightness temperatures are converted (prior to their use here) into SIT using a thermodynamic sea-ice model and a one-ice-layer radiative transfer model (Tian-Kunze et al., 2014). A daily ice thickness SMOS product with a spatial resolution of 12.5 km, gridded on the National Snow and Ice Data Centre (NSIDC) polar-stereographic projection, is available at the Integrated Climate Data Centre from the University of Hamburg (www.cen.uni-hamburg.de/icdc). The most up-to-date product version (v3.2) is used here for assimilation. The SIT retrieval with SMOS data is limited by the saturation of the brightness temperatures with increasing SITs. Therefore, the retrieval method is applicable only for relatively thin ice. Furthermore, the SMOS retrieval method assumes that all derived SITs are obtained at 100% SIC. The violation of this assumption may lead to a negative bias in the SMOS SIT retrievals, the extent of which is estimated in Tian-Kunze et al. (2014) by a simple semi-empirical function based on SIC and brightness temperature values. Although it quickly reaches ~10 cm at 90% SIC for high brightness temperatures, the SIT bias growth in SMOS is much smaller with decreasing SICs for lower brightness temperatures, reaching less than 10 cm at 40% SIC.

The SMOS gridded product contains daily SIT uncertainty estimates, which are given as the sum of uncertainties from each input parameter in the thermodynamic and radiation model, as well as in the thickness distribution function (Tian-Kunze et al., 2014). At present, the uncertainties are calculated for brightness temperature, ice temperature and ice salinity by keeping the other parameters constant. It is worth mentioning that errors caused by the assumption of 100% SIC in the SMOS retrievals have not yet been included, as well as errors derived from assumptions about fluxes and snow thickness.

The total uncertainties provided by the SMOS gridded product are used here as the SMOS measurement uncertainties in NEMOVAR. Since the SMOS observations represent a similar spatial area as the model grid in the Arctic, their representation errors are assumed to be negligible. However, representation errors can also arise from other factors, such as from unresolved sea-ice processes in the model, and observation operator and quality-control uncertainties (e.g. Janjić et al., 2017). Following the similar approaches of Ricker et al. (2017) and Mu et al. (2018a; 2018b), we only assimilate SMOS SIT observations that are equal to or less than 1 m. Additionally, we perform a quality-control check using the OSI SAF ice type product to neglect SMOS grid cells that are located in multi-year ice (MYI) regions, since large biases are expected for SMOS SITs in thicker MYI (Ricker et al., 2017). Therefore, the assimilation of SMOS observations is restricted to regions of Arctic thin ice, and their uncertainties increase with increasing SITs (Figure 1).

CryoSat-2 along-track measurements of Arctic sea ice freeboard, processed by the Centre for Polar Observation and Modelling (CPOM: Tilling et al., 2016), are used in this study. All the steps to derive SITs and their uncertainties from CryoSat-2 freeboard measurements are based on the methodology applied by Fiedler et al. (2022). The freeboard measurements are converted to SIT assuming that the ice is floating in hydrostatic equilibrium (Tilling et al., 2016). This means that estimates of sea ice thickness can be derived from freeboard data, using the densities of water, snow and ice, as well as the snow depth at the observation locations. CPOM and other operational centres use the snow depth climatology of Warren et al. (1999), halved over first-year ice regions, for converting CryoSat-2 freeboard data into SIT. However, as in Fiedler et al. (2022), we choose to use the model snow depth instead, which is supported by Mallett et al. (2021). Their work shows that radar altimetry retrievals of SIT produce much more consistent Arctic variability and trends when the snow cover from Lagrangian snow models are employed rather than the Warren et al. (1999) climatology. Snow depths in FOAM and in Lagrangian snow models used by Mallett et al. (2021) have been evaluated here against snow depth observations from National Aeronautics and Space Administration (NASA) Operation IceBridge (OIB) in March–April 2017. The FOAM snow depth has a root-mean-square difference (RMSD) of 0.11 m, slightly smaller than those from Lagrangian snow models (0.12 m), and a mean difference of −0.09 m relative to OIB observations (see Figure S1 and Table S1). Prior to the conversion to SIT, the model snow depth is...
FIGURE 1  (a) Assimilated sea-ice thickness derived from CryoSat-2 and SMOS within a 24-hour time window, and their uncertainties (b) as a spatial map and (c) as a function of their SITs for 25 November 2016. Note the irregular colour bar intervals in both (a) and (b) to highlight the distinct sea-ice thickness observations and the differences in uncertainty between the satellites. Units are in metres [Colour figure can be viewed at wileyonlinelibrary.com]

also used to correct the freeboard observations, accounting for the reduction in the speed of the altimeter radar pulse due to the presence of snow on the sea ice. More detail about this correction is described in Fiedler et al. (2022). Following the approach of Tilling et al. (2018), a quality control is then applied to reject the corrected freeboard measurements outside the range $-0.3$ to $3.0$ m.

After the freeboard conversion to SIT, super-observations are calculated within a specified radius of 10 km, in order to reduce the noise in the retrievals of CryoSat-2. The 10 km radius is chosen since it is similar to the size of the $1/4^\circ$ ORCA tri-polar grid cell in the Arctic used by FOAM, as well as to the resolution of the assimilated SMOS gridded product. Unlike Fiedler et al. (2022), we use the mean rather than the median for super-obb-ing CryoSat-2 SITs. Whilst the mean is negatively affected by outliers, the median is negatively impacted by small sample sizes, which is the case for the much lower number of CryoSat-2 observations near the ice edge compared to higher latitudes (Figure 1). As mentioned previously, slightly negative freeboards are permitted in the data which form the super-observations. These may result in negative SITs, which are rejected in Fiedler et al. (2022), but accounted for here in the super-obb-ing to allow for random noise, particularly over thin ice regions, as suggested by Tilling et al. (2018). After the averaging, any remaining negative SIT super-observations are rejected before the assimilation.

Unlike SMOS, no observation uncertainties are provided with CPOM CryoSat-2 freeboard measurements. Therefore, we parametrize CryoSat-2 SIT uncertainties as a function of their own SIT values, as in Fiedler et al. (2022). This is performed after super-obb-ing the CryoSat-2 SIT observations. Since the CryoSat-2 uncertainties rise asymptotically towards ice thinner than 1 m (Ricker et al., 2014), the uncertainty estimates for CryoSat-2 SIT super-observations less than around 1 m are set to a very high value (8 m), so that they have very little weight in the analysis (Figure 1b,c). The uncertainty of CryoSat-2 SIT within the range of $1.5-3$ m is at its lowest, increasing again for super-observations thicker than 3 m. On top of these SIT measurement uncertainties, we also add a representation uncertainty of $0.05$ m, as done by Fiedler et al. (2022).

It is worth noting that the observation error estimates do not explicitly take into account the high level of random uncertainty in the CryoSat-2 along-track measurements, caused by speckle noise, sea ice roughness, sea-surface height estimation errors and the variations in densities of snow and ice, which can easily be greater than 1 m (Ricker et al., 2014). These random uncertainties are mitigated by averaging (Ricker et al., 2017), and therefore the approach of creating CryoSat-2 super-observations aims to alleviate this issue to some extent. For example, Fiedler et al. (2022) verified that the RMSD between the analysis and CryoSat-2 observations decreased by almost half after super-obb-ing the observations prior to assimilation. However, as mentioned previously, the number of CryoSat-2 measurements available for creating a super-observation is much lower near the ice edge, since there are fewer
overlapping orbits at these latitudes when compared to higher latitudes (Figure 1).

Figure 1 shows notable SIT discrepancies between CryoSat-2 and SMOS in their overlapping regions, with CryoSat-2 SITs being generally larger than those from SMOS. This is particularly clear in the Barents and Kara Seas, where both satellites can have relatively low observation uncertainties, but CryoSat-2 SITs can be up to ∼1 m larger when compared to SMOS SITs. It should be emphasised that the parametrization applied by Fiedler et al. (2022) to derive CryoSat-2 uncertainties does not consider the location of the observations, only the magnitude of their SITs. Therefore, if CryoSat-2 observations are in areas of thin ice but their SITs lie within 1.5–3 m, their uncertainties will be quite low, and they will be given more weight in the analysis. The implications of this parametrization on data assimilation results, especially when only CryoSat-2 is assimilated, will be discussed in Section 3.

Figure 2 shows the monthly number of assimilated CryoSat-2 and SMOS observations, together with their monthly mean and variability for March 2017, binned onto a 1/4° grid. As described previously, it is worth clarifying that observations in Figure 2 have been quality controlled, and in the case of CryoSat-2, also super-obs. Far more observations are available for assimilation from SMOS (Figure 2b) than from CryoSat-2 (Figure 2a) in their overlapping regions. This is because SMOS-based retrievals provide a daily, complete coverage of the Arctic thin ice when compared to the CryoSat-2 daily tracks, which are sparser at lower latitudes (Figure 1). However, although they are fewer, only CryoSat-2 observations can cover major parts of the Arctic MYI, reinforcing the complementary aspect of SIT data coverage between both satellites. For example, CryoSat-2 observations can represent the regions of very thick ice (up to 5 m) north of Greenland (Figure 2c). Their monthly values in the Arctic marginal seas, however, are considerably larger when compared to SMOS, mostly ranging between 1 and 2 m, whereas SMOS monthly mean SITs are always smaller than 1 m (Figure 2d). Similarly, the monthly observed variability in CryoSat-2 (Figure 2e) is much larger than in SMOS (Figure 2f) over areas of thin ice. Obviously, there are far fewer CryoSat-2 than SMOS observations in those areas, and there could still be a high level of noise in CryoSat-2 super-observations due to fewer measurements near the ice edge. This might add some spurious variability to CryoSat-2 SITs, which also highlights the importance of
using SMOS as a complementary dataset for the assimilation of sea ice thickness in regions of thin ice.

2.3 SIT assimilation

To generate the assimilation increments to be applied to the model, NEMOVAR is provided with the following inputs. For the SIT assimilation, CryoSat-2 and SMOS observations from the previous 24 hr are provided with the model SITs aggregated over all thickness categories and interpolated to the observation locations, at the nearest model time step to the observation times. The model fields used for interpolation come from a 1-day model forecast prior to the assimilation, known as the model background. The uncertainties from the observations and the model background are also supplied to NEMOVAR in the form of observation and background error covariances, respectively. The observation errors are assumed to be uncorrelated, which is a simplification used for other assimilated variables in NEMOVAR (Waters et al., 2015). The background error covariances are represented by a set of spatially and seasonally varying estimates of the error variances, with the off-diagonal entries modelled by a Gaussian correlation function with specified length-scales. Based on 3 years of FOAM hindcast data, Fiedler et al. (2022) estimated the SIT background error covariances using the “Canadian Quick” covariance method (Polavarapu et al., 2005), where the differences between the daily model fields are used as proxy for the model forecast error. The SIT error correlation length-scale found using this method was 50 km and that is applied here. The only exception is the region northward of 87.5 °N, where the length-scale is increased to 100 km as in Fiedler et al. (2022), due to CryoSat-2 data gaps near the North Pole (Figure 1).

In this study, we have also tested smaller error correlation length-scales in the Arctic domain (e.g. 25 km), but improved SIT assimilation results were found using 50 km. Due to the sparse coverage of daily CryoSat-2 tracks in Arctic regions, the choice of a 50 km length-scale seems to be reasonable in order to spread the SIT increments (Figure 3a). It also allows the SIT increments to consistently propagate over thin ice regions when the assimilation of SMOS is considered (Figure 3b). It is worth emphasising that multiple error correlation length-scales can be employed in NEMOVAR (e.g. Mirouze et al., 2016), and the benefits of using this for SIT will be investigated in further evolutions of the SIT assimilation.

Unlike the ocean variables, where a multi-variate assimilation is employed in NEMOVAR, for now both the SIC and SIT assimilations are univariate, and the SIT increments are applied after any SIC assimilation changes at each time step. As in SIC, the SIT increments generated by an assimilation step (see Figure 3a,b for examples) are added incrementally to CICE over a period of 24 hr, through an incremental analysis update (Bloom et al., 1996). It is worth mentioning that CryoSat-2 and SMOS SIT increments are generated and applied together in Figure 3b. In order to maintain the initial volume distribution of ice between CICE categories, the SIT increments are applied proportionally to each of the five sub-grid categories based on their initial volume distribution, if the SIC within that category is above 1% (Blockley and Peterson, 2018; Fiedler et al., 2022). Additionally, they are only applied to grid cells where the model SIC, aggregated over all categories, is greater than 15%. This is the SIC threshold used here to define the ice edge. This also means that only SIC increments can add new ice to the system and the SIT increments are applied only in CICE categories where ice is already present. This approach will be revisited when a multi-variate sea-ice assimilation is implemented in future versions of FOAM.

In Figure 3, contrasting SIT increments are produced in the Arctic marginal seas between the assimilation experiments. When only CryoSat-2 is assimilated, the SIT increments are generally positive in areas of thinner ice, such as in the Baffin and Hudson Bays, Barents and Kara Seas, and near the Bering Strait. The SIT increments in those regions become negative when the SMOS data is also assimilated. This is clear for increments produced on 1 December 2016 (Figure 3a,b) and for the December mean (Figure 3c,d). Such contrasting increments support the very distinct nature of CryoSat-2 and SMOS observations near the ice edge, as shown by Figures 1 and 2. It is also worth reinforcing that the initial condition of A-CS2SMOS originates from A-CS2, so the SMOS assimilation effectively acts to reduce the thickness of the marginal ice already changed by the assimilation of CryoSat-2 observations. The assimilation impacts of SMOS and CryoSat-2 will be discussed in detail in Section 3.

2.4 Datasets used for experiment validation

The assimilation experiments are validated with independent datasets (Figure 4), including airborne observations from NASA Operation IceBridge (OIB: Kurtz et al., 2013). In the OIB campaigns, an aircraft equipped with scanning laser altimeters, a snow radar and high-resolution cameras was used to retrieve sea ice freeboard, thickness and snow depth measurements between March and April from 2009 to 2019. OIB SIT measurements obtained from the Quick-Look V1 product in March–April 2017 are used here, as the more reliable V2 product was only available up to 2014.
FIGURE 3  SIT increments (in m) originated from (a,c) A-CS2 and (b,d) A-CS2SMOS, for (a,b) 1 December 2016 and (c,d) December mean [Colour figure can be viewed at wileyonlinelibrary.com]

at the time of assessment. In the QuickLook V1 product, SIT point measurements spaced by approximately 25 m are averaged over clusters of 50 km, and are only used in the cluster if their uncertainties are less than 1 m for ice thinner than 1 m, up to a maximum uncertainty of 2 m for ice thicker than 4 m (Kurtz et al., 2019). Further processing is conducted here to remove cluster observations with standard deviations greater than 2 m. The SIT values of OIB cluster observations from the campaign of March–April 2017 are shown in Figure 4.

SIT measurements from bottom-anchored moorings, equipped with upward-looking sonars, are also used in the validation of the assimilation experiments, including those from the Beaufort Gyre Exploration Project (BGEP: Krishfield et al., 2014) and the Barents Sea Metocean and Ice Network (BASMIN) Joint Industry Project (Hume-Wright et al., 2020). Both the BGEP and BASMIN moorings can measure the sea ice draft with an estimated accuracy of 0.05–0.10 m, with 2 sec and 1 min intervals, respectively. These high-frequency measurements of sea ice draft are processed by the data providers into daily averages with their respective standard deviations. Further processing is undertaken here to convert the daily sea ice drafts into thickness, by dividing them by a factor of 0.89 (Rothrock et al., 2003). Following the same approach as with the OIB measurements, daily SIT observations with standard deviations greater than 2 m are removed from the BGEP and BASMIN datasets.
FIGURE 4 Independent SIT data used to validate the assimilation experiments. The coloured dots represent the SIT measurements (m) from OIB. The grey and brown stars correspond to the location of the BASMIN-1 and BASMIN-2 mooring clusters, respectively. The blue, green and cyan crosses correspond to BGEP-A, BGEP-B and BGEP-D mooring locations, respectively. Black polygons highlight the regions where BASMIN and BGEP moorings are located [Colour figure can be viewed at wileyonlinelibrary.com]

The BGEP dataset consists of continuous measurements throughout the year at three locations in the Beaufort Sea (Figure 4), namely: BGEP-A, BGEP-B and BGEP-D, which are assessed separately in the validation. There was a BGEP-C mooring, but it was decommissioned in 2008. For BASMIN, due to the proximity of the moorings, they are strategically divided into two clusters instead: BASMIN-1 with two moorings located south of Svalbard, and BASMIN-2 with three moorings located southeast of Svalbard (Figure 4). The averaged SIT of each BASMIN cluster is compared to the average of the model points interpolated to the same mooring locations within the cluster. The mooring measurements used in the validation are from 25 November 2016 to 15 April 2017 for BGEP and from 10 February to 15 April 2017 for BASMIN.

In addition to SIT observations, the assimilation experiments are also compared to the SIT objective analysis from Ricker et al. (2017). Ricker et al. (2017) employ an optimal interpolation scheme to merge CryoSat-2 and SMOS observations, therefore producing a gridded, weekly-averaged SIT product in the Arctic with a resolution of 25 km. Since CryoSat-2 and SMOS observations are used, this product cannot be considered as a fully independent dataset, although it is a relevant source of validation for the FOAM SITs, covering the entire Arctic. Such a comprehensive validation would have not been possible using only the sparse datasets in Figure 4.

Lastly, in order to evaluate the SIT assimilation impacts on improving the SIC and ice edge short-range forecasts, the OSI SAF SIC product (Lavergne et al., 2019) and the National Ice Center (NIC) ice edge data (Helfrich et al., 2007) are also used in the validation, with particular focus on the 5-day forecasts. For the ice edge validation, the daily NIC product is employed rather than OSI SAF since it is known that NIC passive microwave measurements underestimate the extent of ice-covered areas (Agnew and Howell, 2003; Comiso et al., 2003; Posey et al., 2015). The advantages of using the NIC sea ice edge product are that it is based on a multitude of satellite imagery, including visible/infrared, synthetic aperture radar, scatterometer, and passive microwave data; it also includes NIC ice charts, which incorporate in situ observations and ship reports (Helfrich et al., 2007). The final NIC ice edge product is also consistently checked by an ice analyst. As mentioned previously, the model ice edge definition of SIC at 15% is used to compare the model forecast of ice edge locations with the NIC ice edge product.

3 | RESULTS

3.1 Impacts of the SIT assimilation on the mean sea-ice state

In this section, the SIT assimilation impacts on the FOAM mean SITs from 1-day model forecasts are evaluated. Figure 5 shows the mean SITs of the FOAM experiments and their differences averaged over March 2017. The assimilation of CryoSat-2 SIT has a substantial effect in thickening the ice pack in the central Arctic and north of the Canadian Arctic Archipelago (Figure 5b) when compared to the CTL run, in which very thick ice (>3 m) is almost absent (Figure 5a). The SIT underestimation of the Arctic ice pack, particularly north of Greenland, is a common feature in many sea-ice models (Wang et al., 2016) and reanalyses (Uotila et al., 2019). Both Wang et al. (2016) and Uotila et al. (2019) identified that this SIT underestimation can easily reach more than 2 m in February–March, which is consistent with the differences seen between A-CS2 and CTL (Figure 5d). Nonetheless, A-CS2 also increases the ice thickness in several areas of thin ice, with their SIT differences being mostly positive relative to CTL. This SIT increase in A-CS2 is counteracted by a significant sea ice thinning over the marginal seas when SMOS is assimilated (Figure 5f). Such opposite patterns are consistent with the contrasting assimilation increments between A-CS2 and A-CS2SMOS over thin-ice regions, as shown by Figure 3. Therefore, A-CS2SMOS (Figure 5c) has a clear signature
of the assimilation impact coming from both satellites: a much thicker ice pack caused by CryoSat-2 assimilation, and a generally thinner sea ice over the marginal seas imposed by SMOS assimilation, when compared to the CTL run (Figure 5e).

In Figure 6, the FOAM experiments are compared to the Ricker et al. (2017) product in March 2017, all binned onto a 1/4° grid. Out of all the FOAM experiments, A-CS2SMOS gives the smallest mean difference and RMSD with respect to the Ricker et al. (2017) product. Both the mean difference and RMSD in A-CS2 and A-CS2SMOS are significantly reduced within the ice pack, where the CTL ice is too thin. However, A-CS2 shows much thicker ice than the Ricker et al. (2017) product in several areas of seasonal ice cover, including the Hudson and Baffin Bays, Bering Strait, and East Siberian Sea (Figure 6b). This SIT overestimation is also seen in the CTL for the same areas (Figure 6a). As a result, the RMSDs of CTL (Figure 6d) and A-CS2 (Figure 6e) are mostly above 0.8 m in those regions, decreasing to less than 0.4 m in A-CS2SMOS (Figure 6f). Therefore, the SMOS assimilation makes the representation of thin ice much more consistent with Ricker et al. (2017), although there are a few regions where A-CS2SMOS underestimates the SITs from the Ricker et al. (2017) product, such as in the Denmark Strait, Greenland and Barents Seas. In the latter region, the validation results with BASMIN moorings will be shown in Section 3.2.

Although the Ricker et al. (2017) product is not a fully independent dataset, Figure 6 indicates that the combined SIT assimilation of CryoSat-2 and SMOS seems to improve FOAM 1-day model forecasts in distinct Arctic regions. Moreover, it also shows limitations of the CryoSat-2 SIT assimilation in constraining areas of thin ice, which have also been reported by Fiedler et al. (2022). As seen in Figure 2 for March 2017, the assimilated CryoSat-2 super-observations have larger mean values, mostly ranging between 1 and 2 m, and greater variability than SMOS in areas of thin ice. The latter is consistent with the fact that there still might be some random noise in CryoSat-2 super-observations near the ice edge, as there is much less averaging at these latitudes due to sparse observations (Figure 1). In the parametrization from Fiedler et al. (2022), CryoSat-2 SIT uncertainties are at their lowest within the range of 1.5–3.0 m, regardless of the observation location. Therefore, based on the mean values in Figure 2c,
relatively large CryoSat-2 SITs can be assigned low uncertainties in areas of thin ice. Furthermore, since CryoSat-2 super-observations below 1 m are assigned much higher uncertainties compared to the ones within 1.5–3.0 m, the variability around the mean near the ice edge is skewed towards thicker ice in the A-CS2 analysis. This explains the A-CS2 SIT overestimation in the Arctic marginal seas relative to A-CS2SMOS and the Ricker et al. (2017) product, which is reinforced by the comparison of A-CS2 with independent SIT observations (see Section 3.2). This also illustrates the importance to data assimilation of data producers including observation uncertainties as part of the processing chain.

### 3.2 Validation with independent observations

In this section, 1-day SIT forecast outputs from the FOAM experiments are validated using independent daily mean measurements from airborne and moored buoys datasets, details of which are given in Section 2.4. In order to compare FOAM model fields with the independent SIT observations, the daily-mean model fields are interpolated to the observation locations for each date. It is worth mentioning that the Ricker et al. (2017) product is also included in the comparisons, but it corresponds to weekly mean SITs. Therefore, exceptions to employing daily means for the model and observations occur when the calculation of SIT validation statistics, such as the mean difference and RMSD, also include the Ricker et al. (2017) product (Figures 8 and 10). In these cases, weekly means of the FOAM experiments and the Ricker et al. (2017) product are compared to weekly means of SIT observations, yielding equivalent SIT validation statistics.

In Figure 7, the daily SIT time series of the FOAM experiments are compared to daily BGEP measurements at three mooring locations (Figure 4). The weekly-mean product from Ricker et al. (2017), as well as the assimilated SMOS observations, are also interpolated to BGEP locations and included in the comparison. During the early stages of the ice growing season between December and February, A-CS2 overestimates the SITs relative to BGEP observations at all locations. By March, when the...
ice reaches its yearly maximum thickness, there is a
type match between A-CS2 and BGEPSITs. These results
are consistent with Fiedler et al. (2022), who showed that
the SIT validation statistics for CryoSat-2 assimilation
are poorer for BGEP observations under 1 m. In fact,
the BGEP validation statistics in Figure 8, derived from
weekly means, highlight that the RMSD of A-CS2 is sub-
stantially larger than for the other FOAM experiments and
the Ricker et al. (2017) product, especially for BGEP-A
and BGEP-D, which are located in more marginal ice regions
(Figure 4).

SMOS observations are generally present at BGEP loca-
tions until early February, before the ice becomes too thick
(i.e. >1 m). This is clearly seen for BGEP-A (Figure 7a)
and BGEP-D (Figure 7c), where the SITs are thinner than for
BGEP-B. In these two locations (BGEP-A and BGEP-D),
SMOS SITs are consistent with the mooring measure-
ments. As a result, when the SMOS observations are avail-
able, the assimilation brings the model SIT into line with
the BGEP observations. For example, A-CS2SMOS shows
a quick SIT decrease at BGEP-A from the start of the
assimilation experiment (Figure 7a), correcting its initial
condition from A-CS2 where the SIT is overestimated.
After this large initial correction, A-CS2SMOS SITs remain
very close to BGEP-A measurements, whereas the CTL and
particularly A-CS2 overestimate the observed SITs at this
location. Consequently, the mean SIT difference between
A-CS2SMOS and BGEP-A over the whole run period in
Figure 8b is minimal (0.07 m), and the A-CS2SMOS RMSD
is the lowest (0.25 m) out of all the FOAM experiments
in Figure 8a. For BGEP-D (Figure 7c), the SMOS assimil-
ation impact is to some extent less prominent than in
BGEP-A, owing to the presence of slightly thicker ice at the
BGEP-D location and therefore fewer assimilated SMOS
observations. Thus, although BGEP-D validation statistics
are improved in A-CS2SMOS relative to A-CS2, the
former experiment has a very similar RMSD to the CTL
(Figure 8a). Due to gaps in SMOS observations caused by
the presence of thicker ice at the BGEP-D location, there
are instances in December–January when A-CS2SMOS
quickly returns to the state of A-CS2 SITs, before being cor-
rected again by SMOS (Figure 7c). This low–high–low SIT
pattern in A-CS2SMOS at BGEP-D reinforces the impor-
tance of obtaining accurate CryoSat-2 observation uncer-
tainties to mitigate the SIT overestimation in areas of
thinner ice when CryoSat-2 is assimilated.

Unlike BGEP-A and BGEP-D, the assimilated SMOS
observations are nearly absent at the BGEP-B location,
mostly due to the ice being thicker than 1 m. Conse-
sequently, A-CS2SMOS SITs are very similar to those from
A-CS2 (Figure 7b), with their RMSD being worse than
the CTL run at this specific location (Figure 8). It is
also worth emphasising that the CTL run already shows
good SIT validation statistics, except for BGEP-A. There-
fore, when considering the validation statistics of all three
BGEP moorings, the performance of A-CS2SMOS and
CTL are very similar, with A-CS2SMOS being slightly less
biased. Although Ricker et al. (2017) is a weekly-mean
product, purely derived from a statistical approach (i.e. without a dynamical sea-ice model involved), its RMSD and mean difference are also good, slightly outperforming A-CS2SMOS. This indicates that there is room for improving both the model background and observation errors in order to produce more consistent SIT analyses in the Beaufort Sea.

Similar to the BGEP measurements, the daily SIT time series of the BASMIN observations are also compared to the daily FOAM experiments, the weekly Ricker et al. (2017) product and the assimilated SMOS observations interpolated to the mooring locations (Figure 9a,b). The SIT validation statistics, relative to BASMIN observations, are also shown in Figure 10. Unlike at the BGEP locations, the assimilated SMOS observations are continuously present throughout the BASMIN measurement period, and therefore are also included in Figure 10. It is worth reinforcing that BASMIN-1 and BASMIN-2 are defined as two clusters of moorings (Figure 4). The results of the FOAM experiments differ depending on each cluster. For BASMIN-1, A-CS2 and CTL are the FOAM experiments closest to the observed SITs (Figure 9a), showing the best validation statistics (Figure 10), whereas both A-CS2SMOS and SMOS slightly underestimate the SITs. Conversely, A-CS2SMOS has the best performance out of all the FOAM experiments when compared to BASMIN-2 (Figures 9b and 10). It should be emphasised that, as for the BGEP validation, A-CS2 shows much larger SITs than BASMIN-2 measurements by early April, with an RMSD (0.37 m) almost three times larger than A-CS2SMOS. As shown by Hume-Wright et al. (2020), there is a significant overestimation of CryoSat-2 SIT observations relative to BASMIN-2, and therefore A-CS2 causes the growth of an extensive area of relatively thick ice (>1 m) near this mooring cluster. Interestingly, for both BASMIN cluster locations, the Ricker et al. (2017) product also strongly overestimates the SITs (Figures 9 and 10). The BASMIN moorings are in shallow regions close to the coast (Figure 4), with water depths between 50 and 200 m, which might point to issues in the Ricker et al. (2017) product in coastal areas.

Despite SMOS assimilation slightly improving the SITs compared to CTL at the BASMIN-2 cluster, the CTL run shows better SIT validation statistics than A-CS2SMOS at the BASMIN-1 cluster, and therefore is marginally better than A-CS2SMOS when both clusters are considered (Figure 10). The SMOS observations, and consequently A-CS2SMOS, slightly underestimate the measured SITs at both BASMIN clusters, even though the assimilation improves the validation statistics of A-CS2SMOS relative to the assimilated SMOS observations (Figure 10). As shown by Figure 9c, the model and OSI SAF SICs, averaged at all BASMIN locations, are always smaller than 90%.
FIGURE 9  One-day SIT forecasts (m) for the FOAM experiments at (a) BASMIN-1 and (b) BASMIN-2, from 10 February 2017 to 15 April 2017, followed by (c) OSI SAF and FOAM SIC (%) averaged at all BASMIN locations. For all panels, observations are shown in grey with shaded grey areas in (a,b) and (c) corresponding to BASMIN SIT and OSI SAF SIC standard deviation uncertainties, respectively. SMOS observations are included as green dots, whereas weekly SIT analyses from Ricker et al. (2017) are represented by black stars in (a,b) [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 10  (a) SIT RMSD and (b) mean difference (model minus observations) calculated from weekly means of both 1-day FOAM forecasts and BASMIN measurements for the period from 10 February 2017 to 15 April 2017. Corresponding statistics for the weekly averaged SMOS observations and the Ricker et al. (2017) product are also included. Units are in metres [Colour figure can be viewed at wileyonlinelibrary.com]
This clearly violates the SMOS retrieval assumption that all derived SITs are obtained at 100% SIC and might explain the SMOS SIT underestimation in this region (Tian-Kunze et al., 2014). Unlike at the BASMIN locations, the model and OSI SAF SICs are mostly larger than 90% in the Beaufort Sea over the run period (not shown), so this is a likely reason as to why SMOS observations are more consistent with BGEP measurements (Figure 7). It is also worth mentioning that the sea ice model has an approximate resolution of 10 km in the Arctic, and the ice thickness is computed as the model grid cell average. Therefore, there are limitations for the sea ice model to properly represent point measurements, such as BASMIN-1, where clearly all FOAM experiments have deficiencies in reproducing the observed SITs.

The difference between FOAM experiments and the airborne OIB measurements are shown by Figure 11. Consistent with Figures 5 and 6, the CTL run is unable to capture the thick ice pack north of Greenland and in the Canadian Arctic (Figure 11a). As a result, the RMSD of CTL is 0.95 m, with a mean difference (model minus observations) of −0.66 m relative to OIB. Due to CryoSat-2 assimilation, both A-CS2 (Figure 11b) and A-CS2SMOS (Figure 11c) significantly improve the SITs within the ice pack, decreasing their RMSDs to 0.53 and 0.61 m, and their mean differences to 0.07 and −0.11 m with respect to OIB, respectively. Although they have similar OIB validation statistics, it is worth noting that A-CS2SMOS performs slightly worse than A-CS2, since the SMOS assimilation underestimates the SITs in a few OIB trajectories over thin ice (<1 m), particularly the one in the Barents Sea (Figure 12).

Most of the OIB trajectory in Figure 12 is located along the interface between thick and thin ice regions, where a large SIT gradient is found. This is a complex region in which to represent the sea ice, and Figure 12 reinforces how differently the assimilated SMOS observations, FOAM experiments and Ricker et al. (2017) product represent the SIT gradients. It should be mentioned that both SMOS observations and FOAM experiments correspond to daily SITs, matching the date of this OIB trajectory on 20 March 2017, whereas the Ricker et al. (2017) product is a 7-day SIT average, centered on this date, and thus renders a smoother field. As expected, outside of the thick ice region, A-CS2SMOS SITs (Figure 12d) are very similar to those from SMOS (Figure 12a), especially along the OIB trajectory. However, A-CS2SMOS slightly misplaces the position of the SIT gradients relative to OIB, showing thinner ice towards the end of the OIB trajectory (Figure 12f). This is consistent with SMOS and A-CS2SMOS SIT underestimation when compared to BASMIN moorings (Figure 9), which are in the vicinity of these OIB measurements. Nonetheless, it is also important to draw attention to the fact that the OIB product used here is processed as cluster observations by the data providers, averaging all point measurements within 50 km (see Section 2.4). So, care should be taken when comparing the FOAM experiments to OIB trajectories located over fine-scale spatial structures, such as over the steep SIT gradients shown by Figure 12. If this specific OIB trajectory is removed from the validation statistics, very similar RMSDs between A-CS2 and A-CS2SMOS are obtained, with values of 0.50 and 0.51 m, respectively. Although the SIC is very similar along this OIB trajectory for all the model runs, it is also worth mentioning that A-CS2SMOS is in slightly better agreement with OSI SAF SIC observations relative to the other experiments in regions where SIC is lower than 40%, such as to the northeast of the OIB trajectory (not shown). The impact of the SMOS assimilation on the SIC near the ice edge is evaluated in Section 3.3.
Although in slightly different positions, both A-CS2 (Figure 12c) and A-CS2SMOS (Figure 12d) produce sharp SIT gradients in this region, which are not present in the CTL run (Figure 12b) or the weekly Ricker et al. (2017) product (Figure 12e). However, Figure 12f shows that, while A-CS2 overestimates and A-CS2SMOS underestimates the SITs towards the end of the OIB trajectory, the Ricker et al. (2017) product lies between both, in better agreement with the OIB measurements. Even if a weekly-mean SIT is used for the FOAM experiments, centred on 20 March 2017, the SIT underestimation (A-CS2SMOS) and overestimation (A-CS2) still occur towards the end of the OIB trajectory (not shown). This indicates that SIT observation errors for both SMOS and CryoSat-2 need to be further improved, so that the weights given to each type of observation are better accounted for in the assimilation, particularly in such complex transition regions between thick and thin ice.

### 3.3 Assessment of short-range sea ice forecasts

In this section, the impact of SIT assimilation on 5-day sea ice forecasts are investigated for March 2017. The forecast errors at all lead times are assessed for SIT, with respect to: CryoSat-2 and SMOS observations (Figure 13a), and the same independent SIT datasets used in Section 3.2.
(Figure 13b–d). Additionally, the impact of the SIT assimilation on improving the forecast skill of other sea ice variables, such as SIC (Figure 13e,f) and the sea ice edge (Figures 14 and 15), is evaluated.

As in Fritzner et al. (2019) and Fiedler et al. (2022), the error growth of SIT short-range forecasts is very small (Figure 13a–d), so the sea ice model is very effective in retaining the SIT assimilation information. Relative to CryoSat-2 and SMOS observations (Figure 13a), A-CS2SMOS produces the best short-range SIT forecasts, since the assimilation combines the benefits of using both satellites in constraining the ice pack and areas of seasonal ice cover. The RMSD for A-CS2SMOS is 0.42 m, representing a 55% reduction of the CTL RMSD, and its mean difference grows to a maximum of only a few centimetres. However, A-CS2SMOS SIT forecasts are slightly worse than the CTL when compared to BASMIN observations (Figure 13c), which is related to an underestimation of SMOS SITs in the region where these moorings are located (Figure 9). Although the CTL shows good forecast statistics with respect to mooring measurements (Figure 13b,c), its SIT forecast skill is very poor within the central Arctic (Figure 11a), resulting in significant SIT underestimations with respect to OIB (Figure 13d). Lastly, due to issues in the CryoSat-2 assimilation near the ice edge, A-CS2 forecasts overestimate the SITs compared to measurements in areas of thin ice (Figure 13b,c), which contrasts the positive forecast skill within the ice pack, as shown by the OIB comparison (Figures 11b and 13d).

Although the SIT assimilation impact on SIC forecasts is unclear over all ice concentrations (Figure 13e), there is an enhancement of the SIC predictive skill in A-CS2SMOS when the forecasts are compared only to OSI SAF observations below 40% (Figure 13f). This highlights that the SMOS assimilation plays a role in slowing the error growth of SIC forecasts near the ice edge, even though the OSI SAF SIC product is already assimilated by FOAM. For example, in the Labrador Sea (Figure 14a–c), and Greenland and Barents Seas (Figure 15a–c), the 5-day forecast SIC differences between the SIT assimilation experiments and the CTL run are indeed confined to regions near the ice edge, which represent a small proportion of the total sea-ice covered areas.

As previously discussed, A-CS2SMOS SITs in March 2017 are notably reduced over the Arctic marginal seas with respect to CTL (Figure 5e) and A-CS2 (Figure 5f). As one would expect, this SIT decrease is consistent with a 5-day forecast pattern of SIC decrease along the sea ice edge in A-CS2SMOS, resulting in a further retreat of its sea-ice covered areas relative to A-CS2 and CTL (Figures 14 and 15). This retreat of the ice edge in A-CS2SMOS 5-day forecast is very consistent in the Labrador and Greenland Seas, better matching the NIC ice edge product. Improvements of the ice edge forecasts in A-CS2SMOS can also be identified in the Pacific sector (not shown), but they are smaller when compared to the regions of Figures 14 and 15.

4 | FINAL DISCUSSION AND CONCLUSIONS

Sea ice thickness (SIT) data from both CryoSat-2 and SMOS have been successfully assimilated together into the Met Office’s Forecast Ocean Assimilation Model (FOAM). In order to demonstrate the impacts of the SIT assimilation from both satellites, three FOAM runs are evaluated: a control, with the current FOAM assimilation capabilities and no SIT assimilation; an intermediate experiment adding the assimilation of CryoSat-2 SIT derived from along-track freeboard measurements; and a further experiment, initialised from the intermediate one, which combines the assimilation of CryoSat-2 and SMOS SITs.

CryoSat-2 measures thick ice with relatively good accuracy, but it has limitations in representing thinner ice (Ricker et al., 2014). Therefore, consistent with Fiedler et al. (2022), the control’s poor performance in simulating the thick ice pack in the central Arctic is notably improved by CryoSat-2 assimilation relative to airborne measurements from NASA Operation IceBridge. However, when only CryoSat-2 is assimilated, the positive impacts in thick ice regions are counteracted by an SIT overestimation in the Arctic marginal seas (see also Hume-Wright et al., 2020). Adding the SMOS assimilation results in much thinner SITs in those regions, which have better (or at least similar) validation statistics to the control when compared to the Ricker et al. (2017) product and mooring measurements in the Beaufort and Barents Seas. This reinforces the complementarity between CryoSat-2 and SMOS datasets and demonstrates the clear benefits of assimilating SMOS to constrain the SITs in areas of thin ice.

Furthermore, the SMOS assimilation enhances the short-term predictive skill of the sea ice concentration (SIC) near the ice edge, even though SIC observations are already assimilated by FOAM. The positive impacts of SMOS assimilation on the marginal SIC have also been reported by Yang et al. (2014) and Xie et al. (2016). Here, the sea ice thinning, caused by SMOS assimilation, directly relates to a 5-day forecast SIC decrease along the ice edge in the Labrador and Greenland Seas, in better agreement with the NIC ice edge product than the control and the FOAM run only assimilating CryoSat-2.

Although FOAM clearly benefits from the complementarity of both CryoSat-2 and SMOS SIT assimilations, the findings of this study also highlight the need for further improvements in the assimilation
FIGURE 13  SIT RMSD (solid lines) and mean difference (dashed lines) of 1- to 5-day model forecasts with respect to SIT from: (a) CryoSat-2 and SMOS observations, (b) BGEP moorings, (c) BASMIN moorings, and (d) OIB airborne measurements. The SIC RMSD and mean difference (%) of the model forecasts relative to the assimilated OSI SAF observations are also shown for distinct SIC ranges: (e) all OSI SAF observations and (f) only OSI SAF observations less than 40% SIC. The statistics are calculated considering all 31 5-day forecasts initialised in March 2017 [Colour figure can be viewed at wileyonlinelibrary.com]
Figure 14: 5-day forecasts averaged over 25–31 March 2017 for the Labrador Sea, showing (a) CTL SIC (%) and SIC differences (%) for (b) A-CS2 – CTL and (c) A-CS2SMOS – CTL. Panels (d–f) show corresponding forecasts of ice edge defined using a 15% SIC threshold, with white (dark blue) indicating sea-ice (ocean) covered areas. The orange dots are the corresponding NIC ice edge observations [Colour figure can be viewed at wileyonlinelibrary.com]
configuration, particularly related to a better estimation of SIT observation errors. Unlike SMOS, a significant limitation of CPOM CryoSat-2 along-track freeboard retrievals is that their measurement uncertainties are not estimated by the data providers, so they must be somehow parametrized. A first parametrization scheme was developed by Fiedler et al. (2022), assuming the CryoSat-2 uncertainties quickly grow as their derived SITs become thinner, and that observations are unbiased. However, CryoSat-2 super-observations have a positive bias in regions of thin ice, meaning that relatively large CryoSat-2 SITs can be erroneously assigned low uncertainties there. Furthermore, some random noise might still be present in CryoSat-2 super-observations near the ice edge, as there is less averaging at these latitudes due to sparse observations. Since thinner CryoSat-2 SITs (<1 m) are given much less weight by the parametrization than thicker ones, the noise around the mean near the ice edge is skewed towards thicker ice, exacerbating the SIT overestimation when only CryoSat-2 is assimilated.

The SIT biases are likely related to CryoSat-2 freeboard measurements, which have deficiencies in representing thin ice regions, rather than the model snow depth used in the conversion to SIT. As mentioned before, the magnitude of CryoSat-2 SIT biases can easily reach 1 m in the Arctic marginal seas. This is significantly larger than the snow depth RMSD of 0.11 m in FOAM relative to OIB measurements in March–April 2017. Furthermore, FOAM slightly underestimates OIB snow depth observations, and therefore the model snow depth is very unlikely to cause a positive bias in CryoSat-2 SITs near the ice edge. Future work will be undertaken to improve the parametrization of CryoSat-2 observation errors, by inflating them depending on their location or ice age. Alternatively, these could also be inflated based on the number of observations used to create the super-observations, to account for the
likelihood of random noise in CryoSat-2 retrievals near the ice edge. In order to make the model-based approach for snow depth even more robust, future plans also include the assimilation of snow thickness observations from satellite retrievals. Despite its current challenges, it is worth emphasising that the SIT assimilation derived from CryoSat-2 along-track freeboard data is a promising avenue for polar forecasting systems, particularly when assimilated in conjunction with the SMOS SIT data, which alleviates CryoSat-2 SIT assimilation issues in thinner ice regions.

To a lesser extent than CryoSat-2, SMOS observation errors also require additional adjustments, even though their measurement uncertainties are provided as part of the observation processing chain. SMOS observations may underestimate SITs where the SMOS retrieval assumption of 100% SIC is strongly violated (Tian-Kunze et al., 2014). Consequently, this results in SIT underestimations in particular regions, such as the Barents Sea. In agreement with Ricker et al. (2017) and Mu et al. (2018a; 2018b), properly accounting for both CryoSat-2 and SMOS observation errors is key for achieving good SIT assimilation results in transition regions between thick and thin ice, where large SIT discrepancies can be found between the two satellites.

After the successful demonstration of the combined SIT assimilation from CryoSat-2 and SMOS in FOAM, its application can now be extended to the Met Office’s coupled NWP and seasonal forecasting systems. Blockley and Peterson (2018) showed positive impacts on seasonal forecasts by initialising the SIT field with CryoSat-2 observations, using a simple nudging scheme. Improved coupled studies can now be done at the Met Office with a much more robust SIT assimilation methodology, using both CryoSat-2 and SMOS SIT observations. More independent assessments of the SIT assimilation impacts on other sea-ice variables can also be made, for example looking at sea-ice drift.

From an operational perspective, CryoSat-2 along-track freeboard data should be provided with uncertainty estimates and made available closer to real-time. The product used here has a latency of 72 hr but the Met Office operational ocean and coupled assimilation systems need data to be available within 24 hr of their validity time. Moreover, candidate missions to observe the polar regions, such as the Copernicus Polar Ice and Snow Topography Altimeter (CRISTAL) and the Copernicus Imaging Microwave Radiometer (CIMR), are being planned to replace CryoSat-2 and SMOS in the future. This is aligned with Met Office efforts to continuously develop its coupled ocean–sea ice forecasting systems, and further steps are now ready to be taken towards operational SIT assimilation in the Arctic.

**ACKNOWLEDGEMENTS**

Part of this work was carried out under the SEDNA project, which received funding from the European Union’s Horizon 2020 Research and Innovation Programme, under grant agreement no. 723526. BASMIN Joint Industry Project is acknowledged for providing the mooring data used in the validation of the assimilation results. Andy Ridout and Andy Shepherd of CPOM are acknowledged for providing the CryoSat-2 sea ice freeboard daily observations used in the sea ice thickness assimilation experiments. EB further acknowledges funding from the European Union’s Horizon 2020 Research and Innovation Programme through grant agreement no. 727862 (APPLICATE).

**AUTHOR CONTRIBUTIONS**

Davi Mignac: Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft. Matthew Martin: Supervision; writing – review and editing. Emma Fiedler: Methodology; supervision; writing – review and editing. Ed Blockley: Supervision; writing – review and editing. Nicolas Fournier: Funding acquisition; project administration; writing – review and editing.

**CONFLICT OF INTEREST**

The authors declare no competing interests.

**DATA AVAILABILITY STATEMENT**

CryoSat-2 sea ice freeboard observations were provided by the Centre for Polar Observation and Modelling (CPOM) and are available on request for non-commercial research use. SMOS SIT observations were downloaded from https://icdc.cen.uni-hamburg.de (last access: 15 April 2020), now https://www.cen.uni-hamburg.de/icdc. FOAM analyses and forecasts from the SIT assimilation experiments are available on request for non-commercial research use. For the observations used in the validation: the mooring measurements from the Beaufort Gyre Exploration Project (BGEP) were downloaded from https://www2.whoi.edu/site/beaufortgyre/data/mooring-data (last access: 20 February 2021); the QuickLook V1 product from NASA Operation IceBridge was downloaded from http://psc.apl.uw.edu/sea_ice_cdr/data_tables.html (last access: 1 May 2020); the mooring data from the Barents Sea Metocean and Ice Network (BASMIN) Joint Industry Project are available on request for non-commercial research use; and the ice edge product from the National Ice Center was downloaded from https://www.natice.noaa.gov/products/daily_products.html (last access: 26 November 2020).
REFERENCES

Agnew, T. and Howell, S. (2003) The use of operational ice charts for evaluating passive microwave ice concentration data. *Atmosphere–Ocean*, 41, 317–331. https://doi.org/10.3137/ao.410405.

Barbosa Aguiar, A., Waters, J., Price, M., Inverarity, G., Pequignet, C., Maksymczuk, J., Smout-Day, K., Martin, M., Bell, M., King, R., While, J. and Siddorn, J. (2022) The new Met Office global ocean forecast system at 1/12th degree resolution.

Barton, N., Metzger, E.J., Reynolds, C.A., Ruston, B., Rowley, C., Smestad, O.M., Ridout, J.A., Wallcraft, A., Frolov, S., Hogan, P., Janiga, M.A., Shriver, J.F., McClay, J., Thoppill, P., Huang, A., Crawford, W., Whitcomb, T., Bishop, C.H., Zamudio, L. and Phelps, M. (2021) The Navy’s Earth System Prediction Capability: a new global coupled atmosphere–ocean–sea ice prediction system designed for daily to subseasonal forecasting. *Earth and Space Science*, 8(4), e2020EA001199. https://doi.org/10.1029/2020EA001199.

Bauer, P., Magnusson, L., Thépaut, J.-N. and Hamill, T.M. (2016) Recent development of the Met Office operational ocean prediction system for the Atlantic and Arctic oceans. *Journal of Operational Oceanography*, 1(2), 15–18. https://doi.org/10.1080/1755876X.2008.11020098.

Blockley, E.W. and Peterson, K.A. (2018) Improving Met Office seasonal predictions of Arctic sea ice using assimilation of CryoSat-2 thickness. *The Cryosphere*, 12, 3419–3438. https://doi.org/10.5194/tc-12-3419-2018.

Blockley, E.W., Martin, M.J., McLaren, A.J., Ryan, A.G., Waters, J., Lea, D.J., Mirouze, I., Peterson, K.A., Sellar, A. and Storkey, D. (2014) Recent development of the Met Office operational ocean forecasting system: an overview and assessment of the new global FOAM forecasts. *Geoscientific Model Development*, 7, 2613–2638. https://doi.org/10.5194/gmd-7-2613-2014.

Bloom, S.C., Takacs, L.L., da Silva, A.M. and Ledvina, D. (1996) Data assimilation using incremental analysis updates. *Monthly Weather Review*, 124, 1256–1271.

Chen, Z., Liu, J., Song, M., Yang, Q. and Xu, S. (2017) Impacts of assimilating satellite sea ice concentration and thickness on Arctic sea ice prediction in the NCEP climate forecast system. *Journal of Climate*, 30, 8429–8446.

Comiso, J., Cavalieri, D. and Markus, T. (2003) Sea ice concentration, ice temperature, and snow depth using AMSR-E data. *IEEE Transactions on Geoscience and Remote Sensing*, 41, 243–252. https://doi.org/10.1109/TGRS.2002.808317.

Eicken, H. (2013) Ocean science: Arctic sea ice needs better forecasts. *Nature*, 497, 431–433.

Fiedler, E.K., Martin, M., Blockley, E., Mignac, D., Fournier, N., Ridout, A., Shepherd, M. and Tilling, R. (2022) Assimilation of sea ice thickness derived from CryoSat-2 along-track freeboard measurements into the Met Office’s Forecast Ocean Assimilation Model (FOAM). *The Cryosphere*, 16, 61–85. https://doi.org/10.5194/tc-16-61-2022.

Fritzner, S., Graversen, R., Christensen, K.H., Rostosky, P. and Wang, K. (2019) Impact of assimilating sea ice concentration, sea ice thickness and snow depth in a coupled ocean–sea ice modelling system. *The Cryosphere*, 13, 491–509. https://doi.org/10.5194/tc-13-491-2019.

Guiavarc’h, C., Roberts-Jones, J., Harris, C., Lea, D.J., Ryan, A. and Ascione, I. (2019) Assessment of ocean analysis and forecast from an atmosphere–ocean coupled data assimilation operational system. *Ocean Science*, 15, 1307–1326. https://doi.org/10.5194/os-15-1307-2019.

Gulev, S.K., Thorne, P.W., Ahn, J., Dentener, F.J., Domingues, C.M., Gerland, S., Gong, D., Kaufman, D.F., Nnamchi, H.C., Quaas, J., Rivera, A., Sathyendranath, S., Smith, S.L., Trewin, B., von Shutmann, K. and Vose, R.S. (2021) Changing state of the climate system. In: Masson-Delmotte, V.P., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J.B.R., Maycock, T.K., Waterfield, T., Yeleckij, O., Yu, R. and Zhou, B. (Eds.) *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press.

Gupta, M., Caya, A. and Buehner, M. (2021) Assimilation of SMOS sea ice thickness in the regional ice prediction system. *International Journal of Remote Sensing*, 42, 4583–4606. https://doi.org/10.1080/01431161.2021.1897183.

Helfrich, S.R., McNamara, D., Ramsay, B.H., Baldwin, T. and Kashaeta, T. (2007) Enhancements to, and forthcoming developments in the interactive multisensor snow and ice mapping system (IMS). *Hydrological Processes*, 21, 1576–1586. https://doi.org/10.1002/hyp.6720.

Holland, M.M., Bailey, D.A. and Vavrus, S. (2011) Inherent sea ice predictability in the rapidly changing Arctic environment of the Community Climate System Model, version 3. *Climate Dynamics*, 36, 1239–1253. https://doi.org/10.1007/s00382-010-0792-4.

Hume-Wright, L., Fiedler, E., Fournier, N., Mendes, J., Blockley, E., Martin, M. and Eik, K. (2020) Sea ice thickness forecast performance in the Barents Sea. *Polar and Arctic Sciences and Technology, ASME 2020 39th International Conference on Ocean, Offshore and Arctic Engineering*, Virtual, 3–7 August, 1–8. https://doi.org/10.1115/OMAE2020-18039.

Hunke, E.C., Lipscomb, W.H., Turner, A.K., Jeffery, N. and Elliott, S. (2015) *CICE: the Los Alamos sea ice model documentation and software 605 user's manual version 5.1*. User Manual LA-CC-06-012, Los Alamos National Laboratory, NM.

Janjić, T., Bormann, N., Bocquet, M., Carton, J.A., Cohn, S.E., Dance, S.L., Losa, S.N., Nichols, N.K., Potthast, R., Waller, J.A. and Weston, P. (2017) On the representation error in data assimilation. *Quarterly Journal of the Royal Meteorological Society*, 144(713), 1257–1278. https://doi.org/10.1002/qj.3130.

Kaleschke, L., Tian-Kunze, X., Maaß, N., Beitsch, A., Wernerke, A., Mierneki, M., Müller, G., Fock, B.H., Gierisch, A.M., Schlünzen, K.H., Pohlmann, T., Dobrynin, M., Hendricks, S., Asseng, J., Gerdes, R., Jochemmann, P., Reimer, N., Hofert, J., Melsheimer, C., Heygster, G., Spreen, G., Gerland, S., King, J., Skou, N., Søbjerg, S.S., Haas, C., Richter, F. and Casal, T. (2016) SMOS sea ice product: operational application and validation in the Barents
marginal ice zone. Remote Sensing of Environment, 180, 264–273. https://doi.org/10.1016/j.rse.2016.03.009.

Kauker, F., Kaminski, T., Karcher, M., Giering, R., Gerdes, R. and Voßbeck, M. (2009) Adjoint optimization of the 2007 all time Arctic sea-ice minimum. Geophysical Research Letters, 36, L03707. https://doi.org/10.1029/2008GL036323.

Koenigk, T., Caian, M., Nikulin, G. and Schimanke, S. (2016) Regional Arctic sea ice variations as predictor for winter climate conditions. Climate Dynamics, 46, 317–337. https://doi.org/10.1007/s00382-015-2586-1.

Krishfield, R.A., Proshutinsky, A., Tateyama, K., Williams, W.J., Carmack, E.C., McLaughlin, F.A. and Timmermans, M.-L. (2014) Deterioration of perennial sea ice in the Beaufort gyre from 2003 and 2012 and its impact on the oceanic freshwater cycle. Journal of Geophysical Research: Oceans, 119, 1271–1305. https://doi.org/10.1002/2013JC009899.

Kurtz, N., Studinger, M., Harbeck, J., Onana, V.-D.-P. and Farrell, S. (2019) IceBridge sea ice freeboard, snow depth, and thickness, 2015–2017. Digital Media http://nsidc.org/data/idesi32.html.

Kurtz, N.T., Farrell, S.L., Studinger, M., Galin, N., Harbeck, J.P., Lindsey, R., Onana, V.D., Panzer, B. and Sonntag, J.G. (2013) Sea ice thickness, freeboard, and snow depth products from Operation IceBridge airborne data. The Cryosphere, 7, 1035–1056. https://doi.org/10.5194/tc-7-1035-2013.

Kwok, R. and Rothrock, D. (2009) Decline in Arctic sea ice thickness from submarine and ICESat records: 1958–2008. Geophysical Research Letters, 36, L15501. https://doi.org/10.1029/2009GL039035.

Lavergne, T., Sørensen, A.M., Kern, S., Tonboe, R., Notz, D., Aaboe, S., Bell, L., Dybkjær, G., Eastwood, S., Gabarro, C., Heygster, G., Killie, M.A., Brandt Kreiner, M., Lavelle, J., Saldo, R., Sandven, S. and Pedersen, L.T. (2019) Version 2 of the EUMETSAT OSI SAF and ESMC sea-ice concentration climate data records. The Cryosphere, 13, 49–78. https://doi.org/10.5194/tc-13-49-2019.

Laxon, S.W., Giles, K.A., Ridout, A.L., Wingham, D.J., Willatt, R., Cullen, R., Kwok, R., Schweiger, A., Zhang, J., Haas, C., Hendricks, S., Krishfield, R., Kurtz, N., Farrell, S. and Davidson, M. (2013) CryoSat-2 estimates of Arctic sea ice thickness and volume. Geophysical Research Letters, 40, 732–737. https://doi.org/10.1002/grl.50193.

Lea, D.J., Mirozue, I., Martin, M.J., King, R.R., Hines, A., Walters, D. and Thurlow, M. (2015) Assessing a new coupled data assimilation system based on the Met Office coupled atmosphere–land–ocean–sea ice model. Monthly Weather Review, 143, 4678–4694. https://doi.org/10.1175/MWR-D-15-0174.1.

Lemieux, J.-F., Beaudoin, C., Dupont, F., Roy, F., Smith, G.C., Shlyaeva, A., Buehner, M., Caya, A., Chen, J., Carrieres, T., Pogg, L., DeRepentigny, P., Plante, A., Pestieau, P., Pellerin, P., Ritchie, H., Garric, G. and Ferry, N. (2016) The Regional Ice Prediction System (RIPS): verification of forecast sea ice concentration. Quarterly Journal of the Royal Meteorological Society, 142(695), 632–643. https://doi.org/10.1002/qj.2526.

Liseter, K.A., Rosanova, J. and Evesen, G. (2003) Assimilation of ice concentration in a coupled ice–ocean model, using the ensemble Kalman filter. Ocean Dynamics, 53, 368–388. https://doi.org/10.1007/s10236-003-0049-4.

MacLachlan, C., Arribas, A., Peterson, K.A., Maidens, A., Fereday, D., Scathe, A.A., Gordon, M., Vellinga, M., Williams, A., Comer, R.E., Camp, J., Xavier, P. and Madec, G. (2015) Global Seasonal forecast system version 5 (GloSea5): a high-resolution seasonal forecast system. Quarterly Journal of the Royal Meteorological Society, 141(689), 1072–1084. https://doi.org/10.1002/qj.2396.

Madec, G. and Imbard, M. (1996) A global ocean mesh to overcome the North Pole singularity. Climate Dynamics, 12, 381–388.

Madec, G. (2017) NEMO Ocean Engine. Technical Report Number 27. Pole de modélisation de l’Institut Pierre-Simon Laplace Available at: http://hdl.handle.net/2122/13309.

Mallet, R.D.C., Stroeve, J.C., Tsamados, M., Landy, J.C., Willatt, R., Nandan, V. and Liston, G.E. (2021) Faster decline and higher variability in the sea ice thickness of the marginal Arctic seas when accounting for dynamic snow cover. The Cryosphere, 15, 2429–2450. https://doi.org/10.5194/tc-15-2429-2021.

Meier, W.N., Hovelsrud, G.K., van Oort, B.E.H., Key, J.R., Kovacs, K.M., Michel, C., Haas, C., Granskog, M.A., Gerland, S., Perovich, D.K., Makshas, A. and Reist, J.D. (2014) Arctic sea ice in transformation: a review of recent observed changes and impacts on biology and human activity. Reviews of Geophysics, 52, 185–217. https://doi.org/10.1002/2013RG000431.

Mirozue, I., Blockley, E.W., Lea, D.J., Martin, M.J. and Bell, M.J. (2016) A multiple length scale correlation operator for ocean data assimilation. Tellus A, 68(1), 29744. https://doi.org/10.3402/tellusa.v68.29744.

Mu, L.J., Losch, M., Yang, Q.H., Ricker, R., Loza, S.N. and Nerger, L. (2018a) Arctic-wide sea ice thickness estimates from combining satellite remote sensing data and a dynamic ice–ocean model with data assimilation during the CryoSat-2 period. Journal of Geophysical Research: Oceans, 123, 7763–7780. https://doi.org/10.1029/2018JC014316.

Mu, L.J., Yang, Q.H., Losch, M., Sosa, S.N., Ricker, R., Nerger, L. and Liang, X. (2018b) Improving sea ice thickness estimates by assimilating CryoSat-2 and SMOS sea ice thickness data simultaneously. Quarterly Journal of the Royal Meteorological Society, 144(711), 529–538. https://doi.org/10.1002/qj.3225.

Mu, L.J., Nerger, L., Tang, Q., Loza, S.N., Sidorenko, D., Wang, Q., Semmler, T., Zampieri, L., Losch, M. and Goessling, H.F. (2020) Toward a data assimilation system for seamless sea ice prediction based on the AWI climate model. Journal of Advances in Modeling Earth Systems, 12(4), e2019MS001937. https://doi.org/10.1029/2019MS001937.

Pedersen, R.A., Cvijanovic, I., Langen, P.L. and Vinther, B.M. (2016) The impact of regional Arctic sea ice loss on atmospheric circulation and the NAO. Journal of Climate, 29, 889–902. https://doi.org/10.1175/JCLI-D-15-0315.1.

Peterson, K.A., Arribas, A., Hewitt, H.T., Keen, A.B., Lea, D.J. and McLaren, A.J. (2015) Assessing the forecast skill of Arctic sea ice extent in the GloSea4 seasonal prediction system. Climate Dynamics, 44, 147–162. https://doi.org/10.1007/s00382-014-2190-9.

Polavarapu, S., Ren, S., Rochon, Y., Sankey, D., Ek, N., Koshyk, J. and Tarasick, D. (2005) Data assimilation with the Canadian middle atmosphere model. Atmosphere–Ocean, 43, 77–100. https://doi.org/10.3137/ao.430105.

Posey, P.G., Metzger, E.J., Wallcraft, A.J., Hebert, D.A., Allard, R.A., Smedstad, O.M., Philips, M.W., Fetterer, F., Stewart, J.S., Meier, W.N. and Helfrich, S.R. (2015) Improving Arctic sea ice edge forecasts by assimilating high horizontal resolution sea ice concentration data into the US Navy’s ice forecast systems. The Cryosphere, 9, 1735–1745. https://doi.org/10.5194/tc-9-1735-2015.

Ricker, R., Hendricks, S., Helm, V., Skourup, H. and Davidson, M. (2014) Sensitivity of CryoSat-2 Arctic sea-ice freeboard and
thickness on radar-waveform interpretation. *The Cryosphere*, 8, 1607–1622. https://doi.org/10.5194/tc-8-1607-2014.

Ricker, R., Hendriks, S., Kaleschke, L., Tian-Kunze, X., King, J. and Haas, C. (2017) A weekly Arctic sea-ice thickness data record from merged CryoSat-2 and SMOS satellite data. *The Cryosphere*, 11, 1607–1623. https://doi.org/10.5194/tc-11-1607-2017.

Ridley, J.K., Blockley, E.W., Keen, A.B., Rae, J.G.L., West, A.E. and Schroeder, D. (2018) The sea ice model component of HadGEM3-GC3.1. *Geoscientific Model Development*, 11, 713–723. https://doi.org/10.5194/gmd-11-713-2018.

Rothrock, D.A., Zhang, J. & Yu, Y. (2003) The Arctic ice thickness anomaly of the 1990s: A consistent view from observations and models. *Journal of Geophysical Research: Oceans*, 108, 3083. https://doi.org/10.1029/2001JC0001208.

Smith, L.C. and Stephenson, S.R. (2013) New trans-Arctic shipping routes navigable by mid-century. *Proceedings of the National Academy of Sciences of the USA*, 110, E1191–E1195. https://doi.org/10.1073/pnas.1214212110.

Storkey, D., Blaker, A.T., Mathiot, P., Megann, A., Aksenov, Y., Blockley, E.W., Calvert, D., Graham, T., Hewitt, H.T., Hyder, P., Kuhlbrodt, T., Rae, J.G.L. and Sinha, B. (2018) UK Global Ocean GO6 and GO7: a traceable hierarchy of model resolutions. *Geoscientific Model Development*, 11, 3187–3213. https://doi.org/10.5194/gmd-11-3187-2018.

Tilling, R.L., Ridout, A. and Shepherd, A. (2018) Estimating Arctic sea-ice conditions and shipping routes in the twenty-first century using CMIP6 forcing scenarios. *Environmental Research Letters*, 13(10), 103001. https://doi.org/10.1088/1748-9326/aaede5.

Tian-Kunze, X., Kaleschke, L., Maasß, N., Mäkynen, M., Serra, N., Drusch, M. and Krumpen, T. (2014) SMOS-derived thin sea ice thickness: algorithm baseline, product specifications and initial verification. *The Cryosphere*, 8, 997–1018. https://doi.org/10.5194/tc-8-997-2014.

Tilling, R.L., Ridout, A. and Shepherd, A. (2016) Near-real-time Arctic sea ice thickness and volume from CryoSat-2. *The Cryosphere*, 10, 2003–2012. https://doi.org/10.5194/tc-10-2003-2016.

Tilling, R.L., Ridout, A. and Shepherd, A. (2018) Estimating Arctic sea ice thickness and volume using CryoSat-2 radar altimeter data. *Advances in Space Research*, 62, 1203–1225. https://doi.org/10.1016/j.asr.2017.10.051.

Thomas, D.R., Martin, S., Rothrock, D. and Steele, M. (1996) Assimilating satellite concentration data into an Arctic sea ice mass balance model, 1979–1985. *Journal of Geophysical Research*, 101(C9), 20849–20868.

Uotila, P., Goosse, H., Haines, K., Chevallier, M., Barthélemy, A., Bricaud, C., Carton, J., Fučkar, N., Garric, G., Iovino, D., Kauker, F., Korhonen, M., Lien, V.S., Marnela, M., Massonnet, F., Mignac, D., Peterson, K.A., Sadikini, R., Shi, L., Tietsche, S., Toyoda, T., Xie, J. and Zhang, Z. (2019) An assessment of ten ocean reanalyses in the polar regions. *Climate Dynamics*, 52, 1613–1650.

Walters, D.N., Best, M.J., Bushell, A.C., Copley, D., Edwards, J.M., Falloon, P.D., Harris, C.M., Lock, A.P., Manners, J.C., Morcrette, C.J., Roberts, M.J., Stratton, R.A., Webster, S., Wilkinson, J.M., Willett, M.R., Boutle, I.A., Earnshaw, P.D., Hill, P.G., MacLachlan, C., Martin, G.M., Moufouma-Okaia, W., Palmer, M.D., Petch, J.C., Rooney, G.G., Scaife, A.A. and Williams, K.D. (2011) The Met Office unified model global atmosphere 3.0/3.1 and JULES global land 3.0/3.1 configurations. *Geoscientific Model Development*, 4, 919–941. https://doi.org/10.5194/gmd-4-919-2011.

Wang, Q., Ilicak, M., Gerdes, R., Drange, H., Aksenov, Y., Bailey, D.A., Bentsen, M., Biastoeh, A., Bozec, A., Bönning, C., Cassou, C., Chassignet, E., Coward, A.C., Curry, B., Danabasoglu, G., Danilov, S., Fernandez, E., Fogli, P.G., Fuji, Y., Griffies, S.M., Iovino, D., Jahn, A., Jung, T., Large, W.G., Lee, C., Lique, C., Lu, J., Masina, S., Naruse, A.J.G., Rabe, B., Roth, C., Salasy Mélia, D., Samuels, B.L., Spence, P., Tsujino, H., Valcke, S., Voldoire, A., Wang, X. and Yeager, S.G. (2016) An assessment of the Arctic Ocean in a suite of interannual CORE-II simulations. Part I: Sea ice and solid freshwater. *Ocean Modelling*, 99, 110–132. https://doi.org/10.1016/j.ocemod.2015.12.008.

Warren, S.G., Rigor, I.G., Untersteiner, N., Radionov, V.F., Bryagin, N.N., Aleksandrov, Y.I. and Colony, R. (1999) Snow depth on Arctic sea ice. *Journal of Climate*, 12, 1814–1829.

Waters, J., Lea, D.J., Martin, M.J., Mirouze, I., Weaver, A. and While, J. (2015) Implementing a variational data assimilation system in an operational 1/4 degree global ocean model. *Quarterly Journal of the Royal Meteorological Society*, 141(687), 333–349.

Wei, T., Yan, Q., Qi, W., Ding, M. and Wang, C. (2020) Projections of Arctic sea ice conditions and shipping routes in the twenty-first century using CMIP6 forcing scenarios. *Environmental Research Letters*, 15(10), 104079. https://doi.org/10.1088/1748-9326/abb2c8.

Xie, J., Counillon, F., Bertino, L., Tian-Kunze, X. and Kaleschke, L. (2016) Benefits of assimilating thin sea ice thickness from SMOS into the TOPAZ system. *The Cryosphere*, 10, 2745–2761. https://doi.org/10.5194/tc-10-2745-2016.

Yang, Q., Losa, S., Losch, M., Tian-Kunze, X., Nerger, L., Liu, J., Kaleschke, L. and Zhang, Z. (2014) Assimilating SMOS sea ice thickness into a coupled ice–ocean model using a local SEIK filter. *Journal of Geophysical Research: Oceans*, 119, 6680–6692. https://doi.org/10.1002/2014JC009963.

Yang, Q., Losa, S.N., Losch, M., Jung, T. and Nerger, L. (2015) The role of atmospheric uncertainty in Arctic summer sea ice data assimilation and prediction. *Quarterly Journal of the Royal Meteorological Society*, 141(691), 2314–2323. https://doi.org/10.1002/qj.2523.

Yang, Q., Losch, M., Losa, S.N., Jung, T. and Nerger, L. (2016) Taking into account atmospheric uncertainty improves sequential assimilation of SMOS sea ice thickness data in an ice–ocean model. *Journal of Atmospheric and Oceanic Technology*, 33, 397–407. https://doi.org/10.1175/JTECH-D-15-0176.1.

**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Mignac, D., Martin, M., Fiedler, E., Blockley, E. & Fournier, N. (2022) Improving the Met Office’s Forecast Ocean Assimilation Model (FOAM) with the assimilation of satellite-derived sea-ice thickness data from CryoSat-2 and SMOS in the Arctic. *Quarterly Journal of the Royal Meteorological Society*, 148(744), 1144–1167. Available from: https://doi.org/10.1002/qj.4252.