



Sea-ice concentration estimated from microwave radiances in a coupled ocean-atmosphere weather forecasting system

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Abstract. Weather forecasts are increasingly made by earth system models that couple the atmosphere, ocean, sea ice and land surface. These coupled forecasts are best initialised from a coupled data assimilation system, especially if this uses satellite radiances that are simultaneously sensitive to surface and atmosphere. This is more consistent and optimal than using separate geophysical retrievals. Working towards this, microwave imager radiances sensitive to the ocean, sea ice and atmosphere have previously been used in atmospheric data assimilation, with retrieval of sea ice concentration (SIC) at observation locations as a by-product. The current work further activates the assimilation of these SIC retrievals, derived from Advanced Microwave Scanning Radiometer 2 (AMSR2), into a coupled ocean and sea ice model, using an outer loop coupled data assimilation approach. Improvements in modelled SIC are demonstrated indirectly in the marginal ice zones (MIZ) by the 12 h forecast fits to scatterometer wind and radar wave height measurements, where errors are locally reduced by up to 10%. In the Antarctic summer, comparison is made to Ocean and Land Colour Instrument (OLCI) visible radiances and SIC estimates. These comparisons confirm the quality of the AMSR2 SIC retrievals but expose limitations in the modelled sea ice. The data assimilation also suffers spurious sea ice loss of up to 10% in some Arctic winter locations, though effects on the atmosphere are locally contained, and sea ice losses are rapidly corrected by the forecast model. More generally, the atmospheric forecasts are improved in polar regions in the early forecast range, particularly in the winter seasons, confirming overall benefit from coupled SIC assimilation, likely due to improvements in the MIZ. Atmospheric forecast improvements propagate to midlatitudes by day 4, where wind and temperature errors are locally reduced by up to 1%, indicating that sea ice assimilation can improve weather forecasts also outside polar regions.

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1 Introduction

Operational weather forecasting centres use physical models that represent atmosphere, ocean, cryosphere and land surfaces, in order to improve forecast quality and parameter coverage. These forecasts need to be initialised from an analysis that represents the best estimate of the current state of the earth system, which is obtained using data assimilation to combine previous forecasts with new observations. This means that data assimilation, previously done for each component in isolation,



needs to become increasingly coupled, in order to analyse an expanding range of earth system variables (de Rosnay et al., 2022). The current study describes how coupled sea ice assimilation has been included in the European Centre for Medium-range Weather Forecasts (ECMWF) coupled forecasting system.

Sea ice assimilation is achieved in a variety of ways across forecasting centres globally. In some cases, the sea ice analysis is generated by a self-contained data assimilation system and there is no sea ice model involved to propagate the sea ice state forward in time: instead the previous analysis is used as the starting point for the next analysis (e.g. Buehner et al., 2016; Good et al., 2020, the latter combines sea surface temperature and sea ice concentration). Other approaches include sea ice assimilation as part of a broader ocean data assimilation system, using a model that represents the ocean and sea ice state, but where the atmospheric forcings are provided by a separate model (e.g. Smith et al., 2016; Zuo et al., 2024, 2026; Barbosa Aguiar et al., 2024; Browne et al., 2026a). In turn, these components provide sea ice and ocean boundary conditions for the atmospheric model, but this only affects the subsequent cycle of data assimilation. This approach is referred to as weakly coupled data assimilation (e.g. Browne et al., 2019; Skachko et al., 2019; Barton et al., 2021). But for the first time in the operational forecasting system of the European Centre for Medium-Range Weather Forecasts (ECMWF), cycle 50r1 introduces a stronger coupling of ocean, sea ice and atmospheric data assimilation within the same assimilation window, based on an outer loop coupling approach (e.g. Laloyaux et al., 2016; de Rosnay et al., 2022; Browne et al., 2026b, this is further introduced in Sec. 2.1.3).

A big advantage of the outer loop coupling is the possibility to consistently assimilate observations that are sensitive to multiple earth system components, sometimes referred to as interface observations. For example, sea ice concentrations are typically retrieved from radiances measured by passive microwave sensors on satellites in low earth orbit (e.g. Comiso et al., 2003; Spreen et al., 2008; Laverne et al., 2019). Especially at the higher frequencies used by these retrievals (e.g. 37 GHz and 89 GHz), the radiances are also strongly sensitive to the atmosphere, particularly water vapour and water cloud. From the sea ice perspective, these sensitivities are a nuisance that needs to be dealt with, but from the atmospheric data assimilation perspective, this is important information that can help improve weather forecasts (Geer et al., 2017). Further, when generated from a coupled system, the sea ice estimate benefits from the most up-to-date description of the atmospheric state to help eliminate confounding atmospheric signals. Another advantage is the use of physical forward models, which do not just supersede the tie-point method used in most sea ice retrievals (e.g. Stentella et al., 2026). The aim is to develop these models further to extract additional sensitivities present in the radiances, such as bulk sea ice temperature or sea ice thickness (e.g. Tian-Kunze et al., 2014). The application to sea ice concentration is just a starting point.

From a more practical perspective, coupled radiance assimilation can also provide more timely information. In the previous ECMWF weak coupling framework, the sequential nature of the process meant that the sea ice concentration, when used as an atmospheric boundary condition, was already 48 h to 72 h behind real time (Geer, 2024b). In that processing chain, SIC was retrieved by one organisation, gridded by another, then assimilated in the ocean and sea ice data assimilation system, before finally being available as a boundary condition for subsequent atmospheric DA and forecasting activities. In addition to the delays, such a complex processing chain is vulnerable to technical problems across multiple agencies. With the advent of



strongly coupled data assimilation systems, we can aspire to simultaneously, and more optimally, retrieve information for all the earth system domains that are observed by the satellite radiances.

60 At ECMWF, along with the outer-loop coupled assimilation framework, we have introduced an approximate method for coupling the observation operator using extended control variables (Browne et al., 2026b). This allows the data assimilation components for each domain to remain separate, but with exchange of information between them. For example, the atmospheric data assimilation can add a control variable representing skin temperature or sea ice concentration, to be estimated from the observations within the atmospheric DA, even if this is not strictly part of the atmospheric domain. These retrieved surface
65 variables can then be used as if they were another type of conventional observation within the ocean, sea ice or land data assimilation systems.

The possibility of strong coupling is available at ECMWF because DA components are run multiple times within the outer loop of the incremental data assimilation framework. By iteratively exchanging the latest estimates of surface variables between the different DA components, this allows the model state to be simultaneously optimised across the different earth system
70 components to better fit the radiance observations. Cycle 50r1 of the ECMWF system was introduced operationally on 12th May 2026 and it uses this approach to assimilate ocean skin temperature and sea ice concentration into the ocean and sea ice data assimilation framework, described respectively by Scanlon et al. (2026b) and the current work.

Improved sea ice data assimilation, along with ocean-atmosphere coupling, should have major benefits for the atmospheric forecast, given the big differences in heat, moisture and momentum exchanges over water and ice surfaces. Pellerin et al. (2004)
75 showed in a local area model that correctly modelling the ice cover was important to subsequent forecasts locally. In general, improved modelling and assimilation in polar regions is expected to improve the global weather forecast (e.g. Lawrence et al., 2019). But it is hard to find evidence supporting the importance of sea ice to the global forecast. Recent studies on the effect of sea ice coupling in the ECMWF system have found benefits mostly limited to the atmospheric boundary layer and to the sea ice itself, and no clear benefits to medium-range atmospheric forecasts (Keeley and Mogensen, 2018; Day et al., 2022; Croad et al.,
80 2025). In the current work we have some of the first evidence that improving the sea ice representation, by assimilating sea ice concentration observations more optimally, does indeed improve the quality of weather forecasts outside the polar regions. This likely benefits from recent improvements in ocean and sea ice modelling (Keeley et al., 2024), improved data assimilation (Zuo et al., 2024, 2026; Browne et al., 2026a, b) and improved observational approaches for sea ice (Geer, 2024a, b).

This work outlines the new cycle 50r1 coupled data assimilation framework and how sea ice concentration can be assimilated
85 within it (Sec. 2.1) and it describes how the sea ice concentration is derived as part of the atmospheric data assimilation system (Sec. 2.2). The impact of sea ice observations within the coupled ocean and sea ice data assimilation is examined through case studies and through 6 months of experimental testing (Sec. 3). A summary of results, limitations and opportunities for further improvement is found in the conclusion (Sec. 4).



Table 1. Reanalysis and operational sea ice data assimilation streams at ECMWF: ORAS6 and cycle 50r1

Name	Timeliness	Domain	Window	Purpose
ORAS6	Behind real time	Ocean and sea ice	5 day	Reanalysis
OLDA	Near real-time	Ocean and sea ice	8 – 12 day	Reinitialisation of LWDA
LWDA	Near real-time	Full earth system	12 hours	Reinitialisation of ED
Early delivery (ED)	Near real-time	Full earth system	6 hours extending	Forecast initial conditions

2 Method

90 2.1 Coupled data assimilation and forecasting system

2.1.1 Overview of models

ECMWF now uses a single ocean model configuration across all ocean modelling activities. This configuration uses the NEMO v4 model (Madec et al., 2019) adapted to the ECMWF Integrated Forecasting System (IFS) by Keeley et al. (2024) and using a tripolar grid and bathymetry at a nominal horizontal resolution of around 25 km along with 75 vertical levels. The sea ice model
95 in NEMO v4 is SI³ (Sea Ice modelling Integrated Initiative, Sea ice working group, 2018). This is configured for the IFS with five sea ice categories, each having four vertical levels in the ice and one level representing snow (Keeley et al., 2024). Snow and sea ice have constant fixed densities, but ice rheology is governed by an elastic-viscous plastic formulation and prognostic variables represent the thermodynamic state of the ice. Broadly, the prognostic state includes the ice horizontal concentration, volume, enthalpy and salinity, plus snow volume and enthalpy. Melt ponds and melt pond lids are also represented.

100 The ocean and sea ice model can be used independently, if atmospheric forcings are supplied, but in general the IFS runs as a fully coupled ocean, sea ice, wave, land and atmosphere model. When in coupled mode, the atmosphere is provided with albedo and thicknesses of ice and snow that play an important role in determining the model skin temperature. For stability reasons these properties may be bounded when computing such diagnostic parameterisations. The atmospheric component of the IFS has 137 vertical levels and an 8-9 km horizontal resolution (known as TCo1279) in the operational version of the
105 system (ECMWF, 2026). The land surface and wave model components of the IFS are not further described here; instead see ECMWF (2026).

A variety of data assimilation systems at ECMWF use the NEMO v4 model (Table 1). The first to be deployed has been the ECMWF 6th generation ocean and sea ice reanalysis (ORAS6; Zuo et al., 2024, 2026). ORAS6 is not coupled, but rather takes forcings from atmospheric reanalysis with an hourly resolution (ERA5, Hersbach et al., 2020). ORAS6 is not used in this
110 work, but since most of the available documentation for the ocean and sea ice components is based on this, we must define our approach in relation to it.



Since May 12th 2026, the main ECMWF coupled operational data assimilation and forecasting system has included NEMO v4; this version of the IFS is known as cycle 50r1. Here, ocean and sea ice data assimilation is performed in multiple streams. First is a near-real time equivalent of ORAS6, known as the Ocean Long-Window Data Assimilation (OLDA). The main difference is that it is run daily using an extending window of 8 to 12 days, whereas ORAS6 is run behind real time once every 5 days. In either case, the motivation for these long windows is to utilise sparse, late-arriving ocean observations such as those from reprocessed altimetry and other externally processed data products.

The central component of cycle 50r1 is a 12 h cycling Long Window Data Assimilation (LWDA) coupled data assimilation system. This includes data assimilation components for atmosphere, ocean, land and waves. These are described in more detail in subsequent sections, with a focus on the sea ice data assimilation. The purpose of the OLDA is to provide ocean initial conditions (including sea ice) to the LWDA, once every 24h. Finally, there is an early delivery stream that provides initial conditions for operational forecasts (Lean et al., 2021), but which does not contribute to the cycling of the data assimilation and is superseded by the LWDA once that is available. In this study, the OLDA component is not varied, but rather we test the impact of adding sea ice assimilation into the LWDA. We ignore the early delivery stream, as is normal in test configurations, and initialise forecasts from LWDA instead.

2.1.2 Sea ice data assimilation

As with the ocean modelling, a broadly unified ocean data assimilation framework is used across ECMWF operational weather forecasting, starting from cycle 50r1, and in ORAS6. The sea ice data assimilation of ORAS6 is described by Browne et al. (2026a) and is part of the wider ocean data assimilation framework NEMOVAR (Mogensen et al., 2012). This uses incremental 3D-Var with FGAT (First Guess at Appropriate Time) applied to a 5-day window, with a diffusion-based formulation to provide horizontal background error correlations (e.g. Weaver et al., 2016). For ocean variables excluding sea ice, background error covariances are generated from an 11-member ensemble of data assimilations (Chrut et al., 2025). The OLDA standalone ocean data assimilation configuration is very similar to ORAS6, apart from the use of near-real time observations and an extending 8 to 12 day window. The LWDA coupled data assimilation system also uses NEMOVAR as its ocean component, but in a 12 h window outer-loop coupling framework that couples atmospheric and ocean data assimilation as further described in Sec. 2.1.3

For sea ice, horizontal background error correlations use a fixed length scale of approximately 200 km, and the error standard deviation is a constant 0.05. The NEMOVAR control vector (the set of active variables in the data assimilation) includes sea ice concentration, temperature, salinity, two orthogonal components of horizontal velocity and sea surface height. However, there are no background error correlations between sea ice concentration and the other ocean variables, so the sea ice analysis does not interact with the wider ocean analysis; in other words it is effectively univariate.

Sea ice concentration increments (the changes to the background determined by the NEMOVAR data assimilation) are applied to the SI³ model using an Incremental Analysis Update (IAU) procedure, which reduces model shock by applying the increments fractionally over a number of timesteps during the first hour of the forecast. It is necessary to allocate the increments, which apply to the grid box total sea ice concentration, across the five sea ice categories within SI³. The method

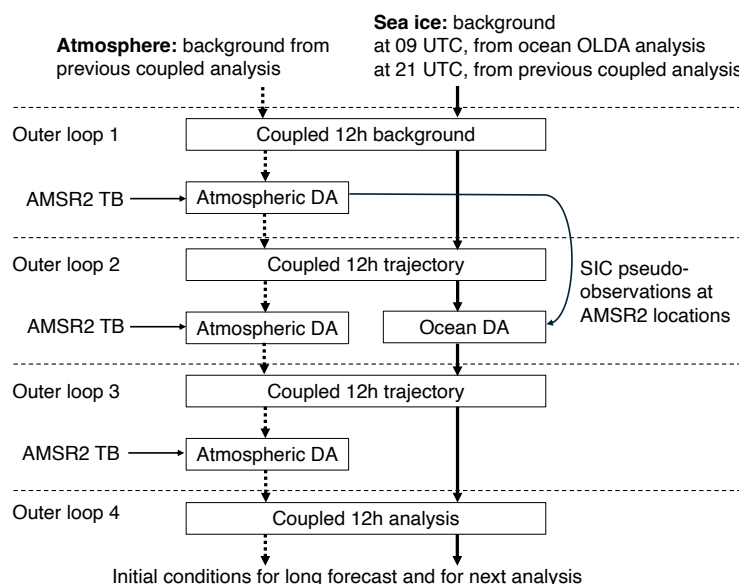


Figure 1. Data flow relating to sea ice within the outer loop coupled data assimilation framework: thick dashed lines indicate atmospheric data; solid thick lines indicate sea ice data; thin lines indicate observations. Illustrated for a 12-hour cycling long window (LWDA) configuration with three inner loops, and using AMSR2 observations as an example.

of Browne et al. (2026a) is to modify the area fraction occupied by each sea ice category in proportion to the thickness of the category, in such a way that the grid box average sea ice thickness remains unchanged. Moreover, variables such as ice volume, ice enthalpy, melt pond volume and salinity volume are conserved, which requires that the per-category, per-level quantities ice thickness, ice temperature, melt pond thickness and ice salinity need to be adjusted when the area fraction of each category changes (plus related snow quantity adjustments). Where sea ice does not already exist, it is added with a thickness of 0.45 m, which is the upper limit of the thinnest ice category in the model, and other properties appropriate to newly formed ice (also see Browne et al., 2026a). An adjustment is also made to the top 19.5 m of the ocean temperature profile to reflect the change in sea ice concentration, so that temperatures are reduced when ice concentration is increased, and increased when ice is removed.

ORAS6 and OLDA assimilate level 3 sea ice concentration observations from products derived from microwave sensors. Sea ice concentration comes from the OSI-SAF SSMIS level 3 product in recent years (OSI-430a) and then moving to the equivalent AMSR2 product since mid 2025 (Browne et al., 2026a). In contrast, in the LWDA operational coupled data assimilation, the sea ice concentration observations are generated directly from microwave radiances in the LWDA atmospheric data assimilation component, as described in this work, specifically Sec. 2.2. These are then assimilated in the sea ice data assimilation component of LWDA.



160 2.1.3 Outer-loop coupled data assimilation

In the cycle 50r1 configuration of the IFS LWDA 12 h cycling data assimilation system, ocean and sea ice are analysed simultaneously with the atmosphere using outer-loop coupling. For atmospheric data assimilation, ECMWF uses incremental four-dimensional data assimilation (4D-Var, e.g. Courtier et al., 1994; Rabier et al., 2000). In the incremental approach, the data assimilation cost function is minimised multiple times, with each minimisation being known as an inner loop. A new
165 12 h trajectory of the coupled model is then run, based on the updated initial conditions, to compute updated departures from observations, as well as to provide a new linearization point from which to compute updated gradient operators. The repetition of trajectories and minimisations forms the outer loop of the incremental framework. Compared to a single minimisation, the incremental approach helps generate an improved analysis and deals with nonlinear phenomena such as clouds and precipitation (e.g. Bonavita et al., 2018).

170 The incremental framework also provides a natural way to extend data assimilation beyond the atmospheric state. As shown in Figure 1, we can include separate components for ocean and atmospheric data assimilation at each inner loop, and then apply the full set of increments to the coupled forecast model at each trajectory. Hence this approach is known as outer loop coupling (Laloyaux et al., 2016; de Rosnay et al., 2022). Although not shown in the figure, the ocean DA also runs in the first inner loop to assimilate conventional ocean observations (but not sea ice) as described in Sec. 2.1.4. Ocean and sea ice data assimilation
175 is omitted from the 3rd and any subsequent inner loops for performance reasons, so that this is not in the critical path towards generating the atmospheric forecast. The configuration shown in Fig. 1 illustrates a 12 h window with three minimisations. This is simplified compared to the more complex early delivery system used in the operational weather forecasts, but it represents a standard test configuration that is also used in the current work.

In general, each data assimilation window generates a forecast that provides the background for the next 12 h data assimilation window in an ongoing cycle. However, when implementing the initial outer-loop coupled assimilation system for cycle
180 50r1, the 12 h assimilation window was not expected to be able to fully constrain the long timescales of the ocean. Hence, specifically for the ocean and sea ice, the background is replaced every 24 h from the longer-window ocean-only OLDA data assimilation framework. Hence, in the 12-hour outer-loop coupling framework, the ocean and sea ice information is only cycled for 24 hours (two assimilation windows) before being reset from the OLDA analyses. Reinitialisation of the ocean and sea ice
185 every 24 h may limit the possible impact of the new sea ice data assimilation, but benefits are still clear, as shown in this work.

2.1.4 Observational usage in coupled data assimilation

In the 12-hour outer loop coupling framework (Fig. 1) ocean observations include in-situ salinity and temperature profiles from ARGO, moorings, mammals and ocean gliders along with sea level anomaly (SLA) L3 products from a range of satellites. These are assimilated within NEMOVAR in the first inner loop as well as the second, though this is not shown in the figure,
190 which focuses on sea ice. In the second inner loop, it is possible to assimilate into the ocean retrievals that have been made as a by-product of the atmospheric data assimilation in the first inner loop. In the current work, we focus on the sea ice concentration retrievals generated from microwave radiances, but ocean skin temperature retrievals are also assimilated, in a similar way, and



are derived from infrared and microwave sensors in the first atmospheric inner loop (Browne et al., 2026b; Scanlon et al., 2026b).

195 AMSR2 sea ice concentration retrievals from the outer loop coupling framework are assimilated into NEMOVAR as effective sea ice concentration, ESIC, which is the SIC minus the open melt pond fraction. This recognises that microwave radiances cannot distinguish between open ocean and melt ponds. An observation error of 0.2 is used (compared to the background error of 0.05 in SIC). To exclude spurious observational sea ice cover caused by aliasing of supercooled liquid water clouds into sea ice (Geer, 2024a, see also Sec. 2.3) ESIC values between 0.05 and 0.25 are ignored. Any values less than 0.05 are reset to zero
200 as well, assuming this is trace cloud rather than trace sea ice concentration. Finally, areas of multi-year ice are excluded since there is a known bias in the sea ice concentration derived from AMSR2 in the atmospheric data assimilation (Geer, 2024a, further details in Sec. 2.3). It is also necessary to exclude areas in the first 15 minutes of the assimilation window, for technical reasons, due to a lack of ESIC transfer from the ocean to atmospheric window in the first timestep of the model (illustrated in Sec. 3.2). Note that no other sea ice data is assimilated in the 12-hour window outer loop coupling framework.

205 The atmospheric part of the data assimilation system also assimilates a full set of atmosphere-related observations from numerous satellites and ground-based observing systems (e.g. ECMWF, 2026; Geer et al., 2017). We describe the atmospheric data assimilation in more detail in the following section.

2.2 Sea ice from the atmospheric DA system

2.2.1 Observations

210 Within the atmospheric data assimilation system, microwave radiances from AMSR2 are some of the few surface-sensitive observations to be assimilated over sea ice. Because ocean and sea-ice surfaces have such distinct radiative signatures, it is necessary to infer the sea-ice concentration at observation locations as part of the assimilation process. This provides the SIC retrievals for assimilation in the ocean component in the current work. Here we summarise the process and describe a number of upgrades in cycle 50r1 compared to the original implementation (Geer, 2024a).

215 AMSR2 (Okuyama and Imaoka, 2015) is a passive conically scanning microwave radiometer (or imager) with a nearly fixed zenith (earth incidence) angle around 53°. It measures both vertical (v) and horizontal (h) earth-relative polarisations, and the channels cover mainly window regions from 6.9 GHz to 89 GHz. In the IFS, AMSR2 channels from 10.65 GHz up to 89 GHz are assimilated over sea ice areas, and in both v and h polarisations, except for the h-polarised 36.5 and 89 GHz channels that are excluded due to long-standing model biases over open ocean. GMI is also assimilated over sea ice as described by Geer
220 (2024a), but due to its more limited polar coverage, its assimilation in the coupled sea ice framework was left for future work, and it is not further discussed here.

From the atmospheric perspective, AMSR2 and other microwave imager observations are assimilated following an ‘all-sky’ approach in order to use their information on water vapour, cloud, precipitation and surface winds (Geer et al., 2017). Utilisation of all-sky microwave imagers at cycle 48r1 is described by Geer et al. (2022) and there have been two main additions to reach
225 the cycle 50r1 configuration used here. These are the aforementioned addition of sea ice scenes Geer (2024a, from cycle 49r1)



Table 2. Characteristics of v1 and v2 sea-ice surface emissivity models

Characteristic	v1	v2
Implementation cycle	49r1	50r1
Trained on	AMSR2	AMSR2, GMI, SSMIS
Training hardware	CPU	GPU
Neural network	Dense linear, 1 layer	Dense non-linear, 2 layer
Trainable parameters	50	58
Frequency range	10 – 89 GHz	10 – 190 GHz

plus the addition of 6.9 and 10.65 GHz channels over open ocean (alongside existing channel usage from 19 GHz upwards) targeting coupled SST assimilation in a similar way to the sea ice (Scanlon et al., 2025, 2026a, b, from cycle 50r1).

The raw AMSR2 observations have a channel-dependent field-of-view size and location, so to bring them onto a unified basis they are superobbed onto a 40 km reduced Gaussian grid before assimilation (see Duncan et al., 2024, for further justification).

230 Only 1 in 8 of these super-observations is allowed to affect the atmospheric state, respecting typical observation thinning distances of 100 km in atmospheric data assimilation, which aim to mitigate against neglected observation error correlations (Bormann et al., 2011). However, all AMSR2 observations are allowed to update the extended control vector that is used to estimate SIC. In this way, the full 40 km density of observations can be used in the coupled assimilation of SIC, giving the possibility of a sharper analysis of the sea ice.

235 2.2.2 Radiance observation operator

The observation operator over sea ice relies on a combination of the RTTOV atmospheric radiative transfer model (Saunders et al., 2018) and an empirical model for the effective sea ice surface emissivity (Geer, 2024b). Skin temperature is provided by the atmospheric model and is not updated directly from the observations. In this simplified description of microwave radiative transfer within the sea ice and snow, the sea ice surface emission is the product of the effective emissivity and skin temperature, and the reflection term is 1 minus the emissivity. Sea-ice surface emission and reflection is strongly variable and depends in a poorly-known way on the macrophysical and micro-structural properties of the sea ice and snow overlying it. These properties are not fully described by any current sea ice physical model. To solve this problem, the empirical sea-ice emissivity model was created inside a combined data assimilation and machine learning framework (Geer, 2024b). This was trained externally to the IFS using a year-long dataset of colocated ECMWF atmospheric data and microwave imager observations, then used as an observation operator inside the ECMWF system.



The inputs for the empirical sea ice emissivity model are three completely empirical variables representing the sea ice and snow physical properties, one physical variable representing the skin temperature, and the channel frequency. Since the three empirical variables are unknown before the data assimilation process, they have to be estimated as part of the data assimilation using an extended control vector at observation locations, alongside the estimation of SIC. An example of an empirical variable is given in Sec. 2.3

Compared to the cycle 49r1 sea ice approach described by Geer (2024a), the current work uses an updated version 2 sea-ice emissivity model (v2, Geer, 2026). Table 2 summarises the main differences, which include use of a nonlinear neural network that helps significantly improve the background fit to observations, compared to the v1 model which used a single dense linear layer (background departure standard deviations are up to around 40% smaller in the 10.65 GHz v-polarised channel, not shown). Since the three empirical input variables are statistical, and their meaning is defined during model training, these meanings have naturally changed in the v2 model compared to v1. In v2 it is the 2nd and 3rd empirical parameters (and not the first) that appear to represent variations between first and multi-year ice.

By contrast to the sea ice emissivity, ocean surface emissivity is reasonably well modelled (as a function of the surface temperature, wind speed and direction from the forecast model) using a fast model trained on a physical reference (SURFEM, Kilic et al., 2023). It is also important to have a good open ocean surface emissivity estimate, in order to correctly describe the contrast between ocean and sea ice surface emissivities which allows the SIC to be estimated.

2.2.3 Assimilation aspects

As mentioned, the three empirical variables and the effective sea ice concentration need to be estimated at observation locations as part of the 4D-Var atmospheric data assimilation. This is done by adding control variables at observation locations of AMSR2 in any location where sea ice might be expected. These ‘sea-ice areas’ are identified as pure ocean (land fraction less than 0.01) and with ocean skin temperatures less than 277 K.

For warmer skin temperatures over ocean, a single control variable at observation locations is used to estimate the skin temperature (Scanlon et al., 2026a). No attempt is made to estimate the skin temperature at sea ice locations but rather the model’s estimated skin temperature is used as if it were the true value. Since cycle 49r2, the IFS model has represented snow on sea ice, which reduces skin temperatures over sea ice to address issues raised by Arduini et al. (2022). Hence, in contrast to the earlier configuration of Geer (2024a), the bulk snow temperature is used as the effective skin temperature when the model has significant snow cover over sea ice (model skin temperature remains used as the effective skin temperature otherwise). The aim of this change was to keep effective temperatures closer to the skin temperature climatology on which the sea ice emissivity model was trained, based on a snow-free sea ice (Geer, 2024b) as well as to minimise disruption to the framework used for microwave imagers over sea ice. If there are errors in these effective skin temperatures, these are expected to be absorbed into the sea ice emissivity retrieval.

As with any control variable in data assimilation, the observation space variables require a background value and a background error. For the sea ice concentration, the background SIC cannot be taken from the forecast model, where the sea ice fields are reset to the potentially out-of-date values from OLDA every 24 hours. Instead, the SIC at AMSR2 locations is es-



280 timated initially from the 10.65 GHz v-polarised observations, using the background atmospheric profile and the background estimate of the sea-ice emissivity in this channel (Geer, 2024a). This reduces the amount of work the 4D-Var assimilation needs to do, and it much reduces the chance that observations are rejected due to a mismatch between the true and modelled sea ice. Background values of the three empirical variables are set to zero. Background errors are 0.25 for the SIC and 0.84, 1.0 and 0.26 for the empirical variables.

285 As shown by Geer (2024a) the SIC retrievals, which are a by-product of the atmospheric data assimilation, appear to be of high quality. However, there is one known problem, that SIC is underestimated in multi-year ice. The v2 model has reduced the problem compared to v1, but in multi year ice areas where SIC is expected to be close to 1.0, retrievals can still be as low as 0.8. When assimilated as pseudo-observations in NEMOVAR, these areas are screened out to avoid biasing the analysis, as illustrated in the next section.

290 A variational bias correction scheme (VarBC Dee, 2004) is also applied to AMSR2 observations, as is done for all other radiances assimilated in the IFS. This can be viewed as an empirical addition to the observation operator, which corrects systematic differences between the observations and the simulations. As further described by Geer (2024a), the VarBC bias correction in sea ice areas is modelled by a constant offset and linear functions of total column water vapour, skin temperature, wind speed over open ocean, sea ice concentration, and a fourth-order polynomial of the instrument scan position. This bias
295 correction aims to reduce systematic errors especially from the ocean surface emissivity modelling (hence the wind speed and skin temperature predictors) and, in the case of AMSR2, to remove known scene-temperature dependent calibration errors. The sea ice concentration predictor was intended to address the scene-temperature calibration issues, and was effective in the current work tested over short periods, but it proved unstable over longer periods and has been removed in the final version of the system that was implemented in cycle 50r1.

300 2.3 Example of outer loop coupled data assimilation

To further introduce the sea ice assimilation, Figure 2 illustrates how the AMSR2 retrievals are assimilated into the NEMOVAR sea ice analysis for the 12 UTC analysis on 21st December 2022. This example is based on the testing configuration which is fully introduced in the next section (Sec. 3). Figure 2a shows the second of the three empirical variables inferred from the AMSR2 radiance observations alongside the ESIC. This typically gives positive values in areas of multi-year ice and negative
305 values in areas of new ice. Colours are only shown where the ESIC is greater than 0.1, so the coloured areas of the figure also help illustrate the sea ice extent analysed at AMSR2 locations. As would be expected in December, the empirical variable shows that new ice has formed in Hudson Bay, Baffin Bay, and Davis Strait, and around the Alaskan and Siberian sides of the Arctic Ocean. Multi-year ice has persisted closer the Canadian Archipelago and Greenland, and a hook shape of this older ice is being advected around the Beaufort Gyre. A wedge of AMSR2 data is missing between Svalbard and the Siberian coast
310 (between 45 and 90 East) due to lack of observational coverage within the 12 h assimilation window.

The difference (departure) between the AMSR2 and modelled ESIC is shown in Fig. 2b. Red patches on the coast of Greenland and in Hudson Bay indicate locations where sea ice needs to be added to the model. Blue areas over much of the rest of the Arctic sea ice indicate that AMSR2 generally shows lower ESIC than the model. However, part of this comes

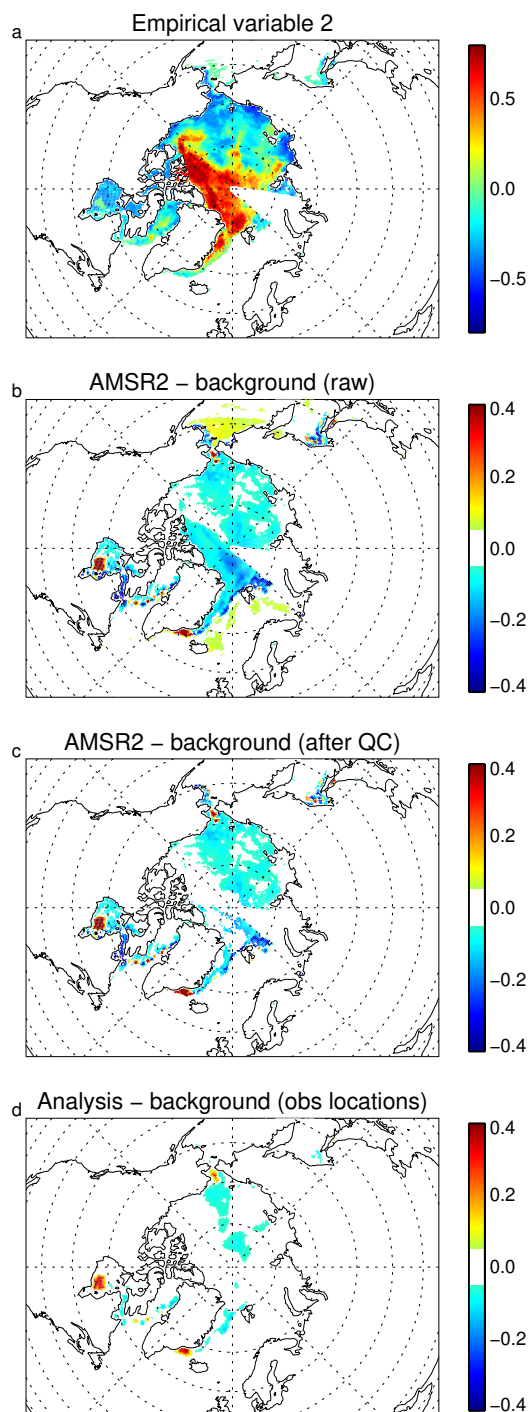


Figure 2. Sea ice fields at observation locations for the 12 UTC analysis on 21st December 2022: a) Empirical variable 2 (distinguishing first and multi-year ice) at locations with AMSR2 ESIC greater than 0.1; b) Departures between AMSR2 ESIC and background ESIC at all available locations; (c) As b, but after quality control; (d) analysis increments at observation locations. Orthographic projection, with longitude lines every 45° and latitude lines every 10°.

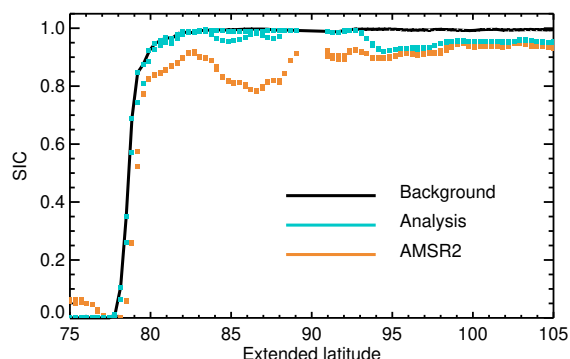


Figure 3. A transect of ESIC at AMSR2 locations close to the Greenwich Meridian and dateline across the N pole, with latitudes used as an extending quantity beyond 90°N. This includes all observations in the analysis window between 0900 UTC and 2100 UTC, so each latitude can have a number of overpasses from AMSR2.

from the known bias in the AMSR2 in multi-year ice. There are also yellow patches outside the sea ice area where AMSR2
 315 retrievals generate spurious low sea ice concentrations due to the presence of supercooled liquid water (SLW) cloud that cannot
 be represented by the forecast model (e.g. Forbes et al., 2016). This illustrates that a significant amount of quality control is
 required to successfully use the observations.

Figure 2c illustrates the sample of observations actually used by the NEMOVAR assimilation, after the quality control
 described in Sec. 2.1.4, which excludes most of the spurious sea ice coverage caused by SLW clouds, due to the removal of
 320 AMSR2 retrievals with values between 0.05 and 0.25. Also, areas of multi-year ice identified by values of empirical variable
 2 larger than or equal to 0.4 (Fig. 2a) have been excluded. The remaining departures preserve positive and negative features
 primarily in the marginal ice zones, suggesting genuine movements and growth of the sea ice observed by AMSR2. There is
 also a slight negative departure in the newer ice on the Alaskan/Siberian side of the Arctic Ocean, which is discussed below.
 The AMSR2-derived ESIC observations after this quality control are then assimilated into NEMOVAR.

325 Figure 2d illustrates the increments in NEMOVAR, in other words the change in ESIC resulting from data assimilation
 (changes in SIC are equivalent). Since an analysis represents a weighting between background and observations, these incre-
 ments are smaller than the departures from which they were generated, but generally the patterns of increased and decreased
 SIC are taken up by the data assimilation. It is also possible to see a slight smoothing and spreading of the observational
 information, which is caused by the background error correlation modelling in NEMOVAR. This smoothing is clearer to see
 330 in later figures.

Although most aspects of this data assimilation process are beneficial, as will be shown later, this example also exposes
 some limitations which will need to be corrected in future upgrades. Figure 3 shows the absolute values of ESIC in a transect
 across the Arctic, up the Greenwich meridian and down the dateline, for the same example as Fig. 2. Background values of
 ESIC are very close to 1.0 in the interior ice, but AMSR2 shows significantly lower values, especially on the left side of



335 the transect, where multi-year ice is present as shown in Fig. 2a. AMSR2 also shows spurious ESIC of around 0.05 due to cloud contamination left of the sea ice edge. However, both of these issues are identified by the quality control procedures as intended, and the analysed ESIC is mostly unaffected. But to the right of the plot, even in the new ice, AMSR2 gives an unrealistically low concentration between 0.9 and 0.95, and this is used in the data assimilation and pulls the analysis down as a result. Further, the observations show the sea ice edge (around 79°N) should be about 1/3 degree (around 40 km) further N
340 than in the background, but this is also not taken up by the analysis. This can be seen in Fig. 2 more generally W of Svalbard, for example in the line of large negative O-B (panel c). This is not taken up in the analysis increments (panel d), but in other areas (such as Hudson bay, Davis Strait and the E coast of Greenland) the sea ice edge is being adjusted to fit the observations as intended. The failure to move the sea ice edge in this case is likely in part due to the narrowness of the feature compared to the background error correlations of 200 km.

345 3 Results

3.1 Experiments

An experiment and a control are used to test the impact of activating the assimilation of AMSR2 ESIC pseudo-observations in the ocean and sea ice analysis in the 12 hour outer-loop coupling framework summarised in Figure 1. External components such as the longer-window OLDA ocean data assimilation system and the ensembles of data assimilation that determine the
350 atmospheric and (non-sea ice) ocean background errors, are not modified and remain the same in both control and experiment. The atmospheric data assimilation configuration within the 12-hour outer loop system is not modified either, but it should benefit from the improved sea ice analysis, and the subsequent atmospheric forecasts should also be improved.

Both experiment and control are built on a development version of the IFS that includes most of the relevant updates included in the final cycle 50r1. The basis of this is a nearly-final version of cycle 49r2, which was created for production of the future
355 ERA6 reanalysis. On top of this, the outer-loop coupling with the atmosphere has been activated for conventional in-situ ocean data and skin temperature pseudo-observations from AMSR2 and GMI (Browne et al., 2026b; Scanlon et al., 2026b, and as described in Sec. 2.1.4). Note that infrared-based skin temperature observations were also activated in outer loop coupling for 50r1, but are not included in either control or experiment here. This is unlikely to affect the overall results. On top of this configuration, which forms the Control, the Experiment activates the assimilation of AMSR2 ESIC pseudo-observations into
360 NEMOVAR.

Control and experiment have been run for a summer and winter period giving a total of six months testing, respectively from 00 UTC 1st June 2022 to 12 UTC 31st August 2022 and from 00 UTC 1st December 2022 to 12 UTC 28th February 2023. In both control and experiment, the initial conditions for the atmosphere come from the current ECMWF operational analyses, whereas the initial ocean state, and the reinitialisation every 24 h, comes from an OLDA ocean data assimilation
365 experiment equivalent to the OLDA used operationally at cycle 50r1 (see Sec. 2.1). In our experiments we use a reduced atmospheric horizontal resolution of around 25 km (known as TCo399) in order to perform the testing more efficiently, but the ocean resolution remains the standard IFS setting, which is 25 km.

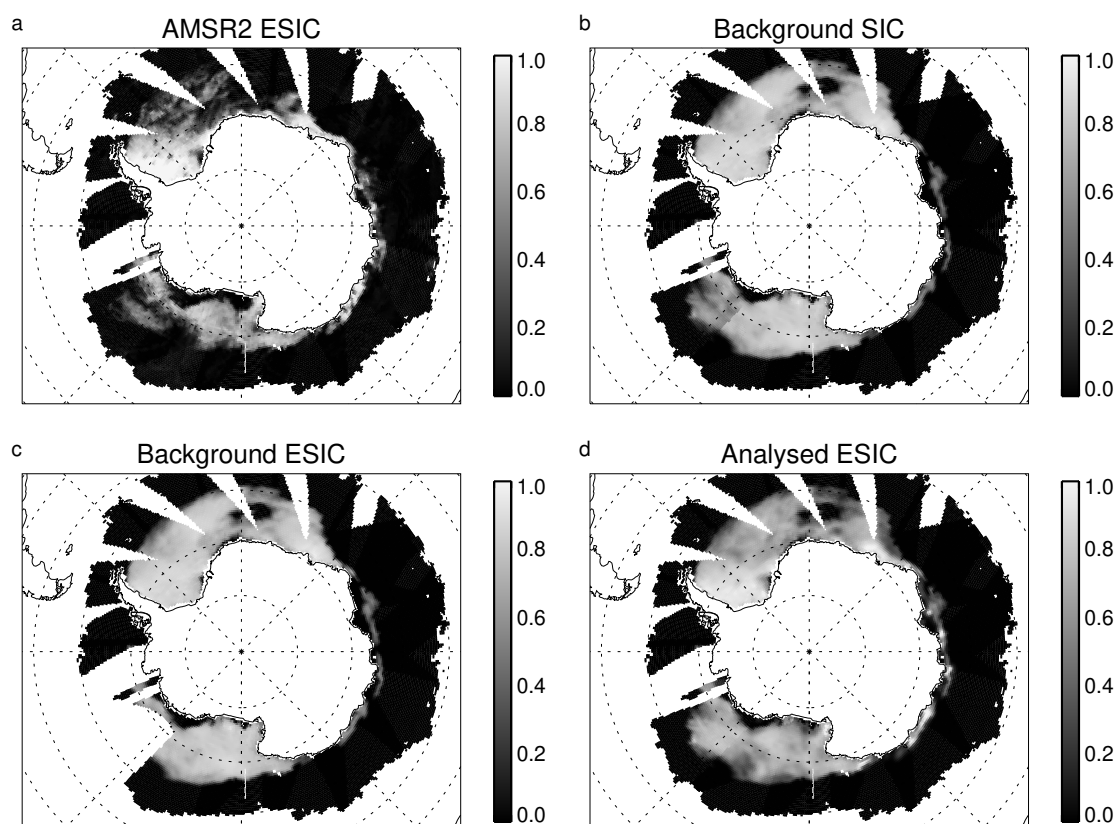


Figure 4. Observed, modelled and analysed ESIC and SIC at AMSR2 observation locations for the 12 UTC analysis on 21st December 2022. AMSR2 locations are only shown where the sea ice estimation is active, meaning land concentration less than 0.01 and ocean skin temperature less than 277 K. On this figure, zero degrees longitude is at 12 o'clock (as if on a clock face) and lines of latitude are drawn every 45 degrees. Orthographic projection.

3.2 Case study of Antarctic summer sea ice

This section provides a further case study to illustrate the sea ice data assimilation, using the same date and analysis window as earlier (Sec. 2.3; Fig. 2) but now focusing on the Antarctic. Figure 4 contrasts the observed AMSR2 ESIC with the background SIC and ESIC, which has been initialised from the OLDA ocean analysis, given this is a 12 UTC assimilation cycle. The SIC and ESIC are very similar, reflecting that simulated melt ponds on this day are very minor. All observational coverage of ESIC is shown on the figure, including large areas of open water: as described earlier, everywhere with an ocean skin temperature less than 277 K is assimilated in the sea ice framework. In polar regions, multiple AMSR2 orbital swaths are overlaid, and provide up to around 3 – 4 observations per 12 hour assimilation cycle at each location (see Geer, 2024b). At lower latitudes, gaps between the swaths are visible, there are also gaps within the swaths, which result from quality control applied in the



atmospheric system to remove areas affected by sunglint (Scanlon et al., 2025). The background ESIC (panel c) is also missing a sector of observations at 145 W, due to the aforementioned technical issue with the first model timestep.

380 In contrast to the situation in the Arctic in this cycle, Fig. 4 shows that there are large discrepancies between the model and observations in the Antarctic. Generally the observations show the sea ice is more broken and much reduced compared to the model. However, close to the Antarctic coast (on the right hand side of Antarctica in the plot) the model has very little sea ice but the observations show patches of residual ice with significantly higher concentrations.

Figure 5a and b show the resulting background departures in ESIC, in other words the AMSR2 observation minus the NEMO/SI³ background forecast. The difference between panels a and b illustrates the application of the QC described in
385 Sec. 2.1.4 with the most active QC in this case being the removal of observed ESICs between 0.05 and 0.25. Unfortunately this is removing significant areas of genuine observations of low concentration summer drift ice, as confirmed later on. The analysis increments in observation space (Fig. 5c) generally follow the patterns of the background departures quite closely, though with approximately half the magnitude (note the change of scale). However, the increments are much lower than would be hoped for in the area East of the Weddell sea, where QC has removed a lot of valid observations. To complete the assessment
390 of the increments, these are also shown on the analysis grid locations in Fig. 5d, noting that increments close to zero are here not plotted. Since the background errors have length scales of around 2° or 200 km, they do not spread the sea ice information far into the observational gaps. For example, gaps left by sun glint screening towards the top of the plot are still visible in the model space increments.

To further investigate the large discrepancies between the AMSR2 pseudo-observation and the modelled SIC, Fig. 6a shows
395 OLCI visible radiances in the Weddell sea in the area shown by the first rectangle on Fig. 5d. These radiances are from the level 1B OL_1_EFR product and specifically, channel 10, at 681.250 nm. The time and location has been chosen due to a rare hole in the clouds; mostly the sea ice is covered with cloud. In the chosen scene, the 300 m resolution OLCI radiances show numerous ice floes between around 1 km and 40 km in size. These are typically packed amongst lower radiance (greyer but localised) features likely composed of mixed ice and water at scales close to and below the resolution of the image, with the ice
400 likely composed of a mix of smaller ice floes and brash ice, which describes ice fragments at scales of 2 m and below. There is plenty of dark open ocean surrounding these features.

Cloud is also present in Fig. 6a, particularly to the bottom and right hand edges of the scene, and one indication is a blurring or obscuring of the ocean surface features. Also the cloud generally has more continuous spatial extent than the broken sea ice features here. Where the sea ice features are sharply visible, they are obviously not cloud, due to their morphology. Another
405 clear indicator of cloud are the regular linear features, seen in places such as the bottom right hand corner, that occur on scales of around 1 km (several 300 m pixels, though this is hard to see in the printed version). These features are likely the result of atmospheric gravity waves, and would not be expected in sea ice. The main ambiguity in the cloud area towards the right and bottom of the scene would be the smaller-scale bright features within the cloudy area, which could be explained by smaller-scale cloud features, or more likely here, sea ice features that have been blurred by the presence of a thin cloud layer. Typically
410 the cloud lightens the scene where the surface is dark (where there is significant presence of open ocean). Where the cloud is thicker, it mainly gives similar brightness to continuous sea ice, though there may be some darkening from cloud shadowing

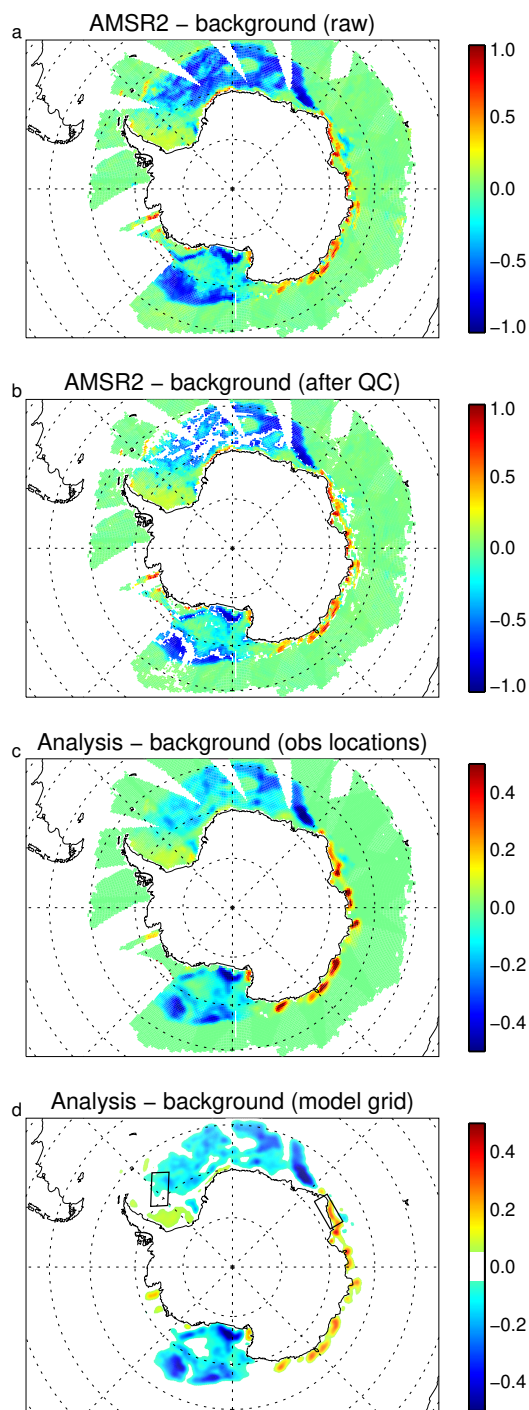


Figure 5. As for Fig. 4 but for (a-c) the ESIC departures and increment at observation locations and (d) the resulting SIC increments on the NEMO grid. The near-rectangles on the last panel indicate the areas shown in Figs. 6 and 7

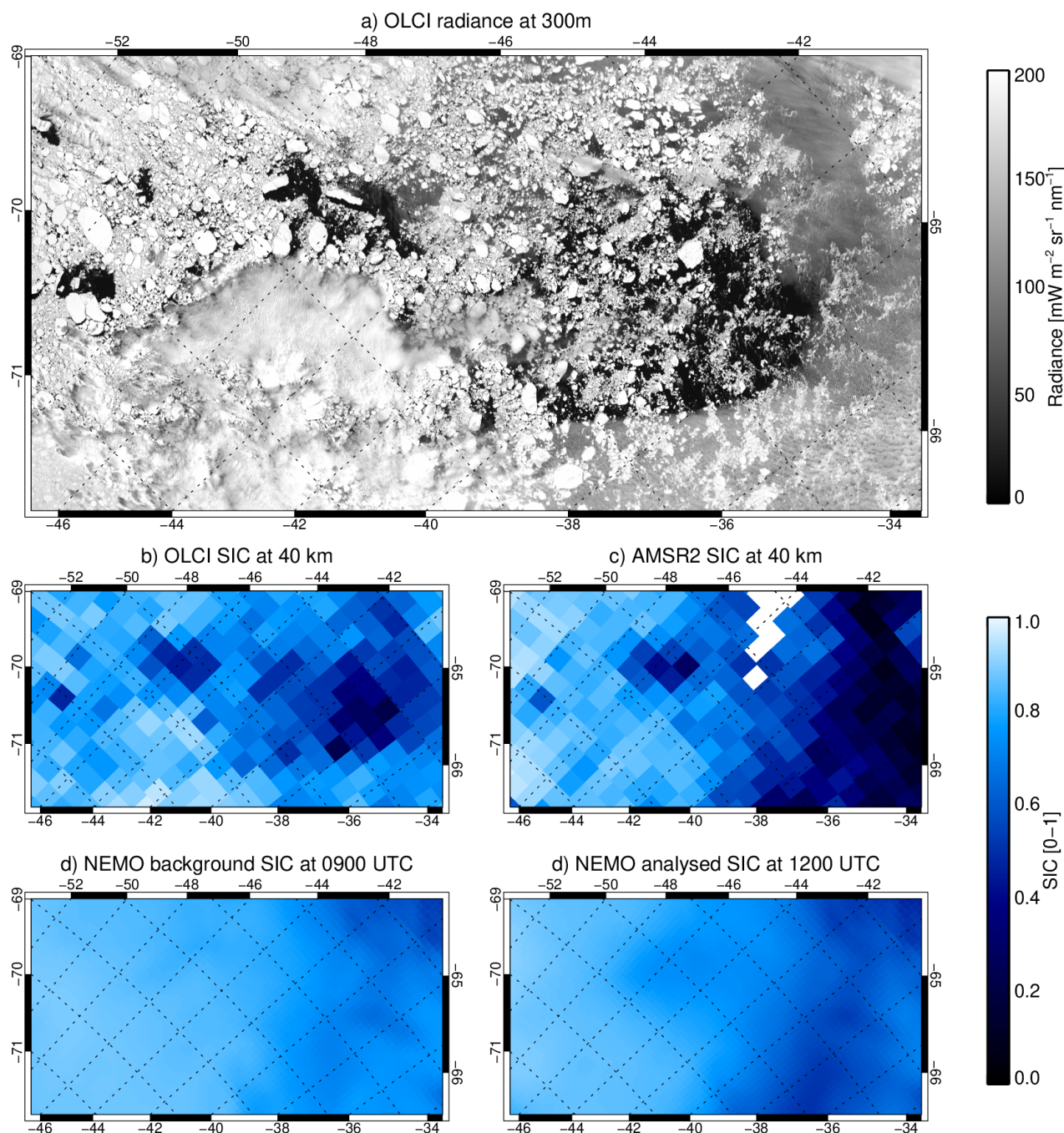


Figure 6. (a) OLCI Sentinel 3A channel 10 radiances and (b) superobbed OLCI sea ice concentration retrievals compared to (c) AMSR2 SIC, (d) NEMO background SIC at 09:00 UTC and (e) NEMO analysed SIC at 12:00 UTC. Based on OLCI overpass at 10:12 UTC and AMSR2 overpasses between 17:00 and 20:00 UTC, on 21st December 2022. Lines of longitude and latitude are annotated; the rectangle near the Weddell sea on Fig. 5d also shows the location. Orthographic projection centred on 68°S and 43°W and rotated 47° to approximately follow the OLCI scan pattern. White squares on panel c indicate a gap between AMSR2 swaths where data is missing.



and from cloud tops that tilt away from the sun in some of the features towards the left of the scene. Visually, it is clear that increasingly larger areas of open ocean are present towards the right of the plot (NE). Melt ponds can be excluded since they would typically be lighter than the open ocean, and due to the obvious appearance of broken pack ice in this image.

415 To compare the OLCI radiances to the AMSR2 and modelled sea ice, we performed an approximate SIC retrieval and then superobbed the results onto the 40 km reduced Gaussian grid (Fig. 6b). The approximate retrieval is based on tie points estimated from Fig. 6a of open ocean at $0 \text{ mW m}^{-2} \text{ sr}^{-1} \text{ mm}^{-1}$ and sea ice at $200 \text{ mW m}^{-2} \text{ sr}^{-1} \text{ mm}^{-1}$. This retrieval assumes linear SIC variation for radiances between these tie points and does not attempt to mitigate the impact of cloud. Despite the approximate nature of the retrieval, the agreement with AMSR2 ESIC (Fig. 6c) is visually close in areas where cloud is absent.

420 Note that since we do not obviously see melt ponds, here SIC and ESIC are treated interchangeably. To illustrate the close visual agreement, the distinct small areas of mostly open water towards the left and centre of the scene are quite consistent between OLCI and AMSR2 at the superob (40 km) scale. Towards the bottom right of the scene, AMSR2 ESIC shows mostly open water whereas the OLCI SIC is high, but this is due to the obvious presence of cloud increasing the radiance in this area. Outside of cloud affected areas, the OLCI data strongly supports the accuracy of the AMSR2 retrievals. By contrast, the

425 modelled background SIC (Fig. 6d) is a smooth field with concentrations declining from around 0.9 to around 0.6 from left to right, and is clearly in error. Data assimilation reduces the sea ice concentration in the open areas, following the AMSR2 observations, shown in the analysed sea ice in Fig. 6e, but it cannot fully correct such large errors in a single DA cycle. Also clearly visible is the smoothing of increments imposed by the 200 km correlation lengths used in the background errors. There may be scope to reduce these correlation lengths in future, to better incorporate the spatial detail provided by the AMSR2

430 radiances, though this could further limit the possibility of spreading information noted in the discussion around Fig. 5.

Figure 7 provides a similar analysis of E Antarctic coastal areas where AMSR2 shows sea ice coverage in places that are ice free in the NEMO background. Figure 7a shows the OLCI radiances in an area chosen similarly for a relative lack of cloud. The Australian Mawson research station is located on a bay just E of the centre of the figure. An extensive area of cloud is present over land and sea to the W, indicated by bright patches where the cloud edges catch the early sun, dark patches where the cloud

435 is tilted away from the sun, and by a blurry effect when compared to the sharper sea ice and land features. Central to the figure is an area of land-fast continuous sea ice edged by points and bays. In the open ocean are lighter patches of what is likely a mix of brash and small ice floes, in other words drift ice, with some larger floes visible (e.g. at 67°S , 62°E). Mawson is usually free from sea ice in February (<https://www.antarctica.gov.au/antarctic-operations/stations-and-field-locations/mawson/living/>) so it makes sense to find an area of land-fast ice in late December.

440 Figure 7b shows the OLCI retrieved SIC using tie points of $0 \text{ mW m}^{-2} \text{ sr}^{-1} \text{ mm}^{-1}$ and $260 \text{ mW m}^{-2} \text{ sr}^{-1} \text{ mm}^{-1}$ and without correction for cloud or land. AMSR2 retrievals are shown in Fig. 7c but coastal and land screening means they are not available close to the coastline. In the areas where both OLCI and AMSR2 provide a retrieval, the patterns of SIC are visually quite consistent, both in the land fast and drift ice. However, the chosen 40 km superobbing resolution blurs the distinction between the two.

445 Figure 7d shows that coastal sea ice is completely absent in the NEMO SIC background. The analysis is able to add sea ice cover near the coast in Figure 7e but only to levels around 0.3 rather than the observed 0.5 to 0.9 in the same area. Also, the

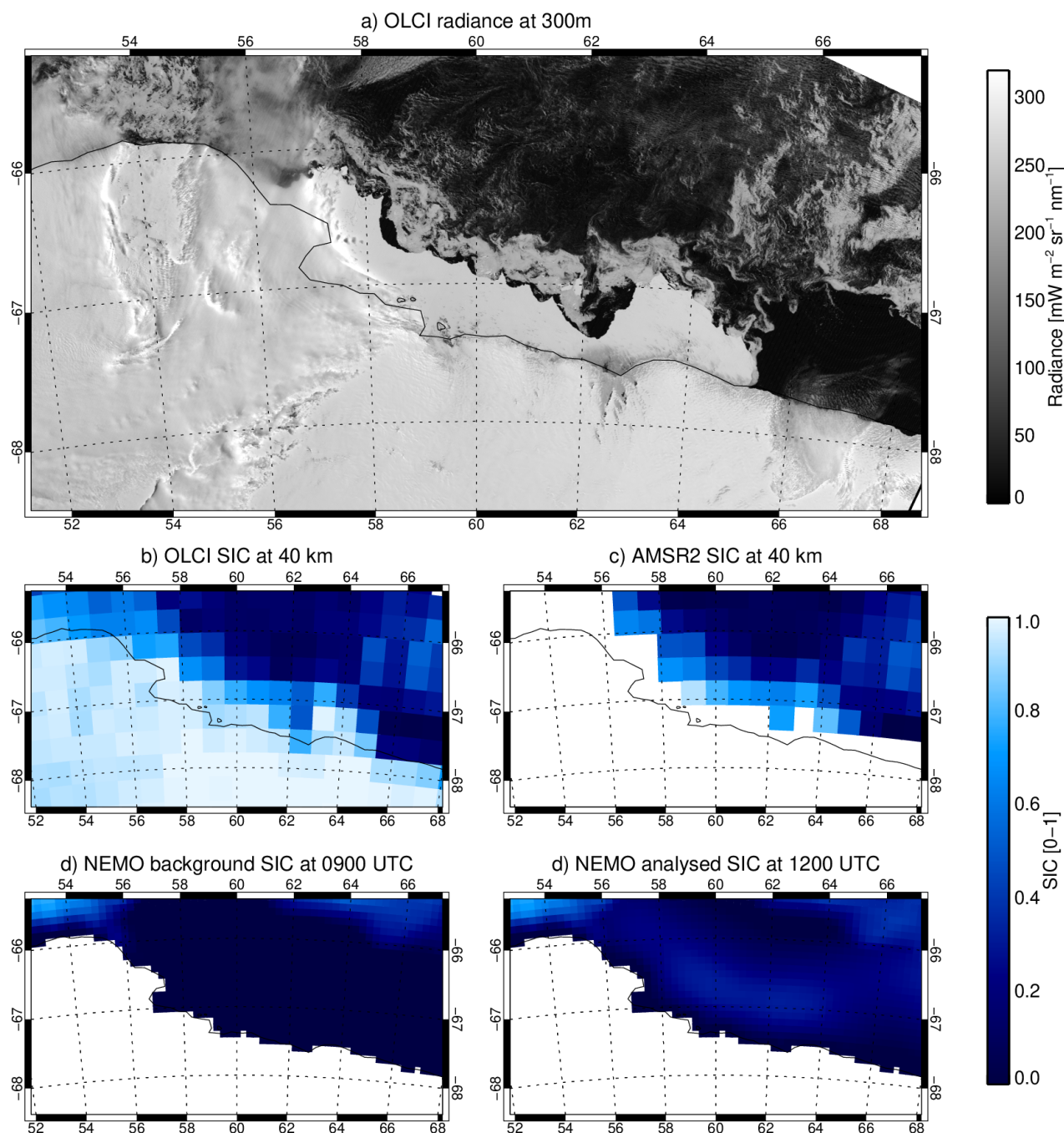


Figure 7. As Fig. 6 but along the E Antarctic coast and based on an OLCI overpass at 04:30 UTC and AMSR2 overpasses between 09:00 and 15:00 UTC, on 21st December 2022. The second rectangle on Fig. 5d also shows the location. Triangular patches on panel a expose the edges of the OLCI granule. White squares on the panels c,d and e indicate where AMSR2 data is missing due to coast and land screening and where the NEMO grid indicates land. Orthographic projection centred on on 67°S and 60°E. Black lines show an approximate coastline.



coastline is still incorrectly shown as free from sea ice, because of the lack of coastal AMSR2 observations. This, together with the 200 km background error correlation lengths, and the relative weighting of background and observation error variances (0.05 to 0.2) likely explains why the analysed sea ice concentration remains unrealistically low.

450 The reason for the missing fast ice along the E Antarctic coast is ultimately to be found in the OLDA ocean-only analyses, which are used to re-initialise the 12 h cycling coupled assimilation every 24 hours. The OSI-SAF L3 OSI-430a sea ice product that is assimilated in OLDA for these dates (e.g. https://osisaf.met.no/quicklooks/reprocessed/ice/conc-cont-reproc/v3p0/2022/12/ice_conc_sh_ease2-250_icdr-v3p0_202212211200.png, not shown) looks visually close to the AMSR2 ESIC in Fig. 4a including a very similar depiction of the fast ice in these areas. Further, the mean SIC increments in the ocean-only
455 analyses in this season are positive around the Antarctic coastline, indicating that data assimilation is trying to use the OSI-SAF observations to correct the issue (not shown). Therefore it is likely that the model forecast is rejecting the added sea ice by melting it, either because the ocean surface temperatures are too warm or because the atmospheric heating is too strong.

The melting may also be faster than expected because the default assigned thickness of 0.45 m (Sec. 2.1.2) is most appropriate for newly formed ice, whereas this ice likely developed over the entire winter season, which might suggest it is substantially
460 thicker. Indeed, a link between sea ice thickness and subsequent sea ice concentration is expected over timescales of months to years (Kauker et al., 2009; Holland et al., 2011). No information on sea ice thickness is assimilated in any of the ECMWF assimilation streams, but clearly this would be a useful future development.

A similar lack of summer Antarctic coastal sea ice was seen, even in the annual mean, when comparing earlier AMSR2 retrievals to the sea ice concentration from the OCEAN5 analyses (Geer, 2024a). This suggests the problem is independent of
465 the sea ice model upgrade to SI³ in the ORAS6 configuration, further suggesting it may ultimately come from a long-standing issue of the ocean or atmospheric model.

3.3 General impact on sea ice forecasts

Figure 8 shows the mean change in modelled SIC in NEMO/SI³ (experiment minus control) at analysis time (T+0) and in the 4-day forecast (T+96) in the Arctic. In Arctic summer (JJA, Fig. 8a) the AMSR2 pseudo-observations generally tend to
470 increase the SIC, mostly at the edge of the sea ice. These changes are maintained into the forecast (Fig. 8c) which suggests they are physically plausible within the model – for example they do not melt away again.

In Arctic winter (DJF, Fig. 8b) there is a general reduction in SIC in the analysis. It is reduced by around 0.02 over much of the Arctic ocean, and by at least 0.2 along the sea ice edge in the Greenland sea. The picture for the whole of DJF is surprisingly consistent with the increments in the case study shown in Fig. 2, even down to the small areas of positive increments on the
475 East coast of Greenland and in Hudson bay. However, there is no big reduction in SIC in multi-year ice regions, which shows that the multi year ice QC (Sec. 2.1.4) has been reasonably effective. Looking to the forecast (Fig. 8d), the main features around the marginal ice zones, including the reduction in the SIC to the E of Greenland, are retained. However, the small reduction in SIC in the interior ice is not retained by the model, which is further evidence that the reduction in concentration to values significantly below 100% (Fig. 3) was physically inconsistent.

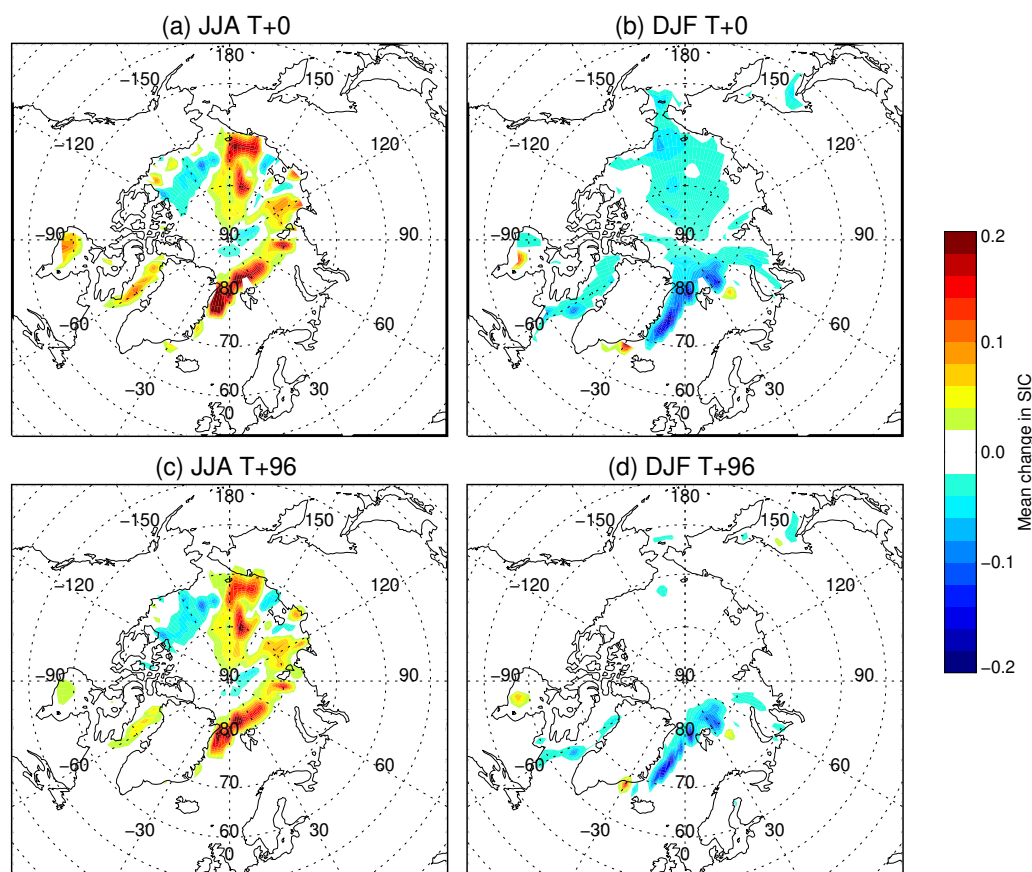


Figure 8. Mean change in Arctic SIC in the coupled model, computed as experiment minus control in (a,c) Summer experiment; (b,d) Winter experiment; at (a,b) analysis; (c,d) at the 96 hour (4 day) forecast.

480 In the Antarctic the patterns are quite different to the equivalent Arctic summer and winter seasons. In the Antarctic winter (JJA, Fig. 9a) the assimilation of AMSR2 SIC increases the SIC at the edge of the sea ice. This ring of increased SIC suggests the OLDA analyses and the SI³ model are developing new ice too slowly. This feature is also surprisingly similar to the deficiencies of the previous OCEAN5 sea ice analyses that were examined in earlier work (Geer, 2024b, a). These changes are retained into the forecast (Fig. 9c), suggesting they are physically plausible.

485 In the Antarctic summer (DJF, Fig. 9b), the three month average is very similar in pattern to the December case study examined in Sec. 3.2. This suggests there is a climatological problem in the OLDA analyses that retain too much sea ice coverage in the summer in these areas (Weddell sea and Eastwards, 50W to 30E; Ross sea and eastwards, 150E to 120W). Almost all the decreases in SIC are retained by the forecast model over 4 days, confirming that the changes are physically supported by the ocean and sea ice model. Unfortunately, in the areas where the OLDA analyses retain too little ice, and where
490 the SIC is increased by data assimilation (primarily land fast ice around the Antarctic coast between approximately 60E and

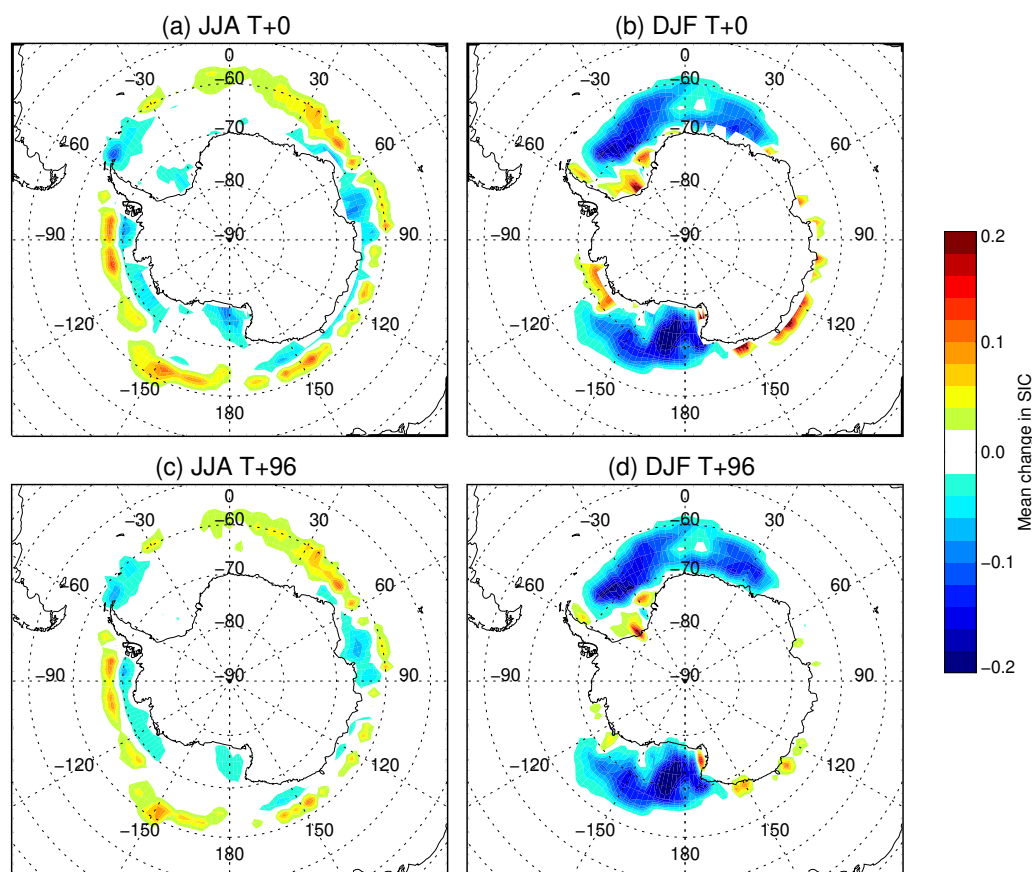


Figure 9. Mean change in SIC, as Fig. 8, but for the Antarctic

150E) the mean changes are partly lost during the 96 hour forecast. As with the OLDA system, discussed in Sec. 3.2, this suggests that the SI³ model is melting away the ice cover that was added. The next section examines the impact of all the changes in SIC on the atmosphere.

3.4 Impact on atmospheric and ocean forecasts

495 3.4.1 Analysis-based evaluation

Figure 10 illustrates the relative changes to the forecast quality at days 1 and 4 (T+24 and T+96) in terms of temperature (T) and vector wind (VW) RMS error (RMSE). Forecast error is evaluated as the difference between the forecast and the experiment's own analysis valid at the same time. The difference in RMSE of the experiment and control is then normalised by the RMSE of the control experiment. This shows that temperature RMSE is reduced by over 4% above the sea ice regions
500 out to day 4, and up to around 700 hPa, with statistical significance. Note that the area of apparent beneficial impact poleward

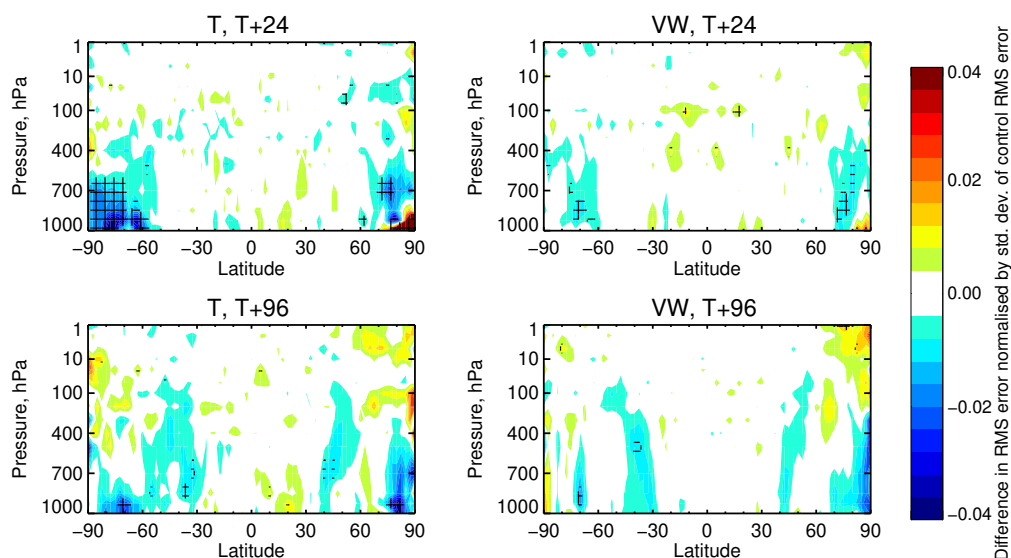


Figure 10. Normalised change in RMSE forecast error (experiment minus control) in (a,c) Temperature, T and (b,d) Vector wind, VW after 24 and 96 hours of forecast. Verification is done against own analysis. Statistical significance at the 95% level (Geer, 2016) is indicated by cross-hatching.

of 75°S is mostly under the surface, generated by extrapolation to standard pressure levels, and hence is ignored. These signals in RMSE are dominated by reductions in mean error, but the std. dev. of error (not shown) also shows reductions over sea ice areas and into the midlatitudes in the longer forecast ranges. On the other hand, there are increases in RMSE at low levels in the Arctic. These come from the small mean reductions in SIC shown in Fig. 8b, which is further evidence that they are not correct. Increasing the open water fraction increases heating of the lowermost atmosphere and results in mean increases in atmospheric 1000 hPa temperature of around 0.5 K over the Arctic sea ice, averaged over both JJA and DJF experiments (not shown). This mean temperature change then increases the temperature RMSE at low levels over the sea ice. However, this only affects the short-range forecast and is gone by day 4 (T+96), likely because the sea ice model has recovered to around 100% sea ice coverage in these areas, as shown in Fig. 8d. Returning to the temperature RMSE, by day 4, there are also signs of a small but in places statistically significant reduction in the midlatitudes (approximately 40° N and S). Similar patterns are also seen in the wind (VW) RMSE at day 4, indicating that the forecast has improved more generally due to the coupled sea ice assimilation.

Figure 11 shows the spatial and seasonal patterns of the changes in temperature forecast RMSE in the NH, though without any testing of statistical significance, given the difficulty of doing this across an entire field of points. The effect of adding sea ice coupling is completely neutral in Arctic summer (JJA, Figure 11a and c, also seen in latitude-pressure plots similar to Fig. 10 but specifically for these months, not shown). All of the benefit of sea ice assimilation in the NH is from the Arctic winter (Figure 11b and d). Here, reductions in temperature RMSE are strongest around Greenland and NE Canada. There is

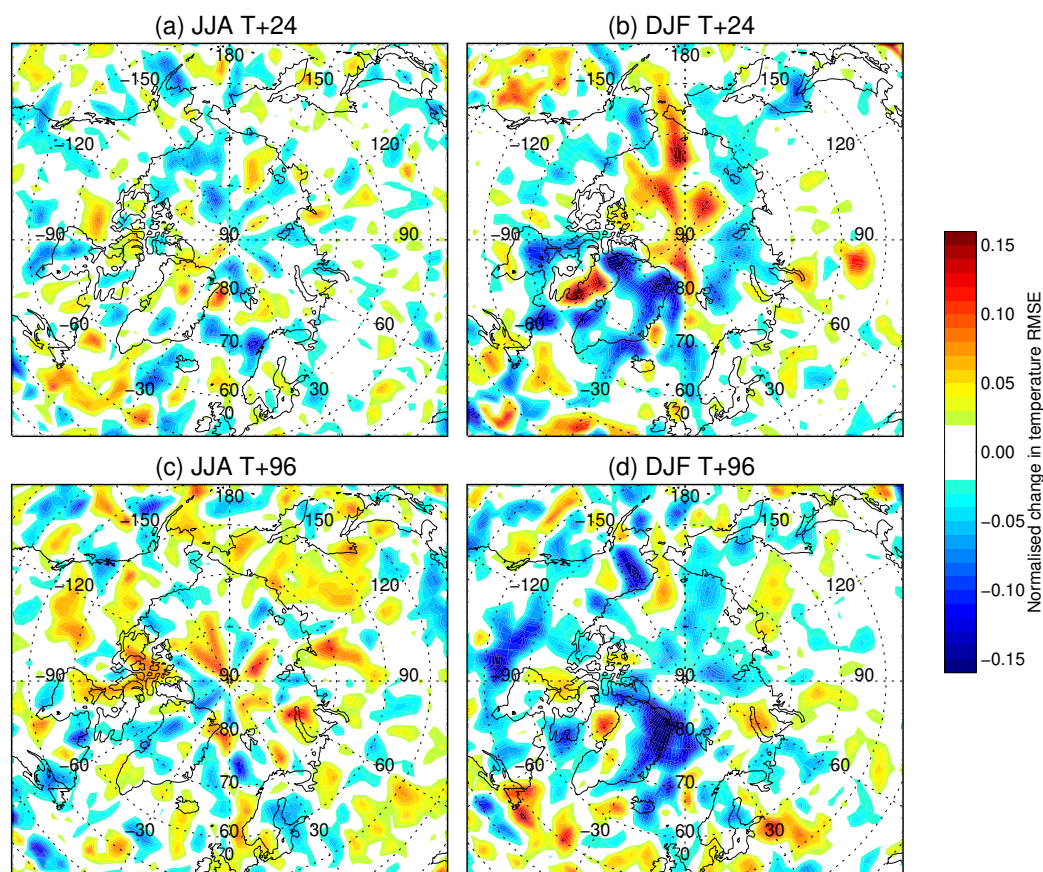


Figure 11. Normalised change in RMSE forecast error, as Fig. 10, but for temperature at 850 hPa in (a,c) Summer experiment; (b,d) Winter experiment; statistical significance testing is not applied. T+24 and T+96 refer to the forecast length in hours.

some increased RMSE at T+24, mostly over the multi year ice regions, as previously explained due to the effect of incorrectly opening up the central ice pack. But by the day 4 forecast (T+96) the RMSE is lower with sea ice assimilation over most of the Arctic ocean and forecasts are strongly improved around Greenland. It is likely that these improvements result from the mean reduction in sea ice concentration in these areas (Fig. 8b,d). There are also signs of improved temperature forecasts over North America. Lawrence et al. (2019) have shown how improved analyses in Arctic regions can lead to improved forecasts in midlatitudes at longer forecast ranges, and it is likely that a similar effect is present here.

Figure 12 examines the spatial and seasonal changes in the forecast quality in the Antarctic region. Here, the strongest improvements are again concentrated in the winter season (JJA, Figure 12a, c), and again there are some signs that the forecast improvements start in the sea ice regions and propagate to lower latitudes over a number of days in the forecast. Here, the strongest reductions in RMSE are in the Ross sea area, but they do not correspond to any strong mean change in the SIC (compare to Fig. 9). We can speculate that improved day-to-day patterns of the sea ice may be responsible for this. Also

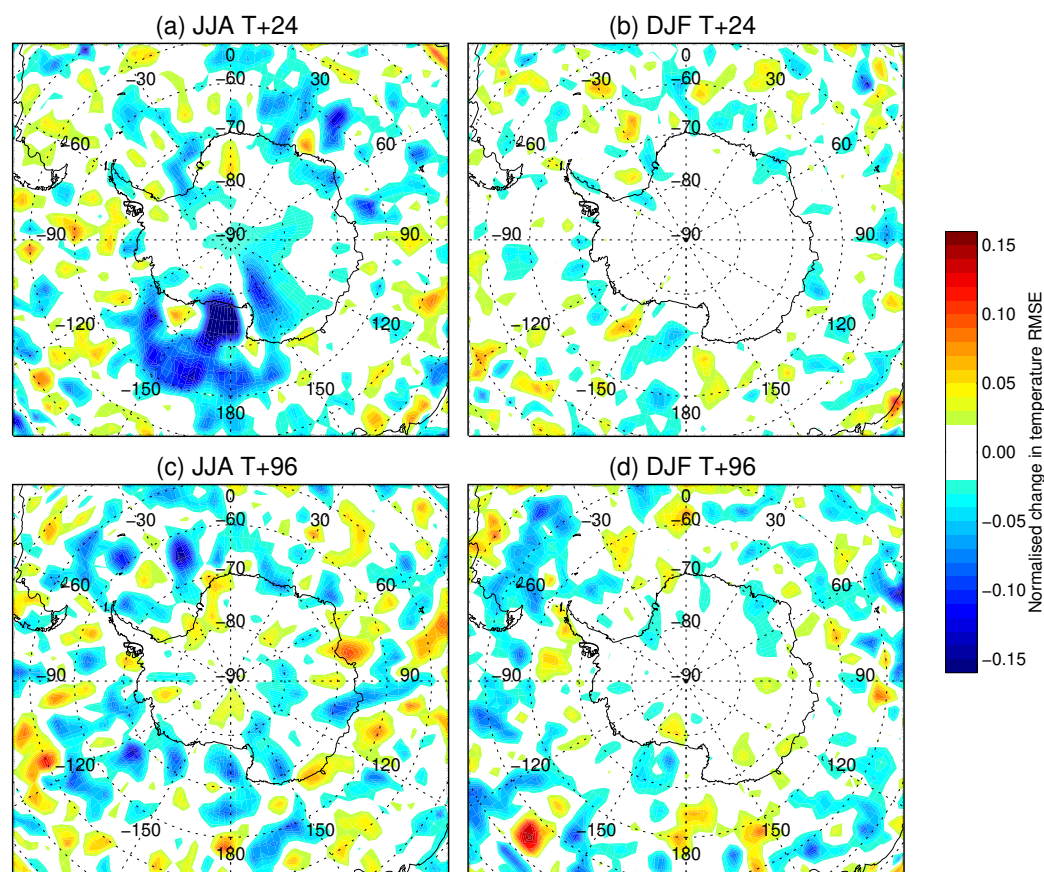


Figure 12. Normalised change in RMSE forecast error, as Fig. 11, but for the Antarctic.

consistent with the Arctic results, the summer (DJF, Figure 12b, d) shows few strong changes, despite large mean differences in
530 SIC (Fig. 9). We can speculate that the atmosphere is less affected by SIC changes in summer due to the relatively smaller skin
temperature contrast between open water and sea ice. However, there are still signs of improvements in the SH midlatitudes by
day 4 in the summer season (backed up by Fig. 10 and the DJF equivalent, not shown). Hence in the SH, sea ice concentration
assimilation appears to be beneficial in both seasons.

3.4.2 Observation-based evaluation

535 Figure 13 evaluates the change in quality of the atmospheric, ocean and land forecast by means of independent observations.
These figures are based on the standard deviation of the background departure for observations used globally in the data
assimilation. The background departure is the observation minus its 12-hour forecast equivalent. The sample of observations
may be slightly different between the experiment and control, due to small differences in utilisation due to the differences in the
forecasts, but in general the changes are small and do not affect the use of these statistics for forecast verification. For all results

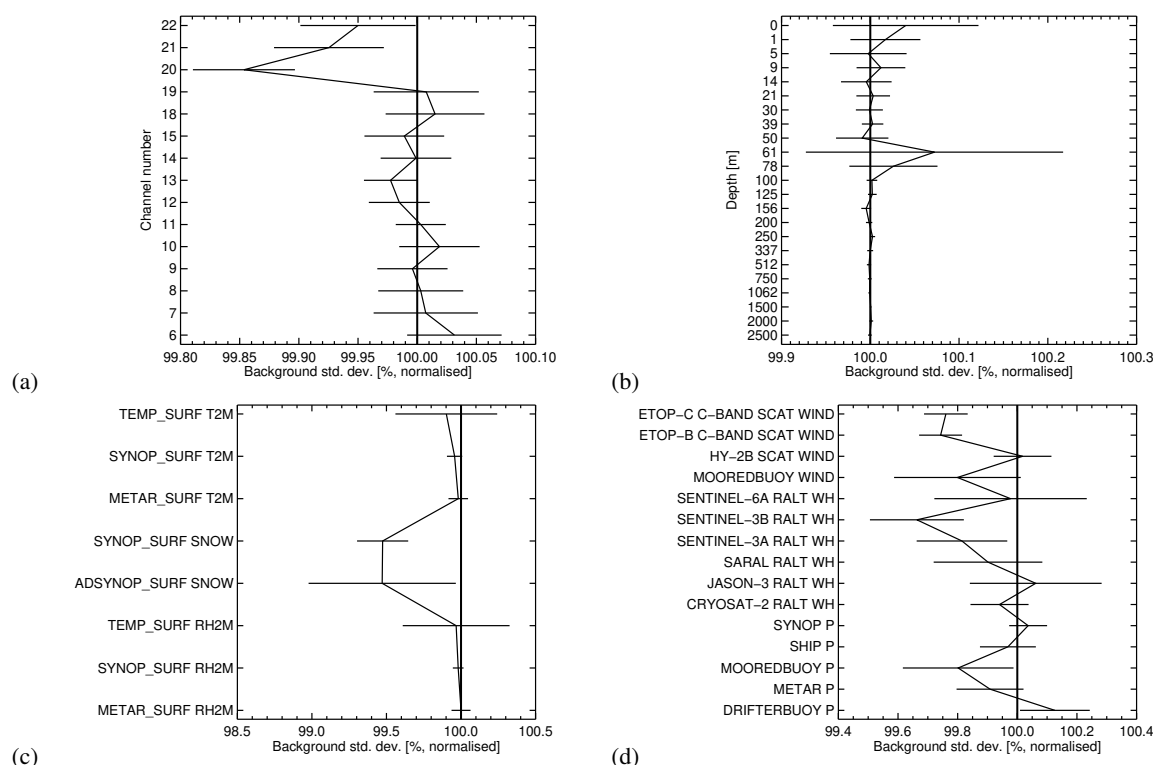


Figure 13. Normalised change in the standard deviation of background departure of independent observations assimilated in the atmospheric, land and ocean components, for a global sample across JJA and DJF experiments: (a) ATMS, a microwave sounder; (b) Argo ocean temperature profiles; (c) Land surface station observations; (d) Ocean surface wind, pressure and wave height observations. Numbers smaller than 100% indicate a reduction in the std. dev. compared to the control experiment. Error bars indicate the 95% confidence interval. Acronyms are further explained in the text.

540 shown here, the change in global sample numbers is below 0.1% with two main exceptions addressed below, where differences reach 0.6%: this is in the wave height observations and ATMS lower tropospheric temperature channels. To summarise the change in forecast quality, the standard deviations of the experiment and control departures are normalised by the standard deviation of the control, with the numbers given in percent, so that the control is 100%.

Figure 13a shows that the fit to Advanced Technology Microwave Sounder observations is improved by about 0.1% in 545 channels 20 to 22, which are sensitive to mid and upper-tropospheric humidity. Other channels, sensitive to temperature at different levels in the atmosphere (channels 6-15) and humidity in the lower troposphere (channels 18 and 19), are not affected. Examination of the maps corresponding to these changes indicates that channels 18 and 19 are not used polewards of 60° but channels 20 to 22 are, and the reduction in standard deviation is mostly localised to Arctic and Antarctic sea ice areas. This backs up the analysis-based atmospheric forecast scores that showing the short-range forecasts are improved in the troposphere 550 in sea ice areas.



Figure 13b shows the fits to ARGO ocean temperature profiles. There is no significant change, suggesting that the assimilation of SIC does not affect the ocean at global scales. One aspect is that ARGO does not have high spatial density in the polar regions (Klatt et al., 2007, though this is being addressed by the Polar ARGO mission team) so these global statistics are dominated by lower latitudes. Evaluation of the polar regions alone (polewards of 60°) has also been done, although it is not shown here, and this reveals a mix of small (less than 1%) improvements and degradations down to around 40 m depth, depending on depth, hemisphere and season. In any case we would not expect a large impact on the wider ocean due to the univariate sea ice analysis, the relatively slow timescales in the ocean, and the reinitialisation of the ocean state every 24 h.

Figure 13c shows the fit to 2m temperature (T2M) and relative humidity (RH2M) and snow cover (SNOW) observations from ground stations. The snow cover observations, distributed almost exclusively in NH high latitudes, are improved by around 0.5%. This may be an indirect effect of the change in SIC in the nearby Arctic ocean, or of the changes to low-level temperatures in these regions.

Figure 13d shows the effect of SIC assimilation on other observations of surface variables globally, including scatterometers (SCAT) providing 10 m wind components over ocean, radar altimeters (RALT) measuring the significant wave height, and buoy (MOORED buoy, DRIFTER buoy), ship and land surface stations (SYNOP, METAR) directly measuring atmospheric pressure and temperature. Satellite names such as Metop-C, Sentinel, Jason and Cryosat are documented at <https://space.oscar.wmo.int/satellites>. The coverage of in-situ platforms such as buoys and ground stations is quite limited in polar regions and hence it is no surprise that the fits to these observations do not significantly change. However, fits to the scatterometer wind and wave height observations are clearly improved.

Figure 14 explores the origin of the improved fits to scatterometer and wave height observations using maps of the normalised change in background departure between experiment and control. Here, the results are also broken down by season, but with the results from all sensors combined. For the scatterometer wind observations (Figs. 14a and b) the improvements are largest in a band around the marginal ice zone in summer (JJA). Rather than representing a direct improvement in the forecast winds in these areas, we interpret this as an improvement in the quality control of the scatterometer winds. These winds are only assimilated in open ocean areas, since the physical basis of the retrieval is the backscatter from ocean capillary waves. In the IFS, the scatterometer screening is based on the model SIC. Hence, the reduced wind departures are likely due to better screening of sea-ice contaminated observations, along with the addition of observations in areas that are in reality ice free. This is an indirect validation of the improved SIC short forecasts in the experiment where AMSR2 is assimilated.

For the wave height observations, Figs. 14c and d, show the main improvements are in the summer (JJA) around the marginal ice zones of Arctic and Antarctic. Wave height observations are assimilated in regions with model SIC ≤ 0.3 . The IFS wave model in the cycle 49r2 configuration used here gives zero wave height in sea ice areas (in reality this is not true and wave penetration into the sea ice was added in the final version of the 50r1; section VII ECMWF, 2026; Kousal et al., 2025). In any case, an improved description of the areas with zero SIC should lead to an improved forecast of wave height in the marginal ice zone. However, in DJF in the Antarctic, the wave height forecasts appear to be worse. This appears to be an artifact of the differing observation QC between the control and the experiment, since the affected regions are places where significantly more wave height observations are being assimilated in the experiment than in the control (not shown). This occurs because

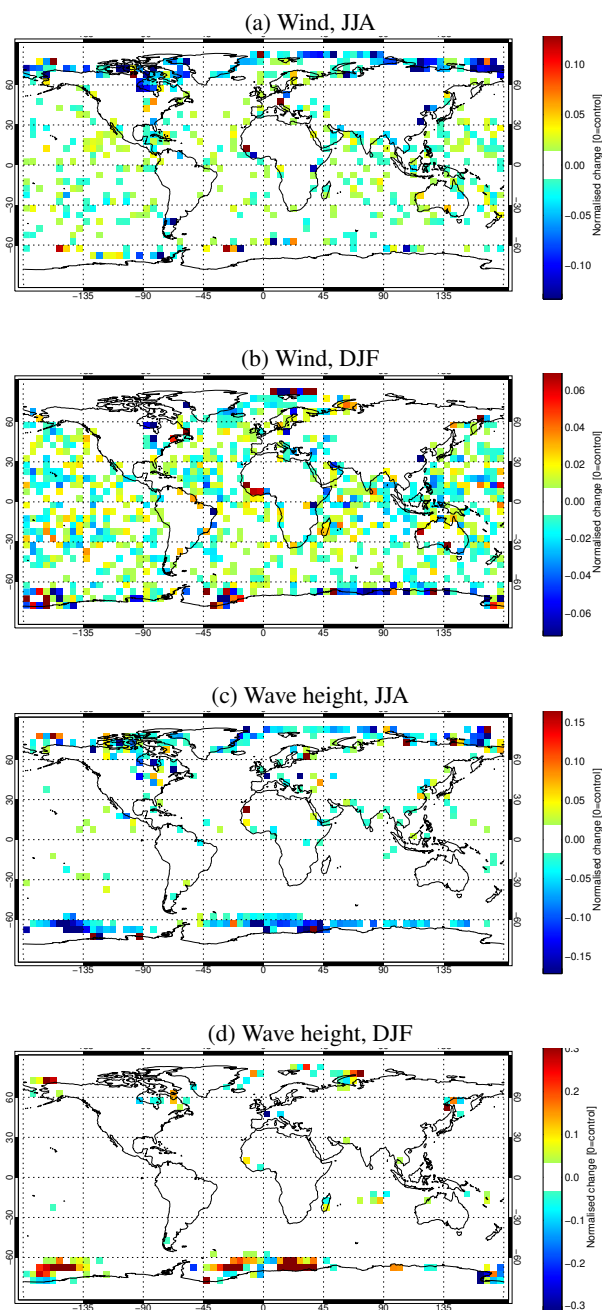


Figure 14. Normalised change in the standard deviation of background departure for (a,b) ocean surface wind observations and (c,d) wave height observations for the (a,c) summer and (b,d) winter experiments compared to the control.



the large reductions in SIC in Antarctic summer (DJF, Fig. 9b) create much more extensive areas with $SIC \leq 0.3$, allowing more wave height observations to be used. Overall, as shown by Fig. 13, fits to wave height observations are in most cases significantly improved, and this appears to be another indirect validation of the improved quality of the SIC.

Figure 13 has only shown a subset from all the observations used in the coupled data assimilation system. In general, most other observations show no significant impact in terms of the global sample. As already mentioned in the context of the Argo temperature profiles, we have also examined similar plots for the winter and summer separately, and in smaller latitude bands including the N and S polar areas, defined as poleward of 60° . In general, these confirm the picture seen in the global results. However, two additional effects stand out (not shown). One is that the N polar radiosondes support the improved lower tropospheric temperatures seen in the NH winter in the analysis-based verification in the early forecast range (Fig. 11). For DJF alone, in the N polar region, the radiosondes show statistically significant reductions in std. dev. of background departure at 600 hPa and below, by up to 0.7% at low levels, indicating that the T+12 forecast is significantly improved. A second effect is that around 9% more observations from ATMS and AMSU-A lower tropospheric temperature sounding channels are used in NH winter, mostly over the central sea ice areas where SIC is erroneously reduced (not shown). Likely the systematic changes in polar near-surface temperatures affect the quality control for these channels, which is based on the size of departures in surface-sensitive channels which are not assimilated (e.g. Duncan et al., 2022). This may have contributed to improved temperature forecasts in polar regions, but most of the additional data is over the central Arctic sea ice in winter, and similar changes are not seen in the Antarctic winter. Hence we argue that improvements in forecast scores in the MIZ in both hemispheres are most likely caused by improvements in the SIC in the model in these regions.

4 Conclusion

This work has described the new outer-loop coupling assimilation of sea ice concentration activated within the ECMWF operational weather forecasting system at cycle 50r1. This system uses the NEMO v4 ocean model including the SI³ sea ice model. Sea ice concentration is retrieved at AMSR2 observation locations as a by-product of the atmospheric radiance data assimilation. These retrievals are then assimilated as effective sea ice concentration (ESIC) within the ocean data assimilation component NEMOVAR. Here, ESIC is defined as the sea ice fraction with any melt ponds removed, since these appear similar to open ocean to the microwave observations. The ESIC is assimilated together with conventional ocean observations and open ocean skin temperatures, which are similarly derived from satellite radiances in the atmospheric system (Scanlon et al., 2026b). This marks the first time that ocean and atmosphere data assimilation have been coupled within the weather forecasting process inside the 12 h atmospheric data assimilation cycle (de Rosnay et al., 2022; Browne et al., 2026b) and the first time that surface-sensitive radiances have been assimilated (through outer loop coupling) into an operational ocean model. The current work examines specifically the impact of activating the sea ice concentration assimilation in NEMOVAR in the 12 h cycling coupled assimilation system.

Assimilation of the AMSR2-derived sea ice into NEMOVAR makes the clearest improvements in the marginal ice zones of both hemispheres, where there are both local and systematic effects. In winter, examples of systematic changes are the



reduction of SIC along the east coast of Greenland (Fig. 8) and the increased marginal ice coverage in the Antarctic (Fig. 9).
620 Forecast fits to scatterometer wind retrievals and radar wave height observations are improved by well over 10% in winter in many parts of the marginal ice zones of both hemispheres (Fig. 14). This is due to an improved description of SIC in the forecast model after 12 hours. Changes in the marginal ice zone are retained during the forecast, too, indicating that they are physically supported by the model.

In the Antarctic summer, there are even larger changes compared to the SIC provided by the OLDA uncoupled near real
625 time sea ice assimilation (Fig. 9). One feature is that the summer sea ice break up is significantly delayed in the control, with far greater extent and concentration than is observed by AMSR2. The validity of the AMSR2 retrievals is supported in case studies by OLCI radiances. Assimilation of AMSR2 sea ice concentration significantly improves the situation in the model, but the impact of data assimilation is limited by quality control decisions that treat low-fraction sea ice as spurious cloud. Another feature is seen along the Antarctic coastline where, by contrast, summer sea ice concentration is removed too completely in
630 the control, whereas the AMSR2 observations show patches of remaining sea ice. This issue was already seen in the ORAS5 configuration in earlier work (Geer, 2024b) but it remains present in the new configuration. Data assimilation helps correct this issue, but the sea ice that is added is removed again over several days of the model forecast, likely because the ocean or atmosphere is too warm. Further, the data assimilation does not make the replacement ice thick enough, indicating the future need for sea ice thickness assimilation as well.

635 For the indirect validation in the Antarctic summer, fits to wave height observations get worse (Fig. 14). This is because there is a large increase in wave height observations being used, in areas that were almost fully ice covered in the control, so the comparison is not meaningful as a measure of forecast quality. But fits to scatterometer winds show that the SIC is better with the data assimilation active in the Antarctic summer, and this is also supported by the OLCI-based case studies. Relatively large changes are also made in the Arctic summer, and there, the accuracy of these changes is supported by improvements both
640 the scatterometer and wave height fits.

The clearest problem in the current framework is in the interior ice in winter, primarily in the Arctic. Here, quality control is applied to avoid assimilating a known low bias in the AMSR2 retrievals in multi year ice, but SIC is pulled down by around 0.05 more generally across most areas of interior ice (Fig. 8b). The SIC is expected to be close to 100% in these regions but this is being reduced by the data assimilation. This is clearly wrong, since the sea ice model itself does not support the changes
645 (sea ice is reformed over subsequent forecast days) and there is a localised increase in lower atmospheric temperature RMSE, from excessive heating by the presence of open water leads. This issue became worse in subsequent pre-operational testing of cycle 50r1 (not covered here) where the AMSR2 bias correction began to drift unsustainably over sea ice, making the low SIC bias larger in the interior ice. By removing the SIC predictor in VarBC, this issue was mostly corrected, though this highlights that bias correction over sea ice needs more development. Further, it is worth continuing to look at the ability of the retrievals to
650 generate close to 100% SIC in the interior ice. Sea ice data assimilation is clearly beneficial in the marginal ice zones, where any systematic errors in the AMSR2 SIC appear to be more than compensated by the improved description of the sea ice location. But in the central regions of consolidated ice, particularly in winter, the model already likely has a good description of the SIC, and assimilation of SIC may be less beneficial, especially if it causes systematic errors.



Improvements in SIC in the marginal ice zones appear to be responsible for reduced 850 hPa RMSE temperature forecast error in similar locations (Figs. 11 and 12). In terms of zonal averages over both seasons, the forecast impact is seen in both winds and temperatures, and it starts in polar regions, with impacts locally greater than 4%, but spreads equatorwards as far as 30° latitude by day 4, with statistically significant impacts locally reaching around 1%. These forecast impacts are dominated by the winter seasons and are weaker or absent in the summer. The contrast between open ocean and sea ice in terms of skin temperature is stronger in winter and hence may help explain this. Although the incorrect reductions in SIC in the interior ice zones create local degradations in the forecast, these problems stay confined to the early forecast range, at low levels over the central sea ice. Overall, the impact of sea ice data assimilation is clearly beneficial.

It is hard to find previously published evidence of the impact of improved sea ice on weather forecasts, outside the atmospheric boundary layer and outside the local area. So this work may be the first evidence that improvements in sea ice concentration do matter to the global medium-range weather forecast, outside polar areas. From the perspective of atmospheric forecasting, these results support both the strategy of improving data assimilation in polar regions in order to improve medium-range forecasts at midlatitudes (e.g. Lawrence et al., 2019) and of improving representation of the earth system more generally through coupled data assimilation (de Rosnay et al., 2022).

This work demonstrates strong potential for coupled data assimilation, but it only represents a starting point for what is possible. There are many aspects where we expect to improve the framework in the next few years, including many detailed issues that have been noted in this work. But at the broadest scale, there are at least three main priorities relating to passive microwave assimilation, which might also help address some of those more detailed issues. First, because the ocean fields are reinitialised, every 24 hours, from the ocean-only analysis (OLDA, which is similar to ORAS6), this limits possibilities for the coupled sea ice data assimilation to improve forecasts, although it also prevents any drifts to unrealistic ocean conditions. So it is a long-term aspiration to remove the ocean reinitialisation and to freely evolve the 12-hour cycling coupled data assimilation. A second major scientific aspiration is to move to full coupling through the observation operator, as advocated by Browne et al. (2026b, their appendix A), which means we would directly assimilate the AMSR2 radiances into NEMOVAR, rather than to first retrieve geophysical parameters like ESIC within the atmospheric data assimilation. Finally, to best exploit any move to direct radiance assimilation for the ocean, there is scope to replace the simplified surface emissivity modelling in the AMSR2 observation operator with a more physical surface emission model. This could help infer additional geophysical parameters from the radiances, such as sea ice and snow temperatures and geometric thicknesses, especially if a wider range of sensors and frequencies (e.g L- and C-band) can be included. Work has already started in some of these areas, along with the inclusion of radar measurements of sea ice freeboard to better constrain sea ice thickness, as part of wider efforts to prepare the coupled data assimilation framework for future earth system sensors (Bormann et al., 2025).

Code and data availability. Sea ice emissivity model version 2 is available at <https://github.com/ecmwf-projects/empirical-state-learning-seaice-emissivity-model>; The IFS coupled data assimilation framework is not publicly accessible, and neither is experimental IFS data from



this work, due to the difficulty of curating and maintaining a huge and complex volume of data. However, selected open data from ECMWF is available, including from the final operational version of cycle 50r1 here: <https://doi.org/10.21957/open-data>.

Author contributions. AG analysed the results and drafted the manuscript with contributions from PB and TS. AG developed the AMSR2 retrievals. PB developed the outer loop coupling framework for assimilating sea ice from AMSR2 in NEMOVAR, with contributions from
690 TS and AG.

Competing interests. None

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