

Gaussian-process fusion of ICESat-2 and SMOS/SMAP data for daily estimates of Arctic sea ice thickness and volume

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Abstract. We present IS2SMGPSIT-V1, a full-coverage, pan-Arctic, 25 km $\times$ 25 km sea ice thickness and volume dataset with daily output spanning seven winter growth seasons between 2018 and 2025. The product fuses ICESat-2 laser-altimetry data with SMOS/SMAP L-band radiometry using Gaussian-process (GP) regression implemented with the open-source GP-Sat package. ICESat-2 provides high-spatial-resolution thickness estimates along defined ground tracks, whereas SMOS and SMAP provide extensive daily coverage of thin ice (≤ 0.5 m) thickness. Using each observation's acquisition time and location reduces sampling artefacts associated with existing monthly binning approaches and fills unobserved grid cells, particularly during early-fall freeze-up. Inner-Arctic-Ocean mean thickness seasonal cycles are broadly consistent with the established IS2SITMOGR4 (ICESat-2 Winter Arctic Monthly Gridded Sea Ice Thickness) Version 4 product, while the fused product extends coverage where the monthly product is sparse. Comparisons with upward-looking sonar measurements from the Beaufort Gyre Exploration Project moorings over 2018–2024 show improved monthly skill relative to IS2SITMOGR4-V4 ($r^2 = 0.91$ versus 0.83; RMSE = 0.19 versus 0.24 m), primarily through improved representation of thin ice. De-seasonalised comparisons show limited sub-monthly skill, indicating that further development and assessment are needed to improve representation of short-timescale variability. The full spatial coverage supports consistent pan-Arctic volume estimates and analysis of interannual anomalies. Version v0.1 of the monthly NetCDF archive is preserved on Zenodo (<https://doi.org/10.5281/zenodo.22147361>; Petty, 2026b). The data are also hosted on Amazon Web Services S3 as monthly NetCDF files, a single Zarr store, and a version-controlled Icechunk repository to enhance accessibility.

1 Introduction

Arctic sea ice area has been monitored continuously at basin scales through passive microwave satellite sensing since the late 1970s. A $\sim 50\%$ reduction has been reported over this ~ 45 -year period (Parkinson and Cavalieri, 2012; Comiso et al., 2008), and is widely used as an indicator of global climate change (IPCC, 2023). Sea ice thickness adds a crucial third dimension to this sea ice record. Arctic sea ice thickness is also thought to have declined by $\sim 50\%$ since the 1980s (Kwok and Rothrock, 2009), and, combined with area, determines sea ice volume and the freshwater fluxes from ice growth and melt that influence ocean stratification and circulation (Haine et al., 2015). Thickness also controls the transmission of light through the ice cover, with direct consequences for under-ice primary production and marine ecosystems (Massicotte et al., 2019; Ardyna

25 and Arrigo, 2020; Payne et al., 2026), and informs assessments of Arctic shipping navigability (Stephenson et al., 2011; Pizzolato et al., 2016) and travel on and around coastal sea ice by local communities (Bell et al., 2014; Segal et al., 2020). The processes controlling sea ice thickness vary seasonally: winter thickness is governed by thermodynamic growth and ice dynamics, whereas the thinner, more fragmented summer ice cover is increasingly influenced by interactions with the upper ocean and the ice–albedo feedback. Spring and summer thickness information is also increasingly valuable for seasonal to
30 sub-seasonal sea ice forecasting (Landy et al., 2022; Zhang et al., 2023; Song et al., 2024; Bushuk et al., 2024).

Satellite estimates of sea ice thickness have to date relied on two primary approaches: active altimetry and passive radiometry. Altimeters (laser or radar) range to the sea ice surface and nearby open-water leads to estimate freeboard, which is converted to thickness assuming hydrostatic equilibrium together with estimates of snow depth, snow density, and sea ice density (Laxon et al., 2013; Kwok and Cunningham, 2015; Hendricks et al., 2016; Petty et al., 2023). Laser altimetry senses the air–snow
35 interface (total freeboard), whereas Ku-band radar altimetry is sensitive to a snow–penetration-dependent scattering horizon that must be interpreted when inferring ice freeboard (Willatt et al., 2010; Nandan et al., 2017, 2020; Landy et al., 2022, 2026). Along-track resolution is high, especially for laser altimetry (~ 10 to 100 m), but gaps between ground tracks can span hundreds of kilometers, particularly at lower latitudes, so data are usually aggregated over multiple days to weeks to generate basin-scale estimates. Wave contamination in the marginal ice zone requires filtering of low-concentration regimes (e.g. $< 50\%$
40 concentration), and clouds cause significant data drop-out for laser altimetry. Passive microwave radiometry, in contrast, uses empirical relationships between measured brightness temperatures and surface emissivity as seawater freezes and thickens (Kaleschke et al., 2012; Tian-Kunze et al., 2014; Patilea et al., 2019). Retrievals show skill only for ice thinner than ~ 0.5 to 1 m, so coverage is focused on the less consolidated marginal ice zone; spatial resolution is coarser than altimetry (~ 10 to 50 km), but daily coverage is far more complete.

45 The complementary advantages and disadvantages of these two remote sensing approaches were leveraged by Ricker et al. (2017) to produce a merged Arctic sea ice thickness record. They combined radar-altimetry-derived thickness from the European Space Agency (ESA) CryoSat-2 mission (for thicker and more consolidated ice) with L-band-radiometry-derived thin-ice thickness from ESA’s Soil Moisture and Ocean Salinity (SMOS) mission, within an optimal-interpolation (OI) framework. This approach continues today as the operational CryoSat-2/Sentinel-3/SMOS (CS3SMOS) product, which now also incorpo-
50 rates Sentinel-3 radar altimetry (Sect. 2.5). In this study, we seek to build on this earlier work by fusing L-band radiometry thin-ice thickness with sea ice thickness estimates obtained from NASA’s ICESat-2 mission. ICESat-2, launched in September 2018, uses a multi-beam photon-counting laser altimeter (ATLAS) to measure total freeboard with high along-track resolution (Markus et al., 2017; Kwok et al., 2019). The ICESat-2 monthly gridded winter Arctic sea ice thickness (IS2SITMOGR4) product (Petty et al., 2025b), disseminated through the National Snow and Ice Data Center (NSIDC), provides monthly grid-
55 ded winter thickness estimates on a 25×25 km Polar Stereographic North grid (EPSG:3411), through the incorporation of ancillary snow loading estimates and a simple drop-in-the-bucket binning of along-track thickness estimates (e.g., Petty et al., 2020, 2023). While the IS2SITMOGR4 product has shown strong performance in independent data validation efforts (e.g., Petty et al., 2023; Ludwig et al., 2026), the monthly bin-averaging approach has important limitations: (i) there is no accounting for the sub-monthly timing of individual satellite passes, introducing clear sampling biases (orbit track aliasing in the

60 monthly maps); (ii) grid cells observed predominantly early or late in a given month will be biased relative to the true monthly mean, particularly during periods of rapid thickness change such as freeze-up and spring melt onset; (iii) larger spatial gaps often remain unfilled, including the satellite pole hole north of $\sim 88^\circ\text{N}$. A simple linear interpolation/smoothing approach has been included in the IS2SITMOGR4 product (since Version 3) to mitigate these concerns, but it does not account for the timing of the underlying observations and imposes no physical or statistical constraint on the values assigned to the filled gaps. The spatial gaps also complicate direct comparison with climate model output: care is needed when using incomplete observational fields to avoid introducing representation biases into model evaluation metrics (Petty et al., 2025a). An improved interpolation routine and incorporation of thin-ice/low concentration thickness data are needed to improve coverage and physical consistency of these gridded thickness estimates across the Arctic.

To fuse and interpolate our input thickness datasets, we use GPSat (Gregory et al., 2024), an open-source Gaussian process (GP) satellite data interpolation package first demonstrated through the fusion of multi-mission radar altimetry data. A GP defines a prior distribution over smooth prescribed functions and, given noisy observations at known locations, produces a posterior mean and variance at any unobserved point, enabling predictions for all desired locations and naturally quantifying the interpolation uncertainty (Rasmussen and Williams, 2006). Each observation enters the GP with its actual acquisition time and location, so the predicted field at a target date weights observations by their spatiotemporal proximity to the prediction location. Because the GP framework supports inference at arbitrary target times and locations, we produce daily fields, though the same trained model could generate output at any prescribed cadence. We target sea ice thickness, total freeboard, and snow depth, and multiply the resulting effective grid-cell thickness fields by grid-cell area to produce daily pan-Arctic volume estimates. We focus on the September–April growth season; the record begins in November 2018, so the first season covers November 2018–April 2019 and the six subsequent seasons cover September–April. An all-season extension (Petty et al., 2026), which requires a different snow loading assumption (SnowModel-LG; Liston et al., 2020), remains under development. Complementary daily gridded Arctic thin-ice thickness information ($\lesssim 0.5$ m) is obtained from a University of Bremen product that combines L-band brightness temperatures from ESA’s Soil Moisture and Ocean Salinity (SMOS) mission and NASA’s Soil Moisture Active Passive (SMAP) mission (Patilea et al., 2019).

This paper presents the resulting fused daily winter Arctic sea ice thickness and volume dataset, IS2SMGPSIT-V1. We assess its consistency against the monthly IS2SITMOGR4 (Version 4) product, provide a diagnostic comparison with CS3SMOS, the closest existing analogue to our fused product, and evaluate seasonal and sub-seasonal skill using Beaufort Gyre Exploration Project (BGEP) upward-looking sonar (ULS) ice drafts through mid-2024, extending the comparisons of Petty et al. (2023) with the 2023 deployment and with anomaly assessments that move beyond seasonal-cycle-dominated metrics. We then present the continuous daily pan-Arctic thickness and volume time series enabled by the product’s complete spatial coverage. The assessment and validation analyses are provided publicly as online interactive notebooks (<https://www.icesat-2-sea-ice-state.info>), extending the analysis that supported our previous ICESat-2 thickness assessments (Petty et al., 2023, 2026).

2 Data

2.1 ICESat-2 10 km mean along-track sea ice thickness data

We use a preliminary Version 2 update of the IS2SITDAT4 along-track sea ice thickness product, following the processing chain originally described in Petty et al. (2020) but regenerated with Release 007 ATL10 total freeboard input data (Kwok et al., 2025), redistributed NESOSIM v1.1 snow depth and density (Petty et al., 2018; Petty, 2026a) and standard additional density assumptions (ice density 916 kg m^{-3} , seawater density 1024 kg m^{-3}) as in IS2SITMOGR4-V4 (Petty et al., 2023, 2025b). The underlying ATL10 freeboard processing masks data where sea ice concentration (from passive microwave data) is below 50 %, a simple filter intended to reduce wave and sea-state contamination near the ice edge. ATL10 coverage is also reduced where clouds attenuate or obscure the laser surface return, or where too few leads are identified to establish a local sea-surface reference, as can occur within highly consolidated ice. Only short gaps between valid reference (10 km) sea surfaces are interpolated along track. More details on ATL10 processing are provided in the Release 007 sea-ice-products ATBD (Kwok et al., 2026).

The IS2SITDAT4 product provides total freeboard, snow depth, and resultant sea ice thickness at the native ATL10 sampling scale ($\sim 30 \text{ m}$ mean overlapping footprints) and as 10 km along-track means. Estimates are available from all three strong beams, which are separated by approximately 3 km across-track. We use only the 10 km along-track mean data in this study. The underlying ICESat-2 data are filtered during significant satellite manoeuvres. To date, ICESat-2 has experienced minimal downtime; the most significant gap was approximately 10 days in April 2022 following a satellite anomaly.

2.2 SMOS/SMAP thin-ice thickness

Thin-ice thickness estimates are obtained from the University of Bremen combined SMOS/SMAP Level-3 daily v300 product (Patilea et al., 2019) (<https://seaice.uni-bremen.de/data-archive/>). These data are provided on a $12.5 \text{ km} \times 12.5 \text{ km}$ NSIDC Polar Stereographic North grid, although the approximately 40 km L-band footprints of SMOS and SMAP set a coarser effective resolution. A combined thickness variable blends both sensors where available and otherwise uses a single-sensor estimate. Its maximum reported thickness is 0.5 m.

The Bremen SMOS/SMAP dataset indicates which sensor contributed to each retrieval (`flags`: 0 none; 1 SMOS-only; 2 SMAP-only; 3 both). Radio-frequency interference (RFI), contamination of L-band observations by human-generated radio emissions, primarily reduces SMOS availability over the Eastern Arctic. RFI-contaminated SMOS snapshots are screened upstream before gridding, so the delivered product carries no explicit RFI mask. Elevated frequency of `flag==2` (SMAP-only) returns over the Eastern Arctic and Barents–Kara sector is the primary result of inferred RFI-related SMOS loss, while `flag==0` and sporadic SMOS-only periods can also reflect orbital gaps, seasonal retrieval limits, or upstream outages (e.g. temporary SMAP unavailability in late 2022–early 2023 and December 2024–January 2025). Over October 2018–December 2025, dual-sensor coverage dominates overall, although SMAP-only retrievals peak in late winter–spring and no-data fractions are higher in summer–autumn (see Supplementary Figs. S1 and S2). Users should treat eastern-Arctic and

Russian-sector thin-ice fields with extra caution where the L-band constraint is frequently SMAP-only or sometimes absent
125 (Sect. 5).

2.3 CDR sea ice concentration

We use daily gridded fields from the NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration (G02202, Version 6) (Meier et al., 2026). The dataset uses the same $25\text{ km} \times 25\text{ km}$ NSIDC Polar Stereographic North grid as the fused thickness dataset. Sea ice concentration is also retained as a variable in the distributed product.

130 2.4 IS2SITMOGR4 Version 4 monthly product

For comparison, we use the monthly gridded winter Arctic sea ice thickness product IS2SITMOGR4 Version 4, available from the NSIDC (Petty et al., 2025b). This product provides monthly-mean winter Arctic thickness, total freeboard, and snow depth on the same $25\text{ km} \times 25\text{ km}$ NSIDC Polar Stereographic North grid as the CDR concentrations and the fused thickness dataset. The first season begins in November 2018, with September–April coverage in the six subsequent seasons through April 2025.

135 IS2SITMOGR4-V4 was produced using Release 007 ATL10 total freeboards with NESOSIM v1.1 snow loading and the same ice and seawater density assumptions as the along-track IS2SITDAT4 product.

2.5 CryoSat-2/Sentinel-3/SMOS v300 merged thickness

For an external satellite-product comparison, we use data from the Alfred Wegener Institute (AWI) CryoSat-2/Sentinel-3/SMOS merged sea-ice-thickness product, version 300 (CS3SMOS; obtained from the AWI data archive, accessed 4 August 2026; <https://spaces.awi.de/display/CS2SMOS>). CS3SMOS extends the CryoSat-2/SMOS optimal-interpolation framework of Ricker et al. (2017) by including Sentinel-3 altimetry and provides centred seven-day estimates on a 12.5 km EASE-Grid 2.0 grid. We use target dates of 25 October 2019 and 15 March 2020. This limited sample supports a diagnostic intercomparison, rather than a full seasonal assessment which we expect to be undertaken in future efforts.

2.6 BGEP ULS ice drafts

145 The Beaufort Gyre Exploration Project (BGEP) provides upward-looking sonar (ULS) ice draft estimates from three moorings (A, B, and D) deployed across the Beaufort Sea (Krishfield et al., 2014). These data provide an independent validation record commonly used for satellite-derived sea ice thickness estimates (Nab et al., 2024; Petty et al., 2023, 2026; Landy et al., 2022). Individual ULS draft measurements have an assumed constant uncertainty of 10 cm. Including the 2023 mooring deployment, the record used here spans November 2018–April 2024 and covers the first six growth seasons coincident with ICESat-2.

150 2.7 Ancillary data

Grid-cell areas are obtained from the NSIDC Polar Stereographic Ancillary Grid Information 25 km cell-area product (NSIDC-0771, Version 1) (Stewart et al., 2022). Regional analyses use the NSIDC Arctic Ocean region mask (NSIDC-0780, Version 1) (National Snow and Ice Data Center, 2021).

3 Methods

155 3.1 Input preprocessing and fusion

The following preprocessing choices were applied to the input training data:

ICESat-2 input selection: We use the 10 km along-track means of the V2 IS2SITDAT4 product from all three strong beams. This retains substantially more spatial information than the monthly gridded product while avoiding the computational cost and limited expected benefit of native-scale ATL10 input at a 25 km output grid spacing.

160 **SMOS/SMAP preprocessing:** We use the combined thickness variable from the University of Bremen SMOS/SMAP Level-3 daily v300 product across the Arctic Ocean and subsample the 12.5 km source grid by a factor of 4 in each direction, giving approximately 50 km training-point spacing. This limits computational cost and avoids over-representing the densely sampled thin-ice domain relative to the sparser ICESat-2 tracks. The source product is capped at 0.5 m, and we apply no additional thickness mask. Retrievals within 100 km of a coastline are discarded. Nearshore values frequently
165 showed spatially incoherent patterns consistent with land contamination of the L-band footprint. The 100 km threshold exceeds the approximate 40 km footprint and prevents these values from propagating thin biases into coastal predictions.

ICESat-2 preference: Where ICESat-2 and SMOS/SMAP observations occur within 10 km of one another, the SMOS/SMAP retrieval is discarded to avoid double-counting and favour the altimetric estimate which we expect to be more accurate.

SIC pseudo-observations: Where SIC is below 0.15, pseudo-observations of zero freeboard and snow depth constrain interpolation at the ice edge and reduce extrapolation into open water. This treatment is not applied to thickness in the
170 production dataset. The CDR sea ice concentration data are subsampled by a factor of 2 when used for this purpose.

3.2 Gaussian process regression and the GPSat framework

To produce our fused/interpolated dataset we use GPSat (Gregory et al., 2024), an open-source Python package designed for scalable interpolation of satellite altimetry data (<https://github.com/CPOMUCL/GPSat>). GPSat acts as a flexible frame-
175 work that wraps established GP libraries, supporting GPflow (Matthews et al., 2017), which runs on TensorFlow and enables GPU-accelerated computation via CUDA, and GPyTorch as alternative backends. It also supports a range of GP model types, including exact GP regression and sparse approximations. In this study we use the default GPflow backend with sparse GP regression (SGPR) as the underlying model, running only on CPUs as described below.

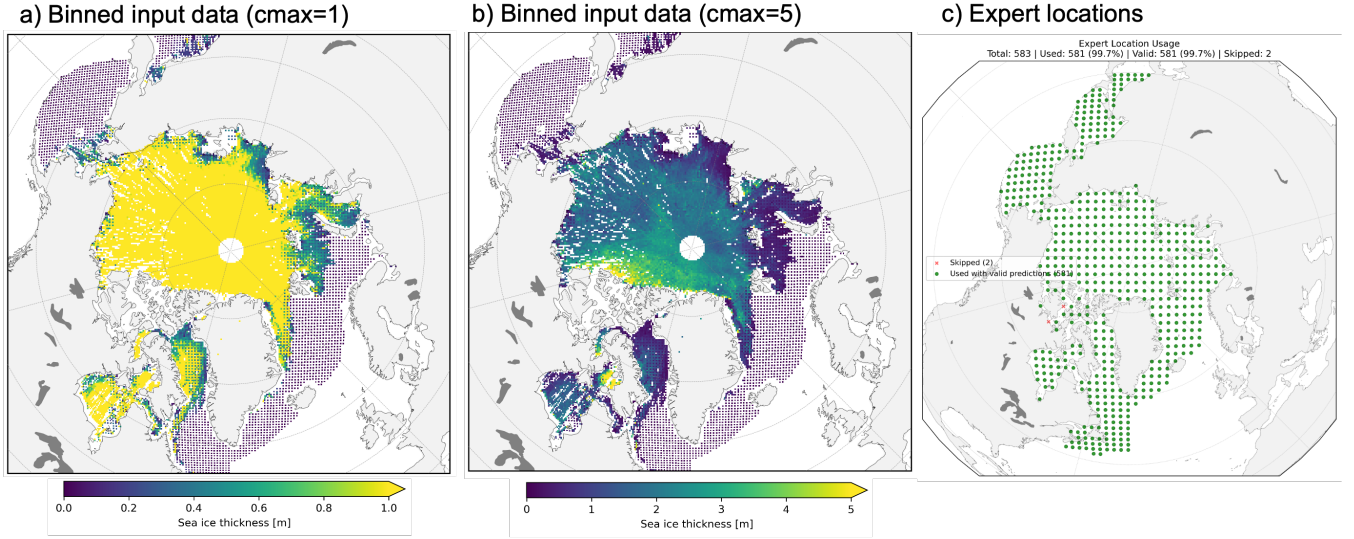


Figure 1. Binned ICESat-2 along-track sea ice thickness (10 km segments) and SMOS/SMAP thin-ice thickness (coarsened $\times 4$) within ± 30 days of 15 March 2020. (a) Colour scale 0–1 m. (b) Colour scale 0–5 m. (c) Local expert grid: valid prediction (green), skipped expert (red cross).

Applying a single GP to the entire Arctic domain is computationally intractable. GPSat instead uses overlapping local experts: individual GPs centred on a prescribed grid. The expert spacing Δ_{expert} controls the distance between their centres. Each expert selects observations within a spatial training radius R_{train} and temporal half-window N_{days} , then predicts output cells within an inference radius R_{infer} . Predictions from neighbouring experts are combined using Gaussian weights governed by the blending length scale ℓ_w . Figure 2 illustrates the configuration, and Table 1 gives the parameter values used for production. This local-expert strategy, together with the monthly hyperparameter reuse described below, makes daily pan-Arctic production computationally feasible.

GPSat uses a zero-mean GP prior, whereas absolute sea ice thickness has a strongly spatially varying background mean. We therefore subtract the local sample mean from each expert’s training observations before optimisation, preventing the background thickness gradient from dominating the covariance fit. The mean is added back to the posterior prediction before neighbouring experts are blended, while the posterior variance is unchanged. Consequently, the kernel variance σ_f^2 controls the amplitude of correlated variation in the latent field f about the expert mean, whereas the likelihood variance σ_n^2 represents uncorrelated residual variation, including measurement error, sub-grid-scale variability, and other representativeness differences. Further mathematical details are provided by Gregory et al. (2024) and in the GPSat documentation (<https://cpomucl.github.io/GPSat/>).

Standard GP inference scales as $\mathcal{O}(n^3)$ in the number of training observations n , which is computationally infeasible given current hardware for the tens of thousands of ICESat-2 segments within a typical expert’s training window. SGPR reduces this to $\mathcal{O}(nm^2)$ by introducing $m \ll n$ inducing points (a small set of pseudo-input locations that summarise the training data

Table 1. GPSat settings used to generate IS2SMGPSIT-V1.

Parameter	Setting
<i>Expert grid and data selection</i>	
Expert spacing (Δ_{expert})	200 km
Training radius (R_{train})	400 km
Inference radius (R_{infer})	500 km
Blending lengthscale (ℓ_w)	250 km
Temporal half-window (N_{days})	30 days
Output grid spacing	25 km
<i>GP model</i>	
Model type	SGPR
Kernel	Matérn-3/2 (ARD)
Inducing points per expert (M)	500
Coordinate scaling (s_x, s_y, s_t)	25 km, 25 km, 1 day
Initial likelihood variance (σ_n^2)	0.09
Jitter (diagonal regularisation)	10^{-3}
Optimiser	L-BFGS-B
Max iterations	10,000
Demeaning	Per-expert demeaning
<i>Hyperparameter smoothing</i>	
Smoothing lengthscale in x/y (ℓ_{smooth})	300 km

and through which all predictions are routed) (Titsias, 2009). The inducing point locations and kernel hyperparameters are optimised jointly by maximising the evidence lower bound (ELBO) on the log marginal likelihood.

We use the default Matérn-3/2 covariance kernel with automatic relevance determination (separate spatial and temporal lengthscales) with up to $M = 500$ inducing points per local expert. To test whether the Matérn smoothness class materially controls the fine-scale structure of the output, we reran the training and inference pipeline for selected dates with an otherwise identical configuration except that the covariance kernel was changed from Matérn-3/2 to Matérn-1/2, which admits rougher, non-differentiable sample paths. For each run we compared gridded thickness and posterior uncertainty, the smoothed GP hyperparameters on the expert grid, and a five-point $|\nabla^2 \text{SIT}|$ as a fine-scale roughness proxy (Supplementary Figs. S3 and S4). Hyperparameter optimisation largely compensated for the change in kernel: Matérn-1/2 converged to longer spatiotemporal lengthscales and a smaller kernel variance, with little change in the likelihood variance. The resulting thickness fields differed only modestly from Matérn-3/2 and were not systematically rougher by the $|\nabla^2 \text{SIT}|$ proxy. We therefore retained Matérn-3/2 for the production runs.

The remaining configuration parameters summarised in Table 1 were determined through a combination of manual tuning and inspection of GP outputs. Choices such as the expert grid spacing (Δ_{expert}), jitter, and number of inducing points (M)

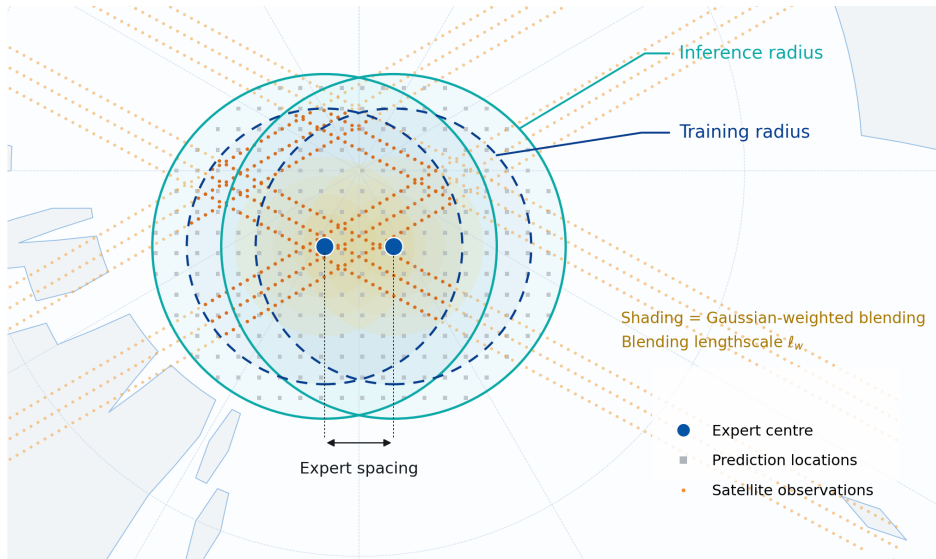


Figure 2. Schematic of the GPSat training and inference configuration.

were set manually based on output assessments, computational cost, and numerical stability across a range of test dates and regions. The temporal training half-window ($N_{\text{days}} = 30$ days) was selected empirically to provide sufficient observations for a well-posed fit at every expert and target date at acceptable computational cost. The temporal lengthscales ℓ_t fitted under this configuration are of a similar order (Fig. 3), but are not independent evidence for the window choice because they are estimated
215 from data already restricted by that window. The implications for resolved temporal variability and priorities for systematic window-length testing are discussed in Sect. 5.

3.3 GP training, inference and output

Kernel hyperparameters ($\ell_x, \ell_y, \ell_t, \sigma_f^2, \sigma_n^2$) are optimised by maximising the evidence lower bound on the log marginal likelihood using training data within $\pm N_{\text{days}}$ days of the middle of each month. The resulting per-expert hyperparameters are
220 then spatially smoothed (smoothing lengthscale ℓ_{smooth} ; Table 1) to remove noisy artefacts from individual expert fits, and the smoothed values are reused for all other days in that calendar month without re-optimisation. This monthly hyperparameter reuse approach reduces computation substantially while preserving the large-scale spatial structure of the covariance. Fig. 3 shows the spatially smoothed GP kernel hyperparameters for 15 February 2019 (± 30 days), a representative mid-winter date. An early-season (15 October 2019) example is provided in Supplementary Fig. S5.

225 While GPSat has been optimised to exploit GPU acceleration (Gregory et al., 2024), all production runs in this study used CPU-only SLURM jobs (TensorFlow with GPU disabled). Using eight CPU cores, mid-month hyperparameter optimisation typically required 2.5–4.5 h and 8–10 GB of memory, with end-to-end production taking approximately 4–5 h. Prediction-only runs using the smoothed hyperparameters completed in tens of minutes.

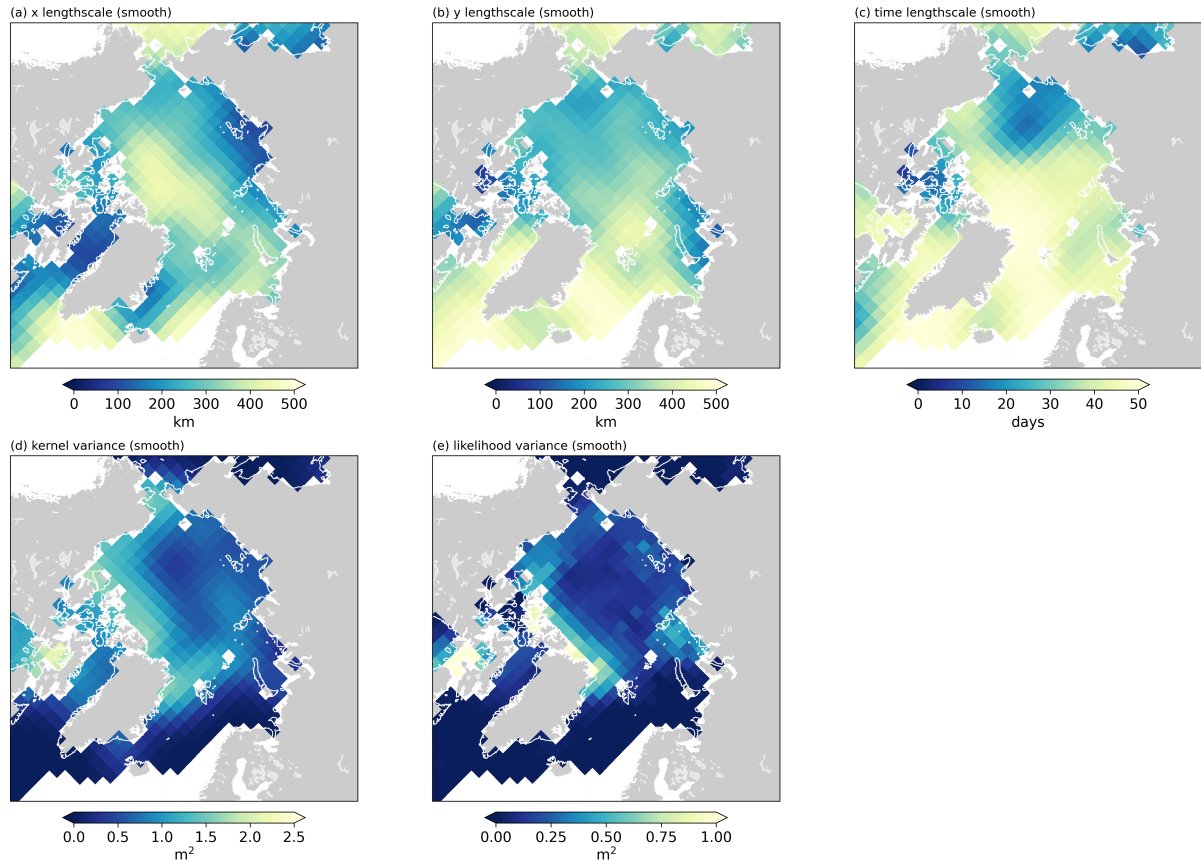


Figure 3. Smoothed GP kernel hyperparameters for 15 February 2019 (± 30 -day training window): ℓ_x , ℓ_y (km); ℓ_t (days); σ_f^2 ; σ_n^2 . Spatial smoothing lengthscale 300 km.

Inference was performed daily across the full 25 km output grid for each day from 1 September through 30 April, except
 230 in the initial 2018–2019 season, which begins on 1 November 2018. This included the Canadian Arctic Archipelago (CAA; NSIDC region 12), but we treat these predictions with caution as its narrow, complex waterways are poorly represented by the 25 km output grid and current local-expert configuration. The accompanying σ_* uncertainty output (shown later) highlights the lower confidence in this region. We prefer to include these values as a baseline for future work. Adaptive expert placement may
 235 guarantee improved representation of steep gradients. For the same reason we exclude the CAA from all basin-scale diagnostics presented below: it is present in the distributed gridded fields and shown in the thickness maps, but is not included in the inner Arctic or pan-Arctic thickness or volume time series.

The resulting dataset provides daily 25 km $\times$ 25 km gridded fields of sea ice thickness, total freeboard and snow depth, each representing the grid-cell-mean value averaged over both ice-covered and open-water fractions (i.e. an effective area-mean
 240 rather than an ice-only estimate). Dividing any of these fields by the co-located daily CDR sea ice concentration yields an

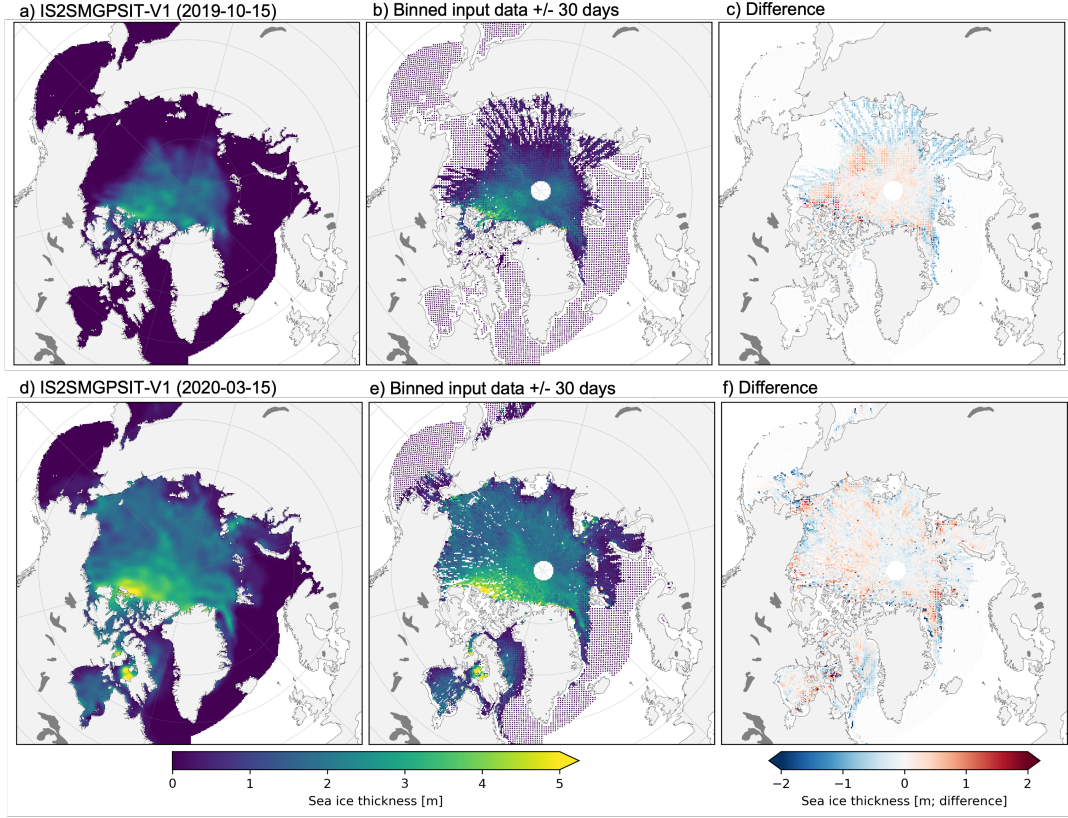


Figure 4. IS2SMGPSIT-V1 output mean sea ice thickness (left), training-window binned observations (centre), and difference (right) for (a–c) 15 October 2019 and (d–f) 15 March 2020.

estimate of the corresponding ice-only value, though this should be treated with caution at low concentrations. The GP posterior standard deviation (σ_*) is provided for all three variables (thickness, freeboard and snow depth). It is the square root of the marginal posterior variance of the latent interpolated field and describes uncertainty in the GP interpolation under the chosen input data and model configuration. It does not include all possible errors in the input retrievals or in the assumptions used to derive sea ice thickness, and should therefore not be interpreted as a complete thickness uncertainty estimate. The dataset also includes sea ice volume per grid cell (thickness $\times$ cell area) and the co-located CDR sea ice concentration. Because the GP training window extends $\pm N_{\text{days}}$ days from each target date, estimates in September and April, which sit at the edges of the seasonal window with observations available on only one side, should be treated with greater caution than mid-season months.

As part of our processing tests we compared the GP output with the binned training-window observations and their difference for every processed month; representative October and March examples are shown in Fig. 4. We found no obvious anomalous spatial patterns in these monthly comparisons, which increased confidence that the input preprocessing and selected GP parameter configuration were producing spatially coherent output fields across the entire time-series.

4 Results

4.1 Data output and comparisons with IS2SITMOGR4

255 Figures 5 and 6 compare monthly-mean sea ice thickness, total freeboard, and snow depth from IS2SMGPSIT-V1 and IS2SITMOGR4-V4 for October 2019 and March 2020. We use the interpolated/smoothed IS2SITMOGR4-V4 fields and calculate the IS2SMGPSIT-V1 fields as arithmetic means of all available daily outputs within each calendar month. The fused product successfully removes the orbit-track aliasing visible in the March 2020 IS2SITMOGR4-V4 composites. Equal weighting of all within-month observations in IS2SITMOGR4-V4 imprints track-aligned sampling discontinuities on the gridded fields, whereas conditioning on acquisition time through the GP spatiotemporal kernel produces smooth, gap-free IS2SMGPSIT-V1 fields.

260 IS2SMGPSIT-V1 is also generally thinner in thickness, freeboard, and snow depth towards the ice margins, with similar patterns in other months (not shown). Near the edge of valid IS2SITMOGR4-V4 coverage, linear interpolation and smoothing can produce locally elevated values where only a few along-track segments constrain the field. The SMOS/SMAP thin-ice estimates and SIC pseudo-observations (Sect. 3.1) reduce these edge artefacts and produce a smoother transition across the marginal ice zone.

Coverage also improves during early-fall freeze-up (September–November), when IS2SITMOGR4-V4 often contains large spatial gaps within a single monthly bin. The GP training window and SMOS/SMAP fusion (Sects. 3.1–3.3) provide continuous fields from the onset of freeze-up (Fig. 5).

270 Figure 7 shows the monthly mean of the daily GP ice-thickness posterior standard deviation for October 2019, March 2020, and also March 2021. As discussed earlier, this field represents the GP interpolation uncertainty at each grid cell, conditional on the available observations and model configuration, rather than a complete estimate of sea ice thickness uncertainty. These values summarise the daily grid-cell uncertainties within each given month. Values are generally lower across much of the peripheral Arctic, where SMOS/SMAP provides extensive thin-ice information, and higher over the central ice pack, where the interpolation relies more strongly on the available ICESat-2 tracks. The more significant increases occur within the CAA and along several coastal regions, particularly in the March examples. March 2021 also shows elevated uncertainty along parts of the eastern Arctic coast, where the filtering of SMOS/SMAP data can reduce the available thin-ice constraints.

4.2 BGEP ULS validation across temporal scales

4.2.1 Monthly comparisons

280 Figure 8 compares monthly mean ice drafts from IS2SITMOGR4-V4 and monthly-resampled IS2SMGPSIT-V1 with coincident BGEP ULS measurements at moorings A, B, and D. We first average the raw ULS observations to daily means and calculate satellite-derived ice draft as thickness minus total freeboard plus snow depth. Following Petty et al. (2023, 2026), the satellite value at each mooring is the mean of all valid grid cells within 100 km; Petty et al. (2023) found little sensitivity to alternative radii.

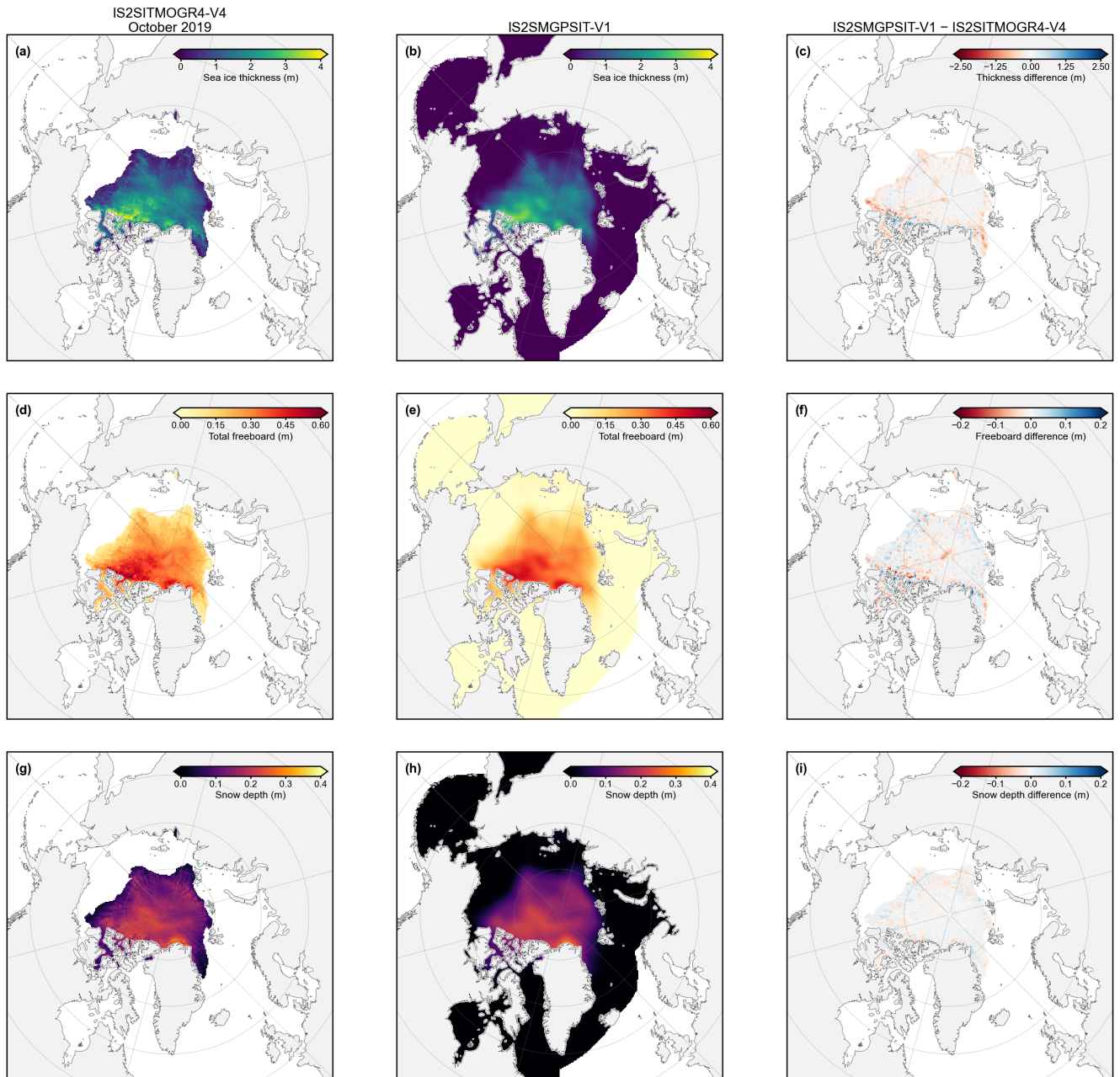


Figure 5. October 2019 monthly-mean comparison maps for sea ice thickness (top row), total freeboard (middle row), and snow depth (bottom row), each in metres. Within each row: IS2SITMOGR4-V4 monthly mean (left); IS2SMGPSIT-V1 calendar-month mean of daily outputs (centre); difference IS2SMGPSIT-V1 – IS2SITMOGR4-V4 (right).

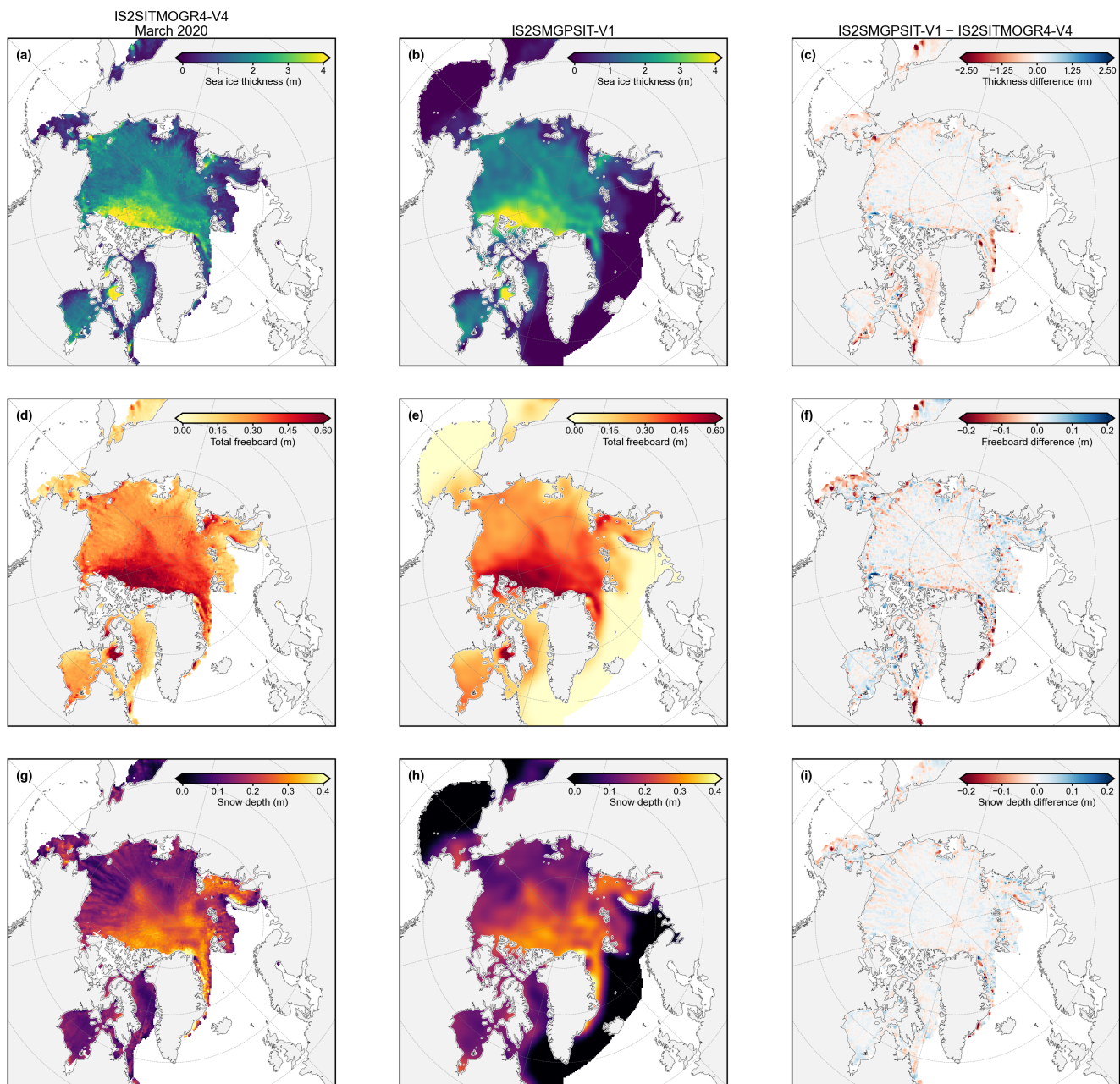


Figure 6. As in Fig. 5 but for the March 2020 monthly means, showing sea ice thickness (top row), total freeboard (middle row), and snow depth (bottom row).

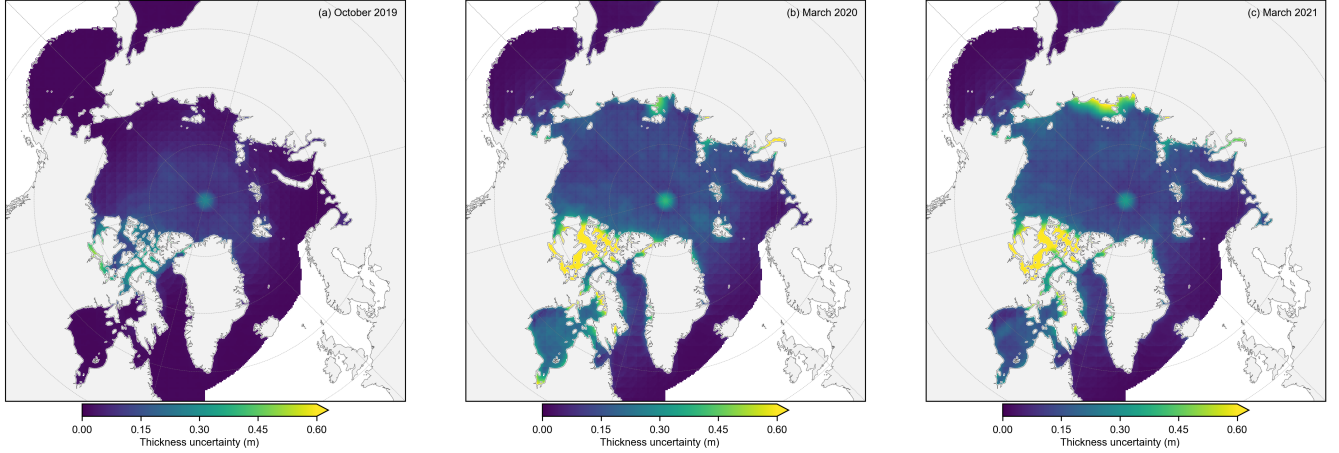


Figure 7. Monthly mean of daily IS2SMGPSIT-V1 ice-thickness posterior standard deviation (m) for (a) October 2019, (b) March 2020, and (c) March 2021. These are means of the daily posterior standard deviations, not uncertainties of monthly-mean fields. The colour scale is limited to 0.6 m for consistency across panels.

We obtain the monthly values by assigning the collocated daily ULS and satellite series to calendar-month bins and taking the mean. Monthly anomalies are calculated separately at each mooring by subtracting the corresponding multi-season calendar-month mean. Relative to IS2SITMOGR4-V4, IS2SMGPSIT-V1 has higher pooled agreement ($r^2 = 0.91$ versus 0.83), lower RMSE (0.19 versus 0.24 m), and a lower mean bias (0.01 versus 0.10 m). It also provides more valid collocations (140 versus 130 mooring-months) because of its more complete spatial coverage. The largest visual improvement is for thin ice (draft $\lesssim 0.3$ m), consistent with the benefits of added SMOS/SMAP data constraint. After removing the climatological seasonal cycle, skill is substantially lower but remains slightly higher for IS2SMGPSIT-V1 than IS2SITMOGR4-V4 ($r^2 = 0.42$ versus 0.36; RMSE 0.16 versus 0.17 m). This reduction confirms that the high full-signal correlations are dominated by the seasonal growth cycle; Sect. 4.2.2 examines the anomaly skill further.

4.2.2 Daily de-seasonal anomaly comparisons

For daily comparisons, we subtract the multi-season day-of-year mean separately at each mooring. These anomalies remove the climatological seasonal cycle but retain both interannual departures from the mean seasonal evolution and variability within individual growth seasons; they should therefore not be interpreted as purely sub-seasonal anomalies. The resulting time series (Supplementary Fig. S6) show that IS2SMGPSIT-V1 captures broad, low-frequency variations but damps higher-frequency variability. Its anomaly standard deviation is only 64–76 % of that observed by the ULS moorings (0.19 versus 0.29 m at A, 0.18 versus 0.23 m at B, and 0.26 versus 0.36 m at D).

Figure 9 compares daily ULS observations with the nearest monthly IS2SITMOGR4-V4 field, the nearest monthly-resampled IS2SMGPSIT-V1 field, and the matched daily IS2SMGPSIT-V1 field. For the full signal, daily and monthly-resampled IS2SMGPSIT-V1 perform similarly ($r^2 = 0.76$ and 0.75, respectively; RMSE = 0.33 m for both), compared with $r^2 = 0.66$ and RMSE

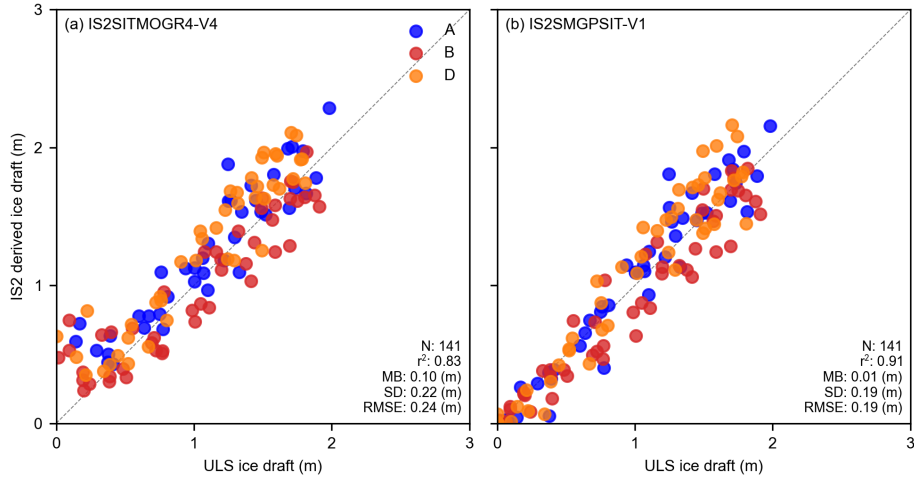


Figure 8. Monthly mean satellite-derived ice draft versus BGEF ULS ice draft at moorings A (blue), B (red), and D (orange); dashed line shows 1:1. (a) IS2SITMOGR4-V4; (b) IS2SMGPSIT-V1 monthly-resampled.

$= 0.37$ m for IS2SITMOGR4-V4. After removing the seasonal cycle, correlations are weak and nearly identical for daily and monthly-resampled IS2SMGPSIT-V1 ($r^2 = 0.15$), with IS2SITMOGR4-V4 only slightly lower ($r^2 = 0.12$); anomaly RMSEs are 0.28–0.30 m. The absence of additional skill in daily IS2SMGPSIT-V1 indicates that this configuration has limited ability to resolve synoptic variability. This is consistent with the month-scale temporal lengthscales in our fitted hyperparameters ($\ell_t \approx 35$ –45 days; Fig. 3), although these should not be interpreted as physical ice-memory timescales given our windowing choices.

To further assess sensitivity to temporal averaging, we assign observations to consecutive, non-overlapping windows of 1, 5, 10, 15, 20, and 30 days and calculate their arithmetic means. We first calculate daily day-of-year anomalies and then aggregate them, keeping the anomaly definition fixed across window lengths. Across these windows, the monthly-only IS2SITMOGR4-V4 record shows a near-parallel improvement despite containing no sub-monthly information: anomaly r^2 rises from 0.15 to 0.38 for IS2SMGPSIT-V1 and from 0.12 to 0.34 for IS2SITMOGR4-V4, while anomaly RMSE falls from 0.29 to 0.16 m and from 0.30 to 0.17 m, respectively (Fig. 10).

Because a monthly product cannot contain real sub-monthly skill, this joint improvement indicates that most of the apparent gain through averaging arises because temporal averaging suppresses high-frequency, local variability in the ULS record that neither product resolves, increasing the correlation without any change in the underlying satellite-derived signal. The modest and roughly constant offset between the two products at every averaging window ($\Delta r^2 \approx 0.03$ –0.06) is the more meaningful quantity and likely reflects the additional thin-ice information and the conditioning on observation timing in IS2SMGPSIT-V1, although other differences between the products may also contribute.

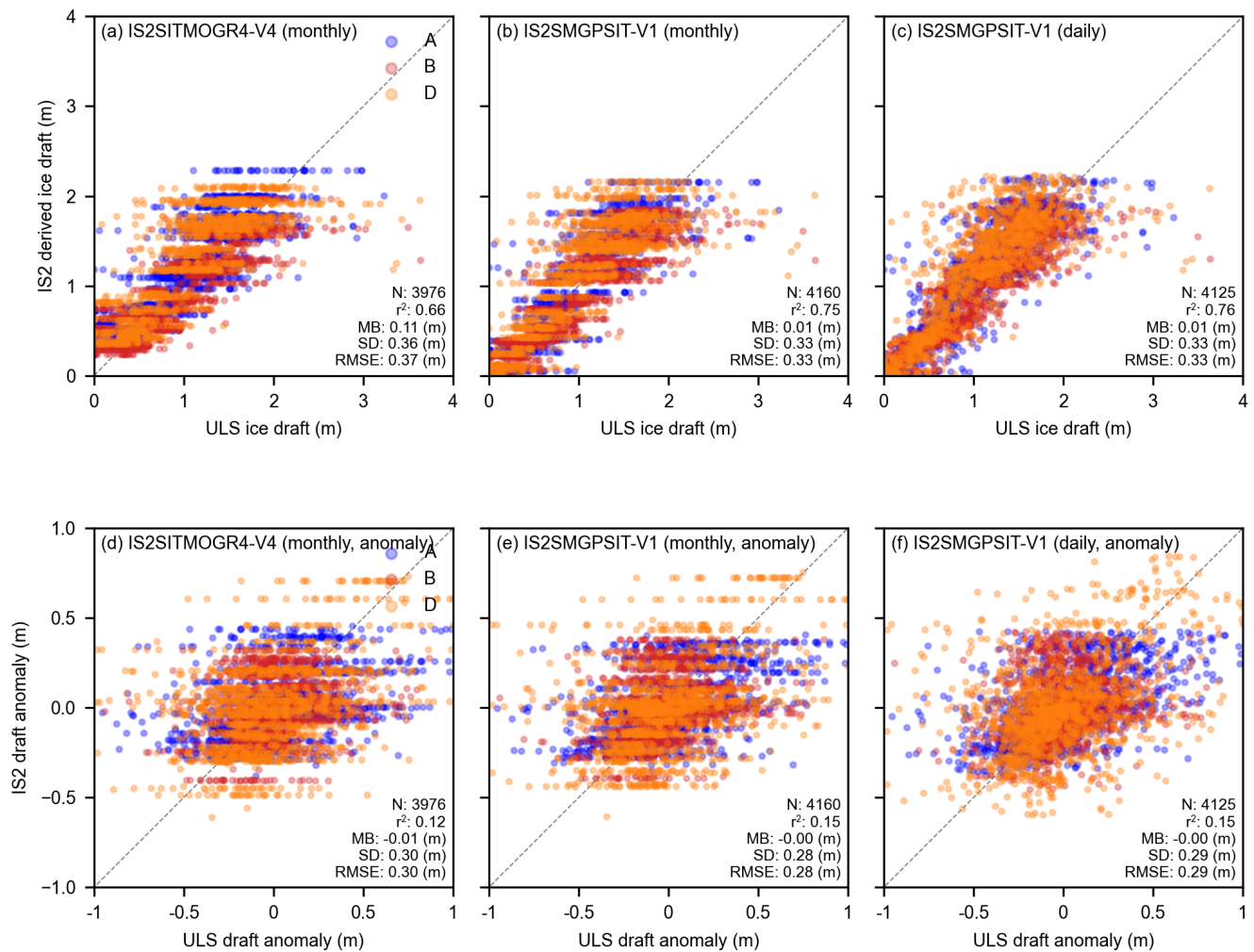


Figure 9. Daily satellite-derived ice draft versus BGEF ULS ice draft. Top row shows comparisons retaining the full seasonal signal for (a) IS2SITMOGR4-V4 monthly (nearest month), (b) IS2SMGPSIT-V1 monthly-resampled (nearest month), and (c) IS2SMGPSIT-V1 daily (matched date); moorings coloured as in Fig. 8. Bottom row shows the same comparisons after removing the climatological seasonal cycle.

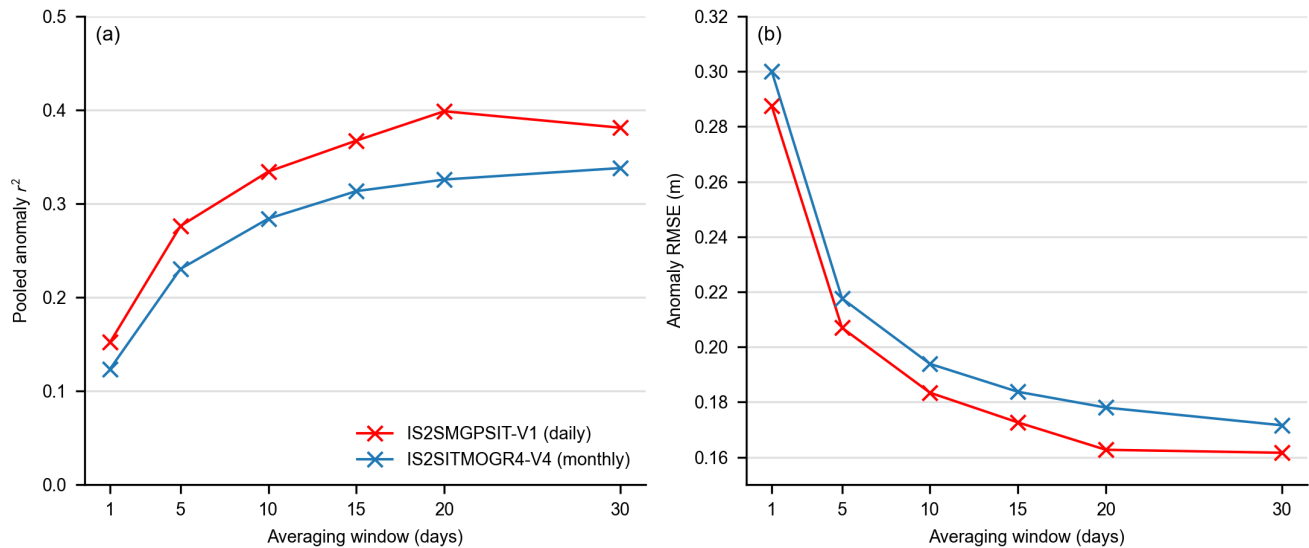


Figure 10. BGEF ULS draft anomaly skill as a function of the temporal averaging window (moorings A, B and D pooled). (a) pooled anomaly r^2 ; (b) anomaly RMSE (m). Red: IS2SMGPSIT-V1 daily; blue: IS2SITMOGR4-V4 monthly (control). A single anomaly definition (daily day-of-year anomalies) is used throughout, with only the averaging window varied, so the seasonal removal is identical at every window. The monthly-only IS2SITMOGR4-V4 control cannot by construction contain real sub-monthly skill, yet improves in near-parallel with the daily fused product, indicating that most of the gain with averaging reflects the suppression of high-frequency variability unresolved by either product, rather than genuine sub-monthly skill.

4.3 Thickness and volume time series

4.3.1 Inner-Arctic-Ocean thickness

Figure 11 compares monthly mean thickness, total freeboard, and snow depth over the inner Arctic Ocean (IAO) domain, defined here as NSIDC regions 1–5: the Central Arctic, Beaufort Sea, Chukchi Sea, East Siberian Sea, and Laptev Sea. This matches the NOAA Arctic Report Card thickness domain (Meier et al., 2024) and excludes the more marginal Kara and Barents Seas included in some previous definitions (Petty et al., 2023). IS2SITMOGR4-V4 and IS2SMGPSIT-V1 are evaluated over their common grid-cell extent, with the full-IAO IS2SMGPSIT-V1 mean also shown. From November onwards, the common-grid-cell extent thickness estimates generally differ by less than 10 cm, indicating no large mean offset between the products. Differences are greatest in September and October, when IS2SITMOGR4-V4 is either unavailable or preferentially samples the more consolidated portion of the pack. The common-grid-cell extent IS2SMGPSIT-V1 estimates show similar positive biases, indicating the role of sampling in driving this bias. Full-coverage IS2SMGPSIT-V1 represents the complete IAO through freeze-up and shows more plausible low (50–80 cm) thicknesses in September and October that then increase smoothly towards the March–April seasonal maximum.

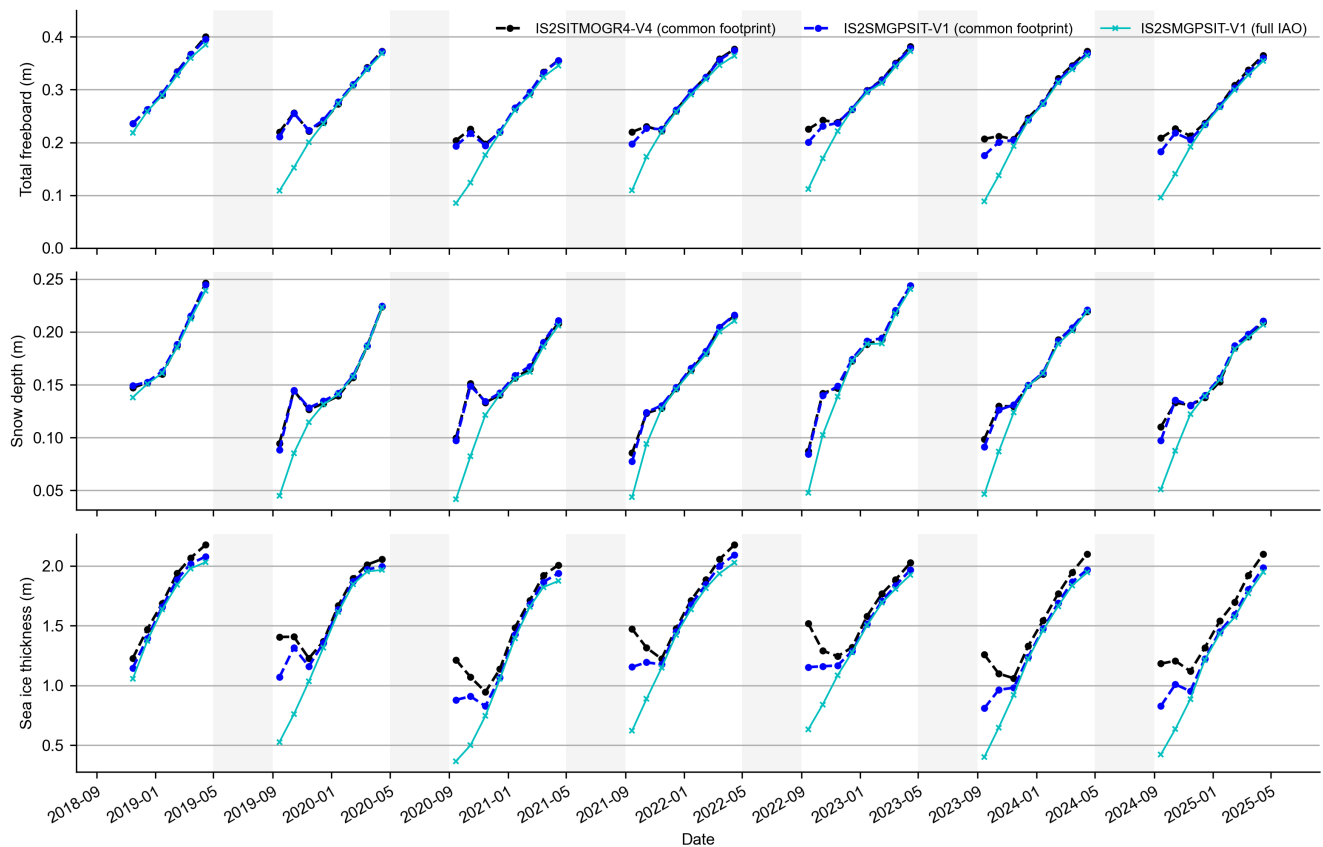


Figure 11. Monthly means over the inner Arctic Ocean (IAO) domain (November 2018–April 2025) of: (top) total freeboard; (middle) snow depth; (bottom) sea ice thickness. IS2SITMOGR4-V4 and IS2SMGPSIT-V1 evaluated over their common monthly footprint (black and blue circles, respectively); IS2SMGPSIT-V1 over the full IAO domain (cyan crosses). May–August melt season shaded.

Figure 12a shows the IAO mean IS2SMGPSIT-V1 daily thickness time series for all seven growth seasons, with monthly means overlaid to more clearly visualise the full IS2SMGPSIT-V1 daily thickness time series. The initial 2018–2019 season begins in November; the six subsequent seasons include the complete September–April period. In those six seasons, IAO mean thickness rises smoothly from 0.4–0.6 m in September and 0.5–0.9 m in October to a March–April peak of 1.8–2.0 m. Interannual variability is dominated by two contrasting growth seasons: 2020–2021 is the thinnest in this record, with monthly-mean deficits of up to -0.23 m sustained from September through January, while the following 2021–2022 season shows the thickest ice, with positive anomalies of up to $+0.18$ m persisting from freeze-up through midwinter. The anomalously low 2020–2021 thickness is consistent with earlier ICESat-2 and joint ICESat-2–CryoSat-2 assessments and the NOAA Arctic Report Card, which also identified notably thin ice across the Inner Arctic Ocean during this winter (Meier et al., 2021; Kacimi and Kwok, 2022; Petty et al., 2023). The remaining winter seasons show thicknesses closer to climatology: 2018–2019 and 2019–2020 are slightly above, and the two most recent winters slightly below. Figure 12b shows the corresponding daily

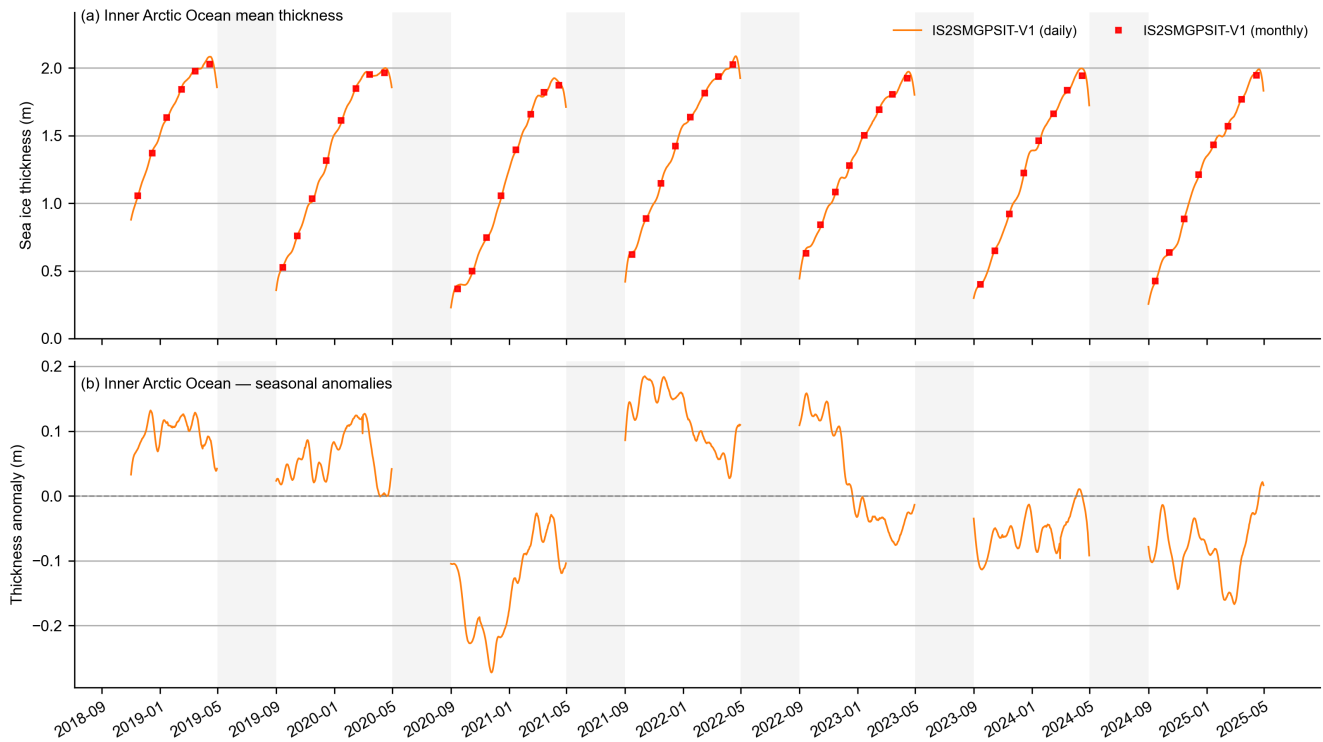


Figure 12. Mean sea ice thickness over the inner Arctic Ocean (IAO) domain across seven growth seasons. The first begins in November 2018; the subsequent six span September–April through April 2025. (a) IS2SMGPSIT-V1 daily means with monthly markers. (b) IS2SMGPSIT-V1 daily thickness anomalies (climatology removed). May–August shaded to indicate no data.

anomalies (seasonal climatology removed) to more clearly highlight the winter differences, which show positive and negative anomalies of up to ± 0.2 – 0.3 m at their extremes, again dominated by the 2020–2021 negative anomaly.

The corresponding pan-Arctic spatial patterns are shown in Fig. 13. November–April winter-mean thickness is computed as the mean of the monthly-mean IS2SMGPSIT-V1 fields for each of the seven growth seasons (2018–2019 through 2024–2025). Absolute winter means (Fig. 13a) show the expected thick multi-year ice north of Greenland and the Canadian Arctic Archipelago, with thinner seasonal ice elsewhere, and gap-free coverage in all winters. Anomalies relative to the seven-winter mean (Fig. 13b) show that the 2020–2021 thinning was widespread across the Inner Arctic Ocean, whereas the 2021–2022 positive anomalies were more regionally confined, largely overlapping the sector that was anomalously thin the previous winter. The spatial pattern of anomalies otherwise differs substantially across even this relatively short period, highlighting the complex interannual variability of winter Arctic sea ice. Equivalent total freeboard and snow depth winter means and anomalies are provided in Supplementary Figs. S7–S10.

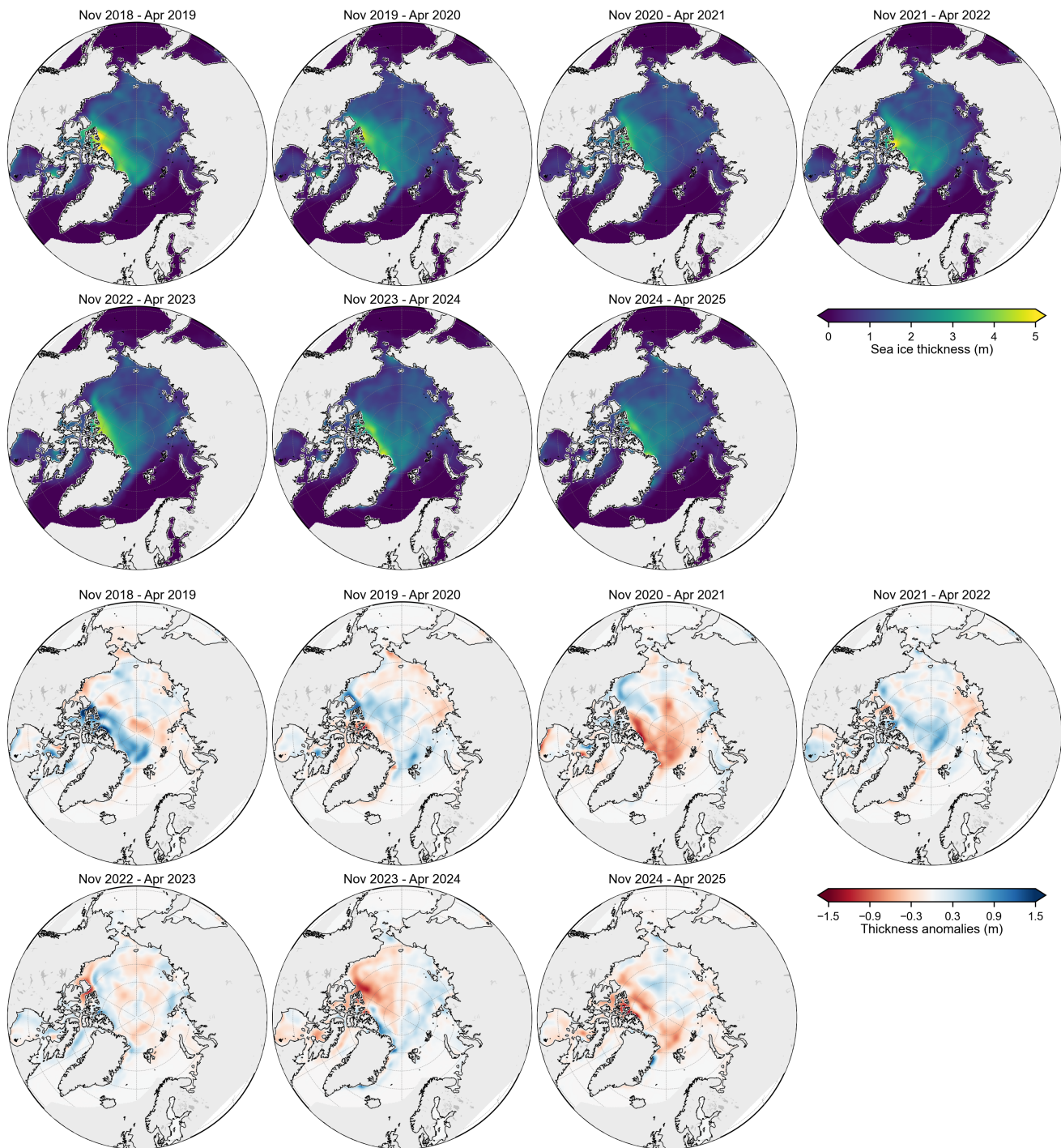


Figure 13. IS2SMGPSIT-V1 November–April winter-mean sea ice thickness for winters 2018–2019 through 2024–2025, computed from monthly-resampled daily fields. (a) Winter-mean thickness (m). (b) Winter-mean thickness anomalies (m) relative to the seven-winter mean.

4.3.2 Diagnostic comparison with CS3SMOS v300

To provide a brief diagnostic comparison with the existing fused Arctic sea ice thickness dataset, we here compare IS2SMGPSIT-V1 with equivalent CS3SMOS data. We pair the CS3SMOS field with the centred seven-day mean of IS2SMGPSIT-V1 and retain all nominal-status CS3SMOS retrievals (from the four valid quality classes) and multiply its ice-only thickness estimates
360 by the supplied sea ice concentration to obtain an effective grid-cell mean thickness. We regrid the CS3SMOS data to the nearest IS2SMGPSIT-V1 grid-cell centre within 20 km and average using ocean-fraction weights. The CS3SMOS data filter all estimates with low sea ice concentration, so the IS2SMGPSIT-V1 fields show more extensive coverage, particularly in October.

The two datasets across just these two months show good agreement in the broad spatial thickness pattern (Fig. 14), with spatial correlations of $r = 0.91$ on 25 October 2019 and $r = 0.83$ on 15 March 2020 (scatter comparison in Supplementary
365 Fig. S11). Both products reproduce the expected thicker ice north of the Canadian Arctic Archipelago and Greenland and thinner ice towards the marginal seas, although the difference maps show large positive and negative differences and more extensive IS2SMGPSIT-V1 coverage, particularly in October, due to the concentration filtering in the CS3SMOS data. Because only two target dates are available here, this comparison is diagnostic and should not be interpreted as evidence of consistent product differences, but instead highlights the need for further intercomparisons that we discuss later.

370 4.3.3 Pan-Arctic sea ice volume

Our spatially complete daily IS2SMGPSIT-V1 thickness data enable production of a continuous pan-Arctic sea ice volume time series. We calculate volume here as $V = \sum_i h_i A_i$, where h_i is effective grid-cell-mean thickness and A_i is the grid-cell area. Because sea ice concentration is already embedded in h_i , we apply no additional concentration weighting. The CAA is retained in the distributed gridded dataset but excluded here from the volume totals because of its high GP posterior uncertainty
375 (Sect. 3.3). Figure 15a shows the pan-Arctic (CAA-excluded) and IAO daily volume series, with monthly means overlaid.

Pan-Arctic sea ice volume increases from $\sim 2.9\text{--}6.7 \times 10^3 \text{ km}^3$ during freeze-up in September–October to a March–April peak of $\sim 16.6\text{--}18.8 \times 10^3 \text{ km}^3$, broadly consistent with previous estimates from satellite altimetry (Kwok, 2018). The IAO accounts for $\sim 75\%$ of pan-Arctic volume at the late-winter peak and $\sim 90\%$ during freeze-up, when little ice exists outside the inner Arctic. The daily de-seasonalised volume anomalies (Fig. 15b) show the same two contrasting growth seasons identified
380 in the IAO thickness record: persistent negative anomalies from September through January in 2020–2021 (largest pan-Arctic monthly-mean deficit -1880 km^3 in November 2020) and sustained positive anomalies from October through December in 2021–2022 (up to $+1250 \text{ km}^3$). The two most recent winters are again negative, with pan-Arctic monthly-mean deficits reaching -1640 km^3 in February 2025, similar to the lows observed in the 2020–2021 winter. The IAO anomalies track the pan-Arctic values closely but with smaller amplitudes, indicating that the Kara, Barents, and other peripheral seas outside the
385 IAO domain also contribute appreciably to the interannual volume signal.

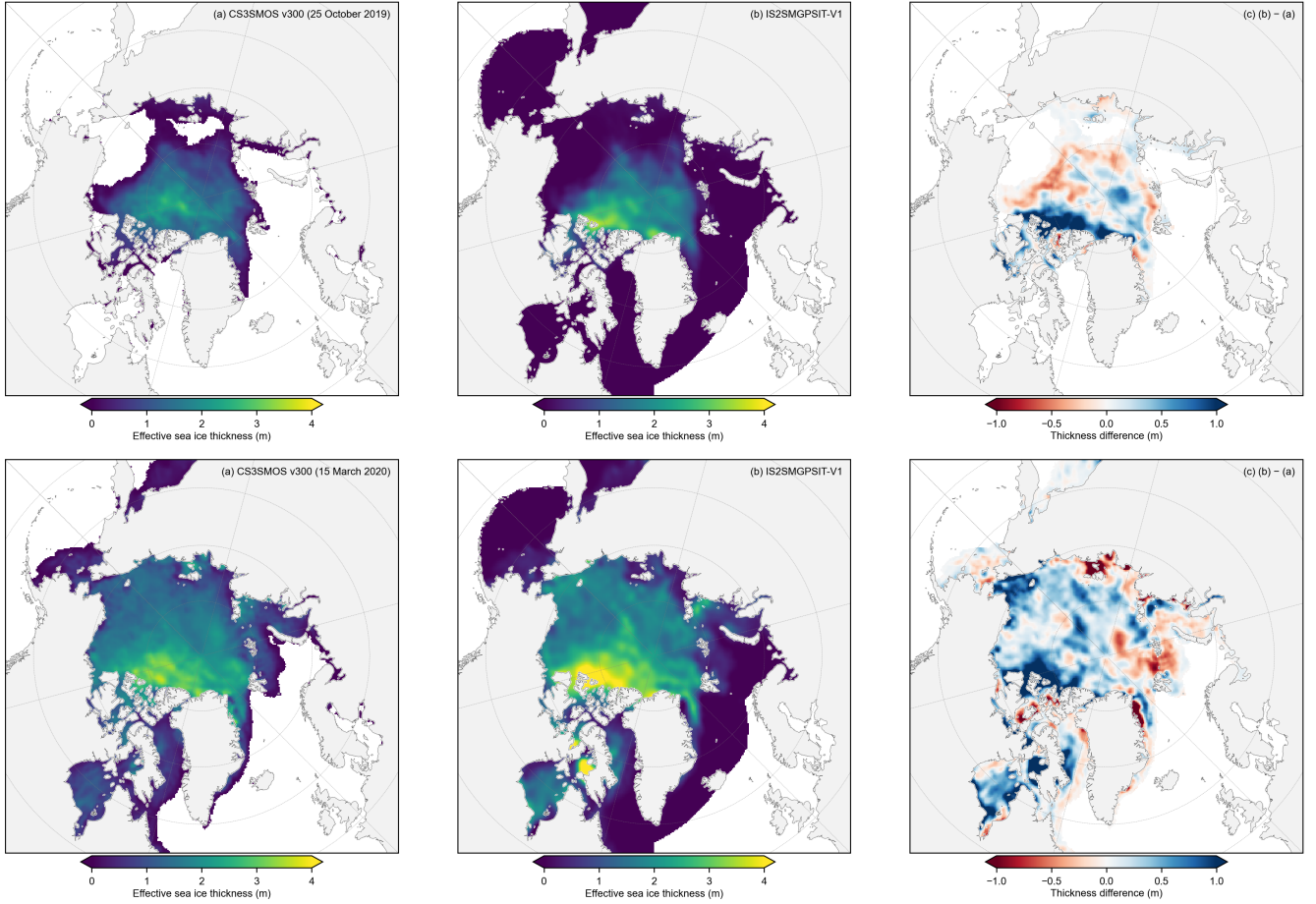


Figure 14. Effective grid-cell sea ice thickness for the centred seven-day analyses on 25 October 2019 (top row) and 15 March 2020 (bottom row). Within each row: (a) CS3SMOS v300; (b) IS2SMGPSIT-V1; (c) difference (IS2SMGPSIT-V1 – CS3SMOS).

5 Discussion

IS2SMGPSIT-V1 improves on the monthly IS2SITMOGR4-V4 product in spatial and temporal coverage and in monthly thickness skill against the BGEP ULS moorings. Unlike IS2SITMOGR4-V4, which assigns equal weight to all along-track observations within a calendar month regardless of acquisition time, the GP is conditioned on each observation’s actual timestamp, reducing sub-monthly sampling biases and filling spatial gaps that are especially pronounced during early-fall freeze-up. Previous monthly skill assessments show high correlations ($r^2 > 0.7$) against ULS moorings (Petty et al., 2023, 2026; Landy et al., 2022), but these are dominated by the seasonal cycle; removing the seasonal cycle here reveals modest anomaly correlations that depend strongly on the averaging window (Fig. 10).

The averaging-window analysis (Sect. 4.2.2) also has implications for the interpretation of daily gridded thickness products more generally. Removing the climatological seasonal cycle retains both sub-seasonal and interannual departures from the

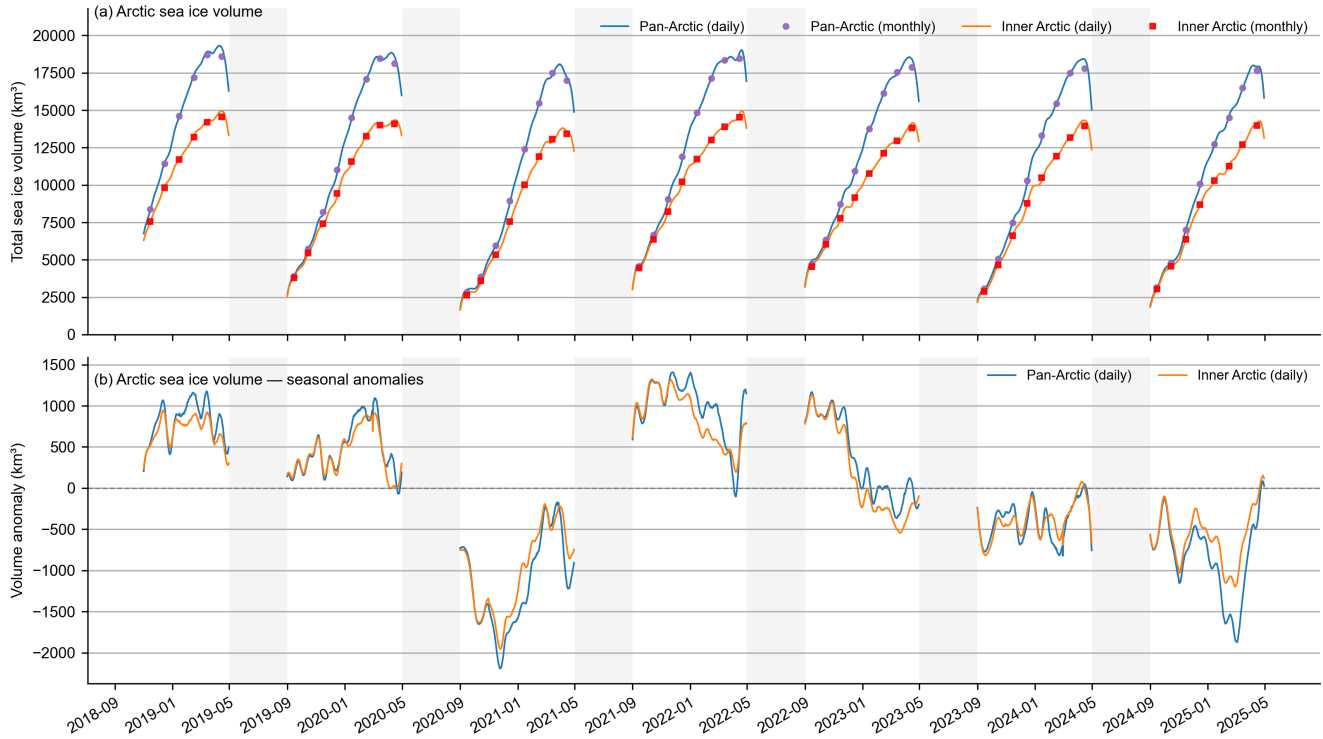


Figure 15. Arctic sea ice volume (November 2018–April 2025). (a) IS2SMGPSIT-V1 daily volume for the pan-Arctic (CAA excluded) and inner Arctic Ocean (IAO) domains, with monthly markers. (b) Pan-Arctic and IAO daily volume anomalies (seasonal climatology removed). May–August are shaded to indicate no data.

mean seasonal cycle. As the averaging window increases, high-frequency local variability is progressively suppressed, and the shared anomaly signal is expected to increasingly reflect persistent interannual differences among growth seasons. Improved anomaly skill with averaging therefore primarily demonstrates agreement in low-frequency, non-seasonal variability rather than skill in resolving sub-monthly variability. This interpretation is supported by the systematic improvement even for the strictly monthly product, which does not contain genuine sub-monthly information. At least three effects are conflated in the daily comparison: (i) the representativeness gap between a 25 km grid-cell mean and a fixed-point ULS record sampling advecting floes; (ii) ICESat-2's ~91-day repeat orbit, which limits how often any given location is directly observed; and (iii) the temporal smoothing inherent in our GPSat configuration. The reduced satellite anomaly amplitudes at the moorings (64–76 % of the ULS values; Sect. 4.2.2) are consistent with a combination of these effects, and we cannot cleanly separate their individual contributions here.

5.1 Limitations and future directions

The main limitations of the current product, and the developments they motivate, are outlined below.

Model configuration and temporal resolution: The 200 km expert spacing, ± 30 -day training window, monthly hyperparameter reuse, and 25 km output grid were selected to balance coverage and computational cost, and together limit the product’s ability to resolve true daily variability (optimised temporal lengthscales $\ell_t \approx 35\text{--}45$ days; Fig. 3). The kernel sensitivity experiment (Sect. 3.2) indicates that output smoothness is governed more by observation density and the training-window configuration than by the kernel smoothness class. Denser expert placement would not necessarily improve the representation of steep gradients: where rapid spatial variation dominates a local training neighbourhood, a single expert can already converge on short spatial correlation lengthscales. Its main benefit would instead be improved representation of spatial non-stationarity, for example where smoothly varying and rapidly varying ice regimes coexist within one expert’s training neighbourhood, as may occur near Fram Strait and the narrow channels of the CAA. Future efforts should therefore focus on systematic testing of the window length (including adaptive windows tied to local observation density), adaptive expert placement in regions of strong non-stationarity, and more frequent hyperparameter re-optimisation during rapid regime changes such as freeze-up, using GPU acceleration to manage the added computational cost.

Uncertainty and observation-noise model: Each local expert fits a single likelihood variance σ_n^2 shared by ICESat-2 and all SMOS/SMAP retrievals, and the output does not propagate the University of Bremen sensor flags, so the posterior uncertainty does not represent the spatially and temporally varying reliability of the L-band input (Sect. 2.2; Supplementary Figs. S1–S2). The GP posterior standard deviation has also not been calibrated against held-out observations and should be treated as a relative measure of interpolation confidence. Future efforts should explore sensor-specific error models and cross-validation, withholding complete ICESat-2 tracks, to test whether predicted uncertainties match observed errors.

Growth-season only: The dataset is limited to September–April. A summer extension building on the all-season ICESat-2 thickness advances of Petty et al. (2026) with all-season NESOSIM snow loading is under development, but melt ponds strongly degrade L-band thin-ice retrievals, so an alternative treatment of the thin-ice and ice-edge constraint may need to be considered.

Input data: The fused product is ultimately driven by the quality of the upstream retrievals. Improvements to the ICESat-2 freeboard processing chain (e.g. emerging photon-level freeboard retrieval methods, Liu et al., 2026), the SMOS/SMAP thin-ice product, and the snow loading used in the ICESat-2 thickness conversion would propagate directly into future versions without changes to the fusion methodology. Incorporating CryoSat-2 and/or Sentinel-3 radar altimetry would increase observation density and coverage during ICESat-2 gaps.

External evaluation: The basic CS3SMOS comparison (Sect. 4.3.2) was not intended to determine which product is more accurate, given the many differences in inputs, masks, and fusion methods (e.g., Ricker et al., 2017), but to demonstrate the product differences that motivate future assessment efforts. We therefore plan a full-record intercomparison with

440 independent validation, ideally through community efforts such as the ESA-funded Sea Ice-thickness product iNter-comparison eXerciSe (SIN'XS; <https://sinxs.noveltis.fr/>).

6 Conclusions

We have presented IS2SMGPSIT-V1, to our knowledge the first spatially complete, pan-Arctic, 25 km, daily gridded sea ice thickness dataset derived from fused ICESat-2 and SMOS/SMAP observations using Gaussian process regression in the GPSat
445 framework. The dataset spans seven Arctic sea ice growth seasons: November–April in 2018–2019 and September–April in each of the following six seasons through April 2025.

Using the acquisition time and location of each observation reduces the sampling artefacts associated with monthly binning, while the SMOS/SMAP thin-ice constraint helps fill spatial gaps, particularly during early-fall freeze-up. The resulting fields reproduce the broad IS2SITMOGR4-V4 seasonal cycle with substantially greater coverage. Monthly BGEP ULS comparisons
450 show improved skill ($r^2 = 0.91$, RMSE = 0.19 m) relative to IS2SITMOGR4-V4 ($r^2 = 0.83$, RMSE = 0.24 m), particularly for thin ice. De-seasonalised anomaly skill improves at longer averaging windows, but a monthly-only control improves in near-parallel. We therefore caution against interpreting the improvement in Fig. 10 as evidence of sub-monthly skill and recommend temporal aggregation for variability studies, notwithstanding the product's daily output cadence.

The complete fields support continuous pan-Arctic volume estimates and simplify climate-model comparison without the
455 spatial masking required for incomplete observational fields (Petty et al., 2025a). Potential applications also include navigability assessment, ecosystem and light-transmission modelling, and freshwater-flux estimation. Future versions will prioritise systematic training-window tests and spatially adaptive expert placement, using the GPU capabilities of GPSat to support the additional computation (Gregory et al., 2024). Extension through the summer melt season is also underway using emerging all-season ICESat-2 freeboard capabilities (Petty et al., 2026).

460 7 Code and data availability

Version v0.1 of the daily gridded sea ice thickness dataset (IS2SMGPSIT-V1) is archived as monthly NetCDF files on Zenodo at <https://doi.org/10.5281/zenodo.22147361> (Petty, 2026b). To enable rapid data access, the data are also hosted on Amazon Web Services S3 as:

- **Monthly NetCDF files** (GPSat_multivar_YYYYMM.nc): one file per month, CF-compliant metadata, NSIDC Polar
465 Stereographic North projection, at `s3://icesat-2-sea-ice-us-west-2/is2smsitgp/dev_v7/netcdf/` (anonymous public access; HTTPS listing under https://icesat-2-sea-ice-us-west-2.s3.us-west-2.amazonaws.com/is2smsitgp/dev_v7/netcdf/).
 - **Zarr store** (GPSat_multivar_20181101–20250430.zarr): single cloud-optimised store spanning November 2018–April 2025, chunked by time for efficient temporal access, at `s3://icesat-2-sea-ice-us-west-2/is2smsitgp/dev_v7/zarr/` (anonymous public access; HTTPS listing under https://icesat-2-sea-ice-us-west-2.s3.us-west-2.amazonaws.com/is2smsitgp/dev_v7/zarr/).
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The dataset is additionally available on Amazon Web Services S3 as a version-controlled Icechunk repository at `s3://icesat-2-sea-ice-us-west-2/is2smsgp/v0.1/icechunk` (anonymous public access). Icechunk records the commit history and data changes with immutable release tags (currently `v0.1`). This also allows a revised dataset to be issued under a new tag during peer review without altering the version used for the original submission. The GPSat framework source code is available at <https://github.com/CPOMUCL/GPSat>. The production pipeline scripts, postprocessing tools, and analysis notebooks are available at <https://www.icesat-2-sea-ice-state.info> and <https://github.com/akpetty/icesat2-book>.

Author contributions. AP performed all data processing and analysis, generated the figures, and wrote the initial manuscript. CC carried out the initial testing and prototyping of GPSat for this application. MT and WG advised on GPSat porting, configuration and development. AC assisted with the validation efforts. All authors provided scientific advice and contributed to manuscript preparation.

Competing interests. The authors declare that they have no conflict of interest.

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References

- 490 Ardyna, M. and Arrigo, K. R.: Phytoplankton dynamics in a changing Arctic Ocean, *Nature Climate Change*, pp. 1–12, <https://doi.org/10.1038/s41558-020-0905-y>, 2020.
- Bell, T., Briggs, R., Bachmayer, R., and Li, S.: Augmenting Inuit knowledge for safe sea-ice travel—The SmartICE information system, in: 2014 Oceans – St. John’s, pp. 1–9, IEEE, <https://doi.org/10.1109/OCEANS.2014.7003290>, 2014.
- Bushuk, M., Ali, A., Bailey, D. A., Bao, Q., Batté, L., Bhatt, U. S., Blanchard-Wrigglesworth, E., Blockley, E., Cawley, G., Chi, J., Counillon, F., Coulombe, P.-G., Cullather, R. I., Diebold, F. X., Dirkson, A., Exarchou, E., Göbel, M., Gregory, W., Guemas, V., Hamilton, L., He, B., Horvath, S., Ionita, M., Kay, J. E., Kim, E., Kimura, N., Kondrashov, D., Labe, Z. M., Lee, W. S., Lee, Y.-J., Li, C., Li, X., Lin, Y., Liu, Y., Maslowski, W., Massonnet, F., Meier, W. N., Merryfield, W. J., Myint, H., Acosta Navarro, J. C., Petty, A. A., Qiao, F., Schröder, D., Schweiger, A., Shu, Q., Sigmond, M., Steele, M., Stroeve, J., Sun, N., Tietsche, S., Tsamados, M., Wang, K., Wang, J., Wang, W., Wang, Y., Wang, Y., Williams, J., Yang, Q., Yuan, X., Zhang, J., and Zhang, Y.: Predicting September Arctic Sea Ice: A Multimodel Seasonal Skill Comparison, *Bulletin of the American Meteorological Society*, 105, E1170–E1203, <https://doi.org/10.1175/BAMS-D-23-0163.1>, 2024.
- 500 Comiso, J. C., Parkinson, C. L., Gersten, R., and Stock, L.: Accelerated decline in the Arctic sea ice cover, *Geophysical Research Letters*, 35, L01 703, <https://doi.org/10.1029/2007GL031972>, 2008.
- Gregory, W., MacEachern, R., Takao, S., Lawrence, I. R., Nab, C., Deisenroth, M. P., and Tsamados, M.: Scalable interpolation of satellite altimetry data with probabilistic machine learning, *Nature Communications*, 15, 7453, <https://doi.org/10.1038/s41467-024-51900-x>, 2024.
- 505 Haine, T. W. N., Curry, B., Gerber, R., Hansen, E., Karcher, M., Lee, C., Rudels, B., Spreen, G., de Steur, L., Stewart, K. D., and Woodgate, R.: Arctic freshwater export: Status, mechanisms, and prospects, *Global and Planetary Change*, 125, 13–35, <https://doi.org/10.1016/j.gloplacha.2014.11.013>, 2015.
- Hendricks, S., Ricker, R., and Helm, V.: ESA CCI+ Sea Ice, European Space Agency, Technical Report, 2016.
- IPCC: Ocean, Cryosphere and Sea Level Change, in: *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Intergovernmental Panel on Climate Change (IPCC), pp. 1211–1362, Cambridge University Press, Cambridge, ISBN 978-1-009-15788-9, <https://doi.org/10.1017/9781009157896.011>, 2023.
- 510 Kacimi, S. and Kwok, R.: Arctic Snow Depth, Ice Thickness, and Volume From ICESat-2 and CryoSat-2: 2018–2021, *Geophysical Research Letters*, 49, e2021GL097 448, <https://doi.org/10.1029/2021GL097448>, 2022.
- 515 Kaleschke, L., Tian-Kunze, X., Maaß, N., Mäkynen, M., and Drusch, M.: Sea ice thickness retrieval from SMOS brightness temperatures during the Arctic freeze-up period, *Geophysical Research Letters*, 39, L05 501, <https://doi.org/10.1029/2012GL050916>, 2012.
- Krishfield, R. A., Proshutinsky, A., Tateyama, K., Williams, W. J., Carmack, E. C., McLaughlin, F. A., and Timmermans, M.-L.: Deterioration of perennial sea ice in the Beaufort Gyre from 2003 to 2012 and its impact on the oceanic freshwater cycle, *Journal of Geophysical Research: Oceans*, 119, 1271–1305, <https://doi.org/10.1002/2013JC008999>, 2014.
- 520 Kwok, R.: Arctic sea ice thickness, volume, and multiyear ice coverage: losses and coupled variability (1958–2018), *Environmental Research Letters*, 13, 105 005, <https://doi.org/10.1088/1748-9326/aae3ec>, 2018.
- Kwok, R. and Cunningham, G. F.: Variability of Arctic sea ice thickness and volume from CryoSat-2, *Philosophical Transactions of the Royal Society A*, 373, 20140 157, <https://doi.org/10.1098/rsta.2014.0157>, 2015.
- Kwok, R. and Rothrock, D. A.: Decline in Arctic sea ice thickness from submarine and ICESat records: 1958–2008, *Geophysical Research Letters*, 36, L15 501, <https://doi.org/10.1029/2009GL039035>, 2009.
- 525

- Kwok, R., Kacimi, S., Markus, T., Kurtz, N. T., Studinger, M., Sonntag, J. G., Manizade, S. S., Boisvert, L. N., and Harbeck, J. P.: ICESat-2 surface height and sea ice freeboard assessed with ATM lidar acquisitions from Operation IceBridge, *Geophysical Research Letters*, 46, 11 228–11 236, <https://doi.org/10.1029/2019GL084976>, 2019.
- Kwok, R., Petty, A. A., Cunningham, G., Markus, T., Hancock III, D. W., Ivanoff, A., Wimert, J., Bagnardi, M., Kurtz, N., and the ICESat-2 Science Team: ATLAS/ICESat-2 L3A Sea Ice Freeboard (ATL10, Version 7), <https://doi.org/10.5067/ATLAS/ATL10.007>, data set, 2025.
- Kwok, R., Kurtz, N., Wimert, J., Petty, A., Cunningham, G., Markus, T., Hancock, D., Ivanoff, A., Bagnardi, M., Herzfeld, U., Trantow, T., and ICESat-2 Science Team: Ice, Cloud, and Land Elevation Satellite (ICESat-2) Project Algorithm Theoretical Basis Document (ATBD) for Sea Ice Products, version 7, Tech. rep., NASA National Snow and Ice Data Center Distributed Active Archive Center (DAAC), <https://doi.org/10.5067/KPMXUOH7TNIY>, release 007, 2026.
- Landy, J. C., Dawson, G. J., Tsamados, M., Bushuk, M., Stroeve, J. C., Howell, S. E. L., Krumpen, T., Bire, D. K., Komarov, A. S., Heorton, H. D. E. S., Belter, H. J., and Tilling, R. L.: A year-round satellite sea-ice thickness record from CryoSat-2, *Nature*, 609, 517–522, <https://doi.org/10.1038/s41586-022-05058-5>, 2022.
- Landy, J. C., de Rijke-Thomas, C., Nab, C., Lawrence, I., Glissenaar, I. A., Mallett, R. D. C., Fredensborg Hansen, R. M., Petty, A., Tsamados, M., Macfarlane, A. R., and Braakmann-Folgmann, A.: Anticipating CRISTAL: an exploration of multi-frequency satellite altimeter snow depth estimates over Arctic sea ice, 2018–2023, *The Cryosphere*, 20, 183–208, <https://doi.org/10.5194/tc-20-183-2026>, 2026.
- 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.: CryoSat-2 estimates of Arctic sea ice thickness and volume, *Geophysical Research Letters*, 40, 732–737, <https://doi.org/10.1002/grl.50193>, 2013.
- Liston, G. E., Itkin, P., Stroeve, J., Tschudi, M., Stewart, J. S., Pedersen, S. H., Reinking, A. K., and Elder, K.: A Lagrangian Snow-Evolution System for Sea-Ice Applications (SnowModel-LG): Part I—Model Description, *Journal of Geophysical Research: Oceans*, 125, e2019JC015 913, <https://doi.org/10.1029/2019JC015913>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2019JC015913>, 2020.
- Liu, W., Lei, R., Jin, T., Sun, H., Tsamados, M., Glissenaar, I. A., Landy, J. C., and Zhou, Y.: Year-round high-resolution sea ice freeboard retrieval using ICESat-2 ATL03 photon data, *EGUsphere* [preprint], <https://doi.org/10.5194/egusphere-2026-766>, 2026.
- Ludwig, V., Ribere, C., Fleury, S., Haas, C., Tsamados, M., El Hajj, M., Bouffard, J., Scagliola, M., Bocquet, M., de Boisseson, E., Boulenger, V., Boutin, G., Connor, L., Edel, L., Hendricks, S., Hernández Macià, F., Huntemann, M., Kaleschke, L., Kauker, F., Landy, J., Megain, T., Petty, A., Soya Rasmussen, T., Hvid Ribergaard, M., Ricker, R., Schweiger, A., Shi, H., Tian-Kunze, X., Yi, D., and Di Bella, A.: Biases, Uncertainties, and Trends in Arctic Sea-Ice Thickness: A Cross-Product Analysis from 1995 to 2023, *EGUsphere* preprint, <https://doi.org/10.5194/egusphere-2025-6201>, preprint, 2026.
- Markus, T., Neumann, T., Martino, A., Abdalati, W., Brunt, K., Csatho, B., Farrell, S., Fricker, H., Gardner, A., Harding, D., Jasinski, M., Kwok, R., Magruder, L., Lubin, D., Luthcke, S., Morison, J., Nelson, R., Neuenschwander, A., Palm, S., Popescu, S., Shum, C. K., Schutz, B. E., Smith, B., Yang, Y., and Zwally, J.: The Ice, Cloud, and land Elevation Satellite-2 (ICESat-2): Science requirements, concept, and implementation, *Remote Sensing of Environment*, 190, 260–273, <https://doi.org/10.1016/j.rse.2016.12.029>, 2017.
- Massicotte, P., Peeken, I., Katlein, C., Flores, H., Huot, Y., Castellani, G., Piontek, J., and Belter, H. J.: Sensitivity of phytoplankton primary production estimates to available irradiance under heterogeneous sea ice conditions, *Journal of Geophysical Research: Oceans*, 124, 5436–5450, <https://doi.org/10.1029/2019JC015007>, 2019.
- Matthews, A. G. d. G., van der Wilk, M., Nickson, T., Fujii, K., Boukouvalas, A., León-Villagrà, P., Ghahramani, Z., and Hensman, J.: GPflow: a Gaussian process library using TensorFlow, *Journal of Machine Learning Research*, 18, 1–6, 2017.

Meier, W. N., Perovich, D., Farrell, S., Haas, C., Hendricks, S., Petty, A. A., Webster, M., Divine, D., Gerland, S., Kaleschke, L., Ricker, R., Steer, A., Tian-Kunze, X., Tschudi, M., and Wood, K.: Sea Ice, in: NOAA Arctic Report Card 2021, edited by Moon, T. A., Druckenmiller, M. L., and Thoman, R. L., National Oceanic and Atmospheric Administration, <https://doi.org/10.25923/y2wd-fn85>, 2021.

Meier, W. N., Petty, A. A., Hendricks, S., Kaleschke, L., Divine, D., Farrell, S., Gerland, S., Perovich, D., Ricker, R., Tian-Kunze, X., and Webster, M.: Sea Ice, in: NOAA Arctic Report Card 2024, edited by Moon, T. A., Druckenmiller, M. L., and Thoman, R. L., National Oceanic and Atmospheric Administration, <https://doi.org/10.25923/aksk-7p66>, 2024.

Meier, W. N., Fetterer, F., Windnagel, A. K., Stewart, J. S., and Stafford, T.: NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration, Version 6, G02202, Version 6, National Snow and Ice Data Center, <https://doi.org/10.7265/b18j-z797>, data set, 2026.

Nab, C., Mallett, R., Nelson, C., Stroeve, J., and Tsamados, M.: Optimising Interannual Sea Ice Thickness Variability Retrieved From CryoSat-2, *Geophysical Research Letters*, 51, e2024GL111071, <https://doi.org/10.1029/2024GL111071>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2024GL111071>, 2024.

Nandan, V., Geldsetzer, T., Yackel, J., Mahmud, M., Scharien, R., Howell, S., King, J., Ricker, R., and Else, B.: Effect of snow salinity on CryoSat-2 Arctic first-year sea ice freeboard measurements, *Geophysical Research Letters*, 44, 10419–10426, <https://doi.org/10.1002/2017GL074506>, 2017.

Nandan, V., Scharien, R. K., Geldsetzer, T., Kwok, R., Yackel, J. J., Mahmud, M. S., Røsel, A., Tonboe, R., Granskog, M., Willatt, R., et al.: Snow property controls on modeled Ku-band altimeter estimates of first-year sea ice thickness: case studies from the Canadian and Norwegian Arctic, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 1082–1096, <https://doi.org/10.1109/JSTARS.2020.2966432>, 2020.

National Snow and Ice Data Center: NSIDC-0780: Arctic sea ice region mask, <https://doi.org/10.5067/CYW3O8ZUNIWC>, 2021.

Parkinson, C. L. and Cavalieri, D. J.: Arctic sea ice variability and trends, 1979–2010, *The Cryosphere*, 6, 881–889, <https://doi.org/10.5194/tc-6-881-2012>, 2012.

Patilea, C., Heygster, G., Huntemann, M., and Spreen, G.: Combined SMAP/SMOS thin sea ice thickness retrieval, *The Cryosphere*, 13, 675–691, <https://doi.org/10.5194/tc-13-675-2019>, 2019.

Payne, C. M., DuVivier, A. K., Krumhardt, K. M., Lovenduski, N. S., and Holland, M. M.: Quantifying Under-Ice Phytoplankton Blooms in the Changing Arctic and Southern Oceans, *Geophysical Research Letters*, 53, e2026GL121750, <https://doi.org/https://doi.org/10.1029/2026GL121750>, e2026GL121750 2026GL121750, 2026.

Petty, A.: NASA Eulerian Snow On Sea Ice Model Version 1.1 (NESOSIMv1.1) data: 1980–2025, Zenodo, <https://doi.org/10.5281/zenodo.5164313>, data set, 2026a.

Petty, A., Cardinale, C., and Smith, M.: Constraining CMIP6 sea ice simulations with ICESat-2, *Geoscientific Model Development*, 18, 6313–6340, <https://doi.org/10.5194/gmd-18-6313-2025>, 2025a.

Petty, A. A.: IS2SMGPSIT-V1: Daily 25 km Arctic sea ice thickness and volume from fused ICESat-2 and SMOS/SMAP observations, 2018–2025, Zenodo, <https://doi.org/10.5281/zenodo.22147361>, data set, version v0.1, 2026b.

Petty, A. A., Webster, M., Boisvert, L., and Markus, T.: The NASA Eulerian Snow on Sea Ice Model (NESOSIM) v1.0: initial model development and analysis, *Geoscientific Model Development*, 11, 4577–4602, <https://doi.org/10.5194/gmd-11-4577-2018>, 2018.

Petty, A. A., Kurtz, N. T., Kwok, R., Markus, T., and Neumann, T. A.: ICESat-2 sea ice thickness and freeboard assessment with independent ground truth data, *Journal of Geophysical Research: Oceans*, 125, e2019JC015764, <https://doi.org/10.1029/2019JC015764>, 2020.

Petty, A. A., Keeney, N., Cabaj, A., Kushner, P., and Bagnardi, M.: Winter Arctic sea ice thickness from ICESat-2: upgrades to free-board and snow loading estimates and an assessment of the first three winters of data collection, *The Cryosphere*, 17, 127–156, <https://doi.org/10.5194/tc-17-127-2023>, 2023.

Petty, A. A., Kurtz, N. T., Kwok, R., Markus, T., Neumann, T. A., Keeney, N., and Cabaj, A.: IS2SITMOGR4 Monthly Gridded Winter Arctic Sea Ice Thickness, Version 4, <https://doi.org/10.5067/TXDHDJ1JT0CG>, 2025b.

Petty, A. A., Cabaj, A., and Landy, J. C.: Initial assessment of all-season Arctic sea ice thickness from ICESat-2, *Journal of Glaciology*, 72, e4, 1–19, <https://doi.org/10.1017/jog.2025.10119>, 2026.

Pizzolato, L., Howell, S. E. L., Dawson, J., Laliberté, F., and Copland, L.: The influence of declining sea ice on shipping activity in the Canadian Arctic, *Geophysical Research Letters*, 43, 12, 146–12, 154, <https://doi.org/10.1002/2016GL071489>, 2016.

Rasmussen, C. E. and Williams, C. K. I.: *Gaussian Processes for Machine Learning*, MIT Press, 2006.

Ricker, R., Hendricks, S., Kaleschke, L., Tian-Kunze, X., King, J., and Haas, C.: 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>, 2017.

Segal, R. A., Scharien, R. K., Duerden, F., and Tam, C.-L.: The Best of Both Worlds: Connecting Remote Sensing and Arctic Communities for Safe Sea Ice Travel, *Arctic*, 73, 461–484, <https://doi.org/10.14430/arctic71896>, 2020.

Song, R., Mu, L., Loza, S. N., Kauker, F., and Chen, X.: Assimilating summer sea-ice thickness observations improves Arctic sea-ice forecast, *Geophysical Research Letters*, 51, e2024GL110405, <https://doi.org/10.1029/2024GL110405>, 2024.

Stephenson, S. R., Smith, L. C., and Agnew, J. A.: Divergent long-term trajectories of human access to the Arctic, *Nature Climate Change*, 1, 156–160, <https://doi.org/10.1038/nclimate1120>, 2011.

Stewart, J. S., Meier, W. N., and Scott, D. J.: Polar Stereographic Ancillary Grid Information, Version 1, NSIDC-0771, NASA National Snow and Ice Data Center Distributed Active Archive Center, <https://doi.org/10.5067/N6INPBT8Y104>, data set, 2022.

Tian-Kunze, X., Kaleschke, L., Maaß, N., Mäkynen, M., Serra, N., Drusch, M., and Krumpen, T.: 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>, 2014.

Titsias, M. K.: Variational learning of inducing variables in sparse Gaussian processes, *Proceedings of the 12th International Conference on Artificial Intelligence and Statistics (AISTATS)*, pp. 567–574, 2009.

Willatt, R. C., Giles, K. A., Laxon, S. W., Stone-Drake, L., and Worby, A. P.: Field investigations of Ku-band radar penetration into snow cover on Antarctic sea ice, *IEEE Transactions on Geoscience and Remote Sensing*, 48, 365–372, <https://doi.org/10.1109/TGRS.2009.2028237>, 2010.

Zhang, Y.-F., Bushuk, M., Winton, M., Hurlin, B., Gregory, W., Landy, J., and Jia, L.: Improvements in September Arctic Sea Ice Predictions Via Assimilation of Summer CryoSat-2 Sea Ice Thickness Observations, *Geophysical Research Letters*, 50, e2023GL105672, <https://doi.org/10.1029/2023GL105672>, 2023.