



Constraining freeboard in ocean state estimates using ICESat-2 and CryoSat-2

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Abstract.

Sea ice thickness plays an important role in the climate system, yet it remains one of the least constrained variables in climate models due to limited spatiotemporal coverage of observations. Satellite missions such as ICESat-2 and CryoSat-2 have provided long records of basin-scale freeboard observations in both hemispheres, enabling estimates of sea ice thickness. Here, we assess uncertainties in freeboard retrievals from these two missions and evaluate their potential for improving the sea ice freeboard representation in the state estimates produced by the project for Estimating the Circulation and Climate of the Ocean (ECCO). From comparisons of ICESat-2, CryoSat-2 and a preliminary ECCO version 5 forward model simulation, we find general consistency between the two observational products but substantial differences between modeled and observed freeboard across time-mean, seasonal, and monthly timescales. Biases in total freeboard (ice freeboard plus snow depth) are primarily attributed to the misrepresentation of the ice freeboard in the model. Time-mean model-observation misfits are typically more than 4 times larger than estimated data errors over the majority of the polar regions, while monthly misfits exceed data errors by a factor of ~ 2 . These results indicate that assimilating both total and ice freeboard observations could substantially improve the sea ice representation in ECCO state estimates across all timescales.

1 Introduction

Warming in the Earth system is amplified in both poles. Sea ice volume, governed by its area and thickness, has undergone complicated changes in both hemispheres in the last few decades in response to anthropogenic forcing (e.g., Fogt et al., 2022; Meier and Stroeve, 2022; Wang et al., 2022; Raphael and Handcock, 2022; Purich and Doddridge, 2023; Shokr and Ye, 2023). The Arctic sea ice has declined at an unprecedented rate, both in area and thickness, resulting in an Arctic warming at two to four times the rate of the entire globe via ice-albedo feedback (e.g., Serreze and Barry, 2011; Esau et al., 2023). However, this reduction has been reported to have slowed down after 2007 due to a decrease in sea ice export despite continuously increasing air temperature (Zhang, 2021). The Antarctic sea ice volume, conversely, exhibits mixed changes across different regions. Despite a generally increasing trend before 2015, a significant drop has been observed since 2016. In fact, Antarctic sea ice extent was a record low in 2023 (e.g., Purich and Doddridge, 2023; Gilbert and Holmes, 2024; Josey et al., 2024) and has yet to recover to the levels seen a decade ago. These large changes in sea ice volume could potentially impact both the



25 atmosphere (e.g., air-sea heat and moisture exchange) and ocean (e.g., ecosystems, mixing, freshwater and heat content) (e.g., Allende et al., 2024; Oldenburg et al., 2024).

Despite its importance in the climate system, sea ice remains one of the climate variables that are most poorly constrained, with large inter-model spreads, especially in sea ice thickness (e.g., Notz and Community, 2020; Nie et al., 2023; Xu and Li, 2023), which governs ice volume variability in both poles (Bocquet et al., 2024). One of the reasons for model differences
 30 is the complicated physics and interactions between atmosphere, ice, and ocean, involving sea ice melt/growth, rheology, and transport (e.g., Nie et al., 2023; Raphael et al., 2024). Moreover, although point-wise measurements of sea ice thickness are available from field campaigns (e.g., Jackson et al., 2013; Raphael et al., 2024), direct polar observational records with broad spatiotemporal coverage are still lacking. As a result, previous studies involving ice thickness often rely on reanalysis products or estimates derived from other observations (e.g., Wang et al., 2016), hindering robust validation of model-produced sea ice,
 35 which further increases the uncertainties in future climate projections.

Satellites developed more recently allow for continuous measurements of sea ice freeboard (i.e., the height of sea ice and/or snow above the ocean surface), which can then be converted to sea ice thickness. To our knowledge, so far only four satellites measure freeboard directly: Envisat (2002-2012), CryoSat-2 (CS2, 2010-present), and Ice, Cloud, and land Elevation Satellite (ICESat, 2003-2010) and ICESat-2 (IS2, 2018-present).

40 In this study, we examine the potential benefits of using IS2 and CS2 freeboard to improve sea ice simulations in ocean state estimates from the project for Estimating the Circulation and Climate of the Ocean (ECCO; www.ecco-group.org; Wunsch et al., 2009), a data assimilation effort that continues to be constrained by emerging observations. Although several studies have explored the usefulness of CS2 and IS2 freeboard data for improving the representation of sea ice thickness in climate models (e.g., Fiedler et al., 2022; Sievers et al., 2023; Petty et al., 2025), the assimilation of IS2 freeboard data has only recently
 45 been tried in two upcoming ECCO solutions (version 4 release 6 and version 5 release 1). These exploratory attempts assumed a spatially uniform IS2 data uncertainty for both time-mean and time-variable freeboard and yielded only very marginal reductions in model-data misfits. Moreover, CS2-derived freeboards were not used for constraining these ECCO estimates. Here, we take advantage of both IS2 and CS2 data and perform a detailed comparison of respective freeboard fields and those from ECCO estimates to refine the uncertainty estimates of IS2, develop uncertainty estimates for CS2, and assess the potential
 50 relevance of the data as a useful constraint for future ECCO solutions.

2 Data and Methods

2.1 ICESat-2 freeboard product

Launched on 15 September 2018, IS2 carries a photon-counting laser altimeter that measures the elevation of various reflecting surfaces. IS2 orbits the Earth 15 times per day and covers latitudes from 88°S to 88°N. The total number of tracks is 1387
 55 over each revisit period of 91 days. Individual photon height and geolocation are first calculated, and then processed into different level products. Details of the IS2 mission are available in Markus et al. (2017) and the official IS2 website (<https://icesat-2.gsfc.nasa.gov/>).

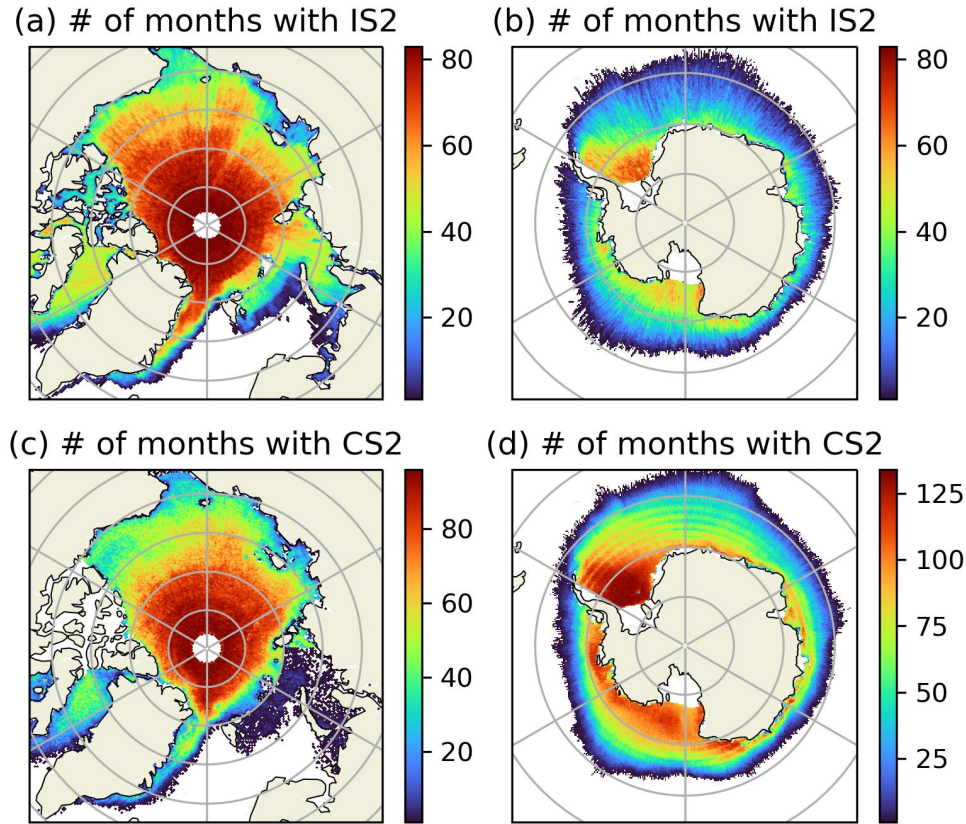


Figure 1. Number of months with (a,b) IS2 and (c,d) CS2 freeboard data.

In this work, we use monthly data from the latest version (v5) of the IS2 ATL20 product, which provides daily and monthly gridded total freeboard h_t (i.e., the sum of ice freeboard h_i and snow depth h_s) at a resolution of 25 km on Polar Stereographic grids in both hemispheres. ATL20 is derived from the ATL10 product, which provides along-track values of h_t calculated by subtracting a reference sea surface height (derived from ice leads) from sea ice height within each segment. Segment height is estimated from 150 photons using histogram-based processing of individual photon heights. Readers can refer to the algorithm theoretical basis document for sea ice product (ATBD; Kwok et al., 2022) for further details. The ATL20 monthly h_t fields were available from October 2018 to August 2025 at the time of data access. Considering the distribution of IS2 tracks, cloud coverage, data quality, and ice presence, the number of months with h_t data in each grid is non-uniform, with generally increasing coverage towards higher latitudes (Figure 1a-b).

2.2 CryoSat-2 freeboard product

Launched on 8 April 2010, CS2 carries a Ku-band radar altimeter aiming to monitor polar sea ice thickness and changes in ice sheets. CS2 orbits from 88°S to 88°N, with a total of 5344 orbits and a long repeat period of 369 days. Details of the satellite



70 are available in Wingham et al. (2006). By analyzing the shape of the returned CS2 radar pulse, the surface type (ice/lead) is classified, and a physically modeled waveform is fitted to retrieve the elevation and further derive freeboard. As the Ku-band radar signal penetrates the snow and reaches snow-ice interface, CS2 measures h_i .

For the Arctic, we use CS2 freeboard data distributed by the National Snow and Ice Data Center (NSIDC; <https://nsidc.org/data/rdeft4/versions/1>). Data are available on Polar Stereographic SSM/I grid with 25 km resolution. Only wintertime (October
75 to April) h_i is provided daily, available from October 2010 to February 2024 at the time of data access. In some years, data are also available for several days in September and May. Besides CS2-derived h_i , h_s is also constructed from a modified climatology (Warren et al., 1999). For comparison with IS2-derived freeboard, we interpolate CS2 fields onto IS2 grids, and average daily data to monthly means for October to April, when complete monthly coverage is available.

For the Antarctic, freeboard data generated from Fons et al. (2023) are assessed in our work. Data for the period July 2010
80 to August 2021 and covering all seasons are available at <https://zenodo.org/records/7327711>. Both h_i and h_s are derived from a comprehensive retrieval method (a physical waveform model and a waveform-fitting process that fits modeled waveforms to CS2 data). Details of the algorithm can be found in Fons et al. (2023). Data are provided on NSIDC 25 km Polar Stereographic grid.

2.3 ECCO fields

85 Ocean and sea ice state estimates from ECCO are produced by constraining simulations of the Massachusetts Institute of Technology general circulation model to most available ocean observations in a physically and statistically consistent manner (www.ecco-group.org; Wunsch et al., 2009). Different versions of ECCO solutions have been released with various model setups. In this study, we use the monthly freeboard (h_t and its two components h_i and h_s) from an ECCO preliminary simulation for version 5 analysis (v5sim), which provides an initial estimate of the sea ice and ocean states from a forward model run
90 before any data constraints are considered. The v5sim run is forced by surface atmospheric variables from Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2; Gelaro et al. (2017)), with initial conditions from an (unadjusted) spin-up run (Zhang et al., 2018; Nakayama et al., 2024). In the course of an ECCO optimization, such original atmospheric variables and initial conditions are adjusted to minimize misfits with observations. Readers can refer to Forget et al. (2015) and Fukumori et al. (2019) for full details of the ECCO framework. Monthly freeboard fields from v5sim are available
95 for the period between January 1992 and December 2023 on the model native grids with nominal $\sim 1/3$ degree resolution. Like the preprocessing of CS2 freeboard, we interpolate the v5sim-derived freeboard onto IS2 grids for comparison.

2.4 Error and cost estimates

For deriving time-varying freeboard errors, we adopt the following method used previously by Fu et al. (1993), Quinn and Ponte (2008) and Vinogradova et al. (2014), among others. Denoting s , D , and M as the “true” signal, data and model freeboard
100 values, then the corresponding errors can be represented as

$$\varepsilon_D = D - s, \quad (1)$$



$$\varepsilon_M = M - s, \quad (2)$$

where ε_D and ε_M are data and model errors in a given location over the time domain. Using *var* and *cov* for variance and covariance operators, the difference between variances of equation (1) and (2) (i.e., $\text{var}[(1)] - \text{var}[(2)]$), and variance of the difference between equation (1) and (2) (i.e., $\text{var}[(1) - (2)]$) yields

$$\text{var}(\varepsilon_{D'}) = \text{var}(D) - \text{cov}(D, M) - \text{cov}(s, \varepsilon_{D'}) + \text{cov}(s, \varepsilon_{M'}) + \text{cov}(\varepsilon_{D'}, \varepsilon_{M'}), \quad (3)$$

where hereafter primes indicate time-varying quantities with zero means. Under the assumption that “true” freeboard and errors $\varepsilon_{D'}$ and $\varepsilon_{M'}$ are all uncorrelated, i.e., the last three terms in equation (3) can be ignored, the data error variance is approximated as

$$\text{var}(\varepsilon_{D'}) = \text{var}(D) - \text{cov}(D, M). \quad (4)$$

While one expects model and data errors to be uncorrelated, such assumptions are more difficult to assert for the relation between errors and the signal. In practice, neglected covariance terms in equation (3) are never zero and in some cases equation (4) can yield negative (unphysical) values. To correct for such instances and also to avoid severely underestimating data errors, one can floor values of $\text{var}(\varepsilon_{D'})$ at some percentage of $\text{var}(D - M)$, which provides an approximate value for the sum $\text{var}(\varepsilon_{D'}) + \text{var}(\varepsilon_{M'})$ for the case of uncorrelated errors. Previous works (e.g., Vinogradova et al., 2014) have set the minimum value of $\text{var}(\varepsilon_{D'})$ at 10% of $\text{var}(D - M)$, equivalent to assuming that model error contributions to model-data misfits are at most 90% of the total variance.

Data errors estimated from equation (4) include both instrument errors and representation errors. Instrument errors in IS2 and CS2 freeboard are associated with the uncertainties in their raw satellite returns and the algorithms to generate freeboard products. Representation errors arise from signals that can be measured by IS2 and CS2, but are not represented in ECCO model due to lack of sufficient resolution or relevant physics. Therefore, large values of $\varepsilon_{D'}$ do not necessarily indicate poor data quality, but may instead reflect for example observational variability at scales unresolved by the model. Considering representation errors is especially important for data assimilation efforts, as it avoids constraining the model to data signals that the model cannot represent.

For time-mean freeboard, we use the absolute value of the difference between IS2 and CS2-derived $\overline{h}_t$ (overbar indicates time mean hereafter) as an estimate of its errors ($\varepsilon_{\overline{D}}$). This difference provides an estimate of the combined uncertainties (instrument noise, data processing algorithms) in the two data sets but can lead to overestimated errors if the IS2 and CS2 time means bracket the true mean (i.e., their errors have opposite signs). Underestimation is also possible in the case of same-sign errors, for which the true mean lies outside the IS2-CS2 range.

Data error estimates allow us to evaluate the potential of satellite-derived freeboard to improve ECCO ice and ocean states. As with most optimization efforts, the parameter used to evaluate such potential is **cost**, defined as the ratio of squared model-data misfits to data error variances, i.e., $(\overline{D} - \overline{M})^2 / \varepsilon_{\overline{D}}^2$ for time-mean and $\text{var}(D - M) / \text{var}(\varepsilon_{D'})$ for time-varying freeboard



fields. Costs larger than 1 imply that the model-data misfits exceed data errors. In such cases, constraining the model output to
135 the data within respective uncertainties could improve the model performance.

3 Basic comparisons of ECCO v5sim and data products

3.1 Mean-state freeboard biases

3.1.1 Arctic

Time-mean freeboard comparisons using all three products can only be done over winter time, given the limited CS2 data
140 availability. In the Arctic, observed $\overline{h_t}$ ranges from ~ 0.1 to ~ 0.65 m (Figure 2a-b). In both IS2 and CS2 products, largest $\overline{h_t}$
is found north of Greenland and the Canadian Arctic Archipelago, where the thickest multi-year ice (MYI) is present. Despite
their consistency in spatial distribution, IS2-derived $\overline{h_t}$ is mostly smaller than that from CS2, especially in the northern part of
the MYI region, with a difference of more than 0.1 m. The v5sim-derived $\overline{h_t}$, in contrast, shows a discrepancy with observations
145 in both spatial pattern and amplitude. Although v5sim is able to reproduce the largest $\overline{h_t}$ in MYI, biases are highest (> 0.4 m)
in the old ice belt, a narrow belt along the northern coast of the Canadian Arctic Archipelago and Greenland where the oldest
(> 4 years) sea ice resides. A second maximum of ~ 0.75 m in $\overline{h_t}$ is shown in the Beaufort Gyre region, which is not supported
by observations (Figure 2a-c). This maximum radiates south to the Beaufort Sea and west to the East Siberian Sea, where $\overline{h_t}$
from v5sim is about twice the height of that from IS2. Values of $\overline{h_t}$ in v5sim are comparable to observations only from the
eastern part of the Fram Strait to the Laptev Sea.

150 To interpret the v5sim-data discrepancy in $\overline{h_t}$, we assess $\overline{h_i}$ and $\overline{h_s}$ separately. An examination of these two components in
CS2 suggests that spatial patterns in $\overline{h_i}$ and $\overline{h_s}$ are similar to those in $\overline{h_t}$ (Figure 2d,f) and correspond, respectively, to $\sim 45\%$
and 55% of $\overline{h_t}$, on average. This similarity is consistent with Kwok et al. (2020), who found $h_s \approx 0.53h_t$ across the Arctic
in ice-growing seasons. The regional contribution of $\overline{h_s}$ roughly aligns with ice age (not shown), as thicker ice allows for the
accumulation of snow, and thin ice is more prone to melting and deformation.

155 The v5sim estimates of $\overline{h_i}$ and $\overline{h_s}$ are off, both in spatial pattern and magnitude (Figure 2e,g). In the Beaufort Gyre, v5sim ex-
hibits a local minimum in $\overline{h_i}$, smaller than that from CS2 by ~ 0.05 m, but v5sim-derived $\overline{h_s}$ exceeds 0.7 m, about 4 times larger
than observations, resulting in the $\overline{h_t}$ local maximum in the Beaufort Gyre discussed in Figure 2c. Biases are mixed in MYI: $\overline{h_i}$
is overestimated and $\overline{h_s}$ underestimated in v5sim in the straits and channels of the Canadian Arctic Archipelago and Greenland;
biases are reversed in the remaining MYI. Unlike CS2, $\overline{h_s}$ in v5sim accounts for $> 75\%$ of $\overline{h_t}$ almost everywhere, except for
160 the Siberian Shelf and straits and channels across the Canadian Arctic Archipelago and Greenland, where the percentage falls
to $\sim 40\%$ (not shown).

As CS2 only provides Arctic freeboard in the ice growing season, we also examine the time-mean freeboard in overlapping
period between IS2 and v5sim (i.e., all months from October 2018 to December 2023), which include the melting season as
well. The results (not shown) are similar to Figure 2.

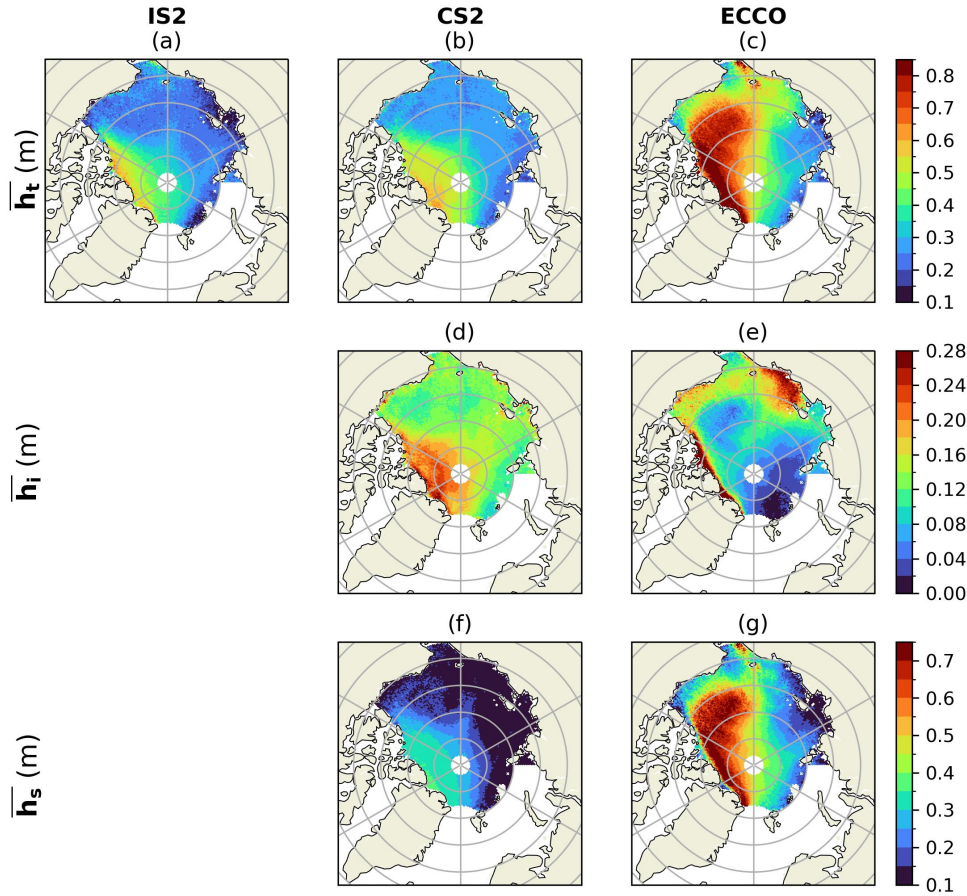


Figure 2. Values of (a-c) $\overline{h_t}$, (d-e) $\overline{h_i}$ and (f-g) $\overline{h_s}$ in (a) IS2, (b,d,f) CS2 and (c,e,g) v5sim, computed on each grid cell over their common period (generally between October 2018 and December 2023 in sea ice growing season, October to April). Units are meters.

165 3.1.2 Antarctic

In the Antarctic, modeled $\overline{h_t}$ shows similar spatial pattern with observations (Figure 3a-c). The magnitude of $\overline{h_t}$ is larger (>0.5 m) along the continent where sea ice may survive through the austral summer, particularly in the western Antarctic, and decreases to <0.3 m away from the coasts. The differences in $\overline{h_t}$ magnitude among IS2, CS2 and v5sim are on the order of ~ 0.1 m off the coast, with smallest magnitudes in CS2 and largest in v5sim. Model-data differences in $\overline{h_t}$ are largest (~ 0.3 m) along the coasts, with pronounced positive biases from $\sim 60^\circ\text{W}$ - 0° - 80°E and the Ross Sea, and negative biases in the other parts of the Antarctic.

Comparisons of $\overline{h_i}$ and $\overline{h_s}$ in CS2 and v5sim reveal greater discrepancies than those found for $\overline{h_t}$ (Figure 3d-g). In particular, v5sim greatly underestimates $\overline{h_i}$: v5sim-derived offshore $\overline{h_i}$ magnitudes are smaller than 0.02 m, compared to 0.1 m in CS2.

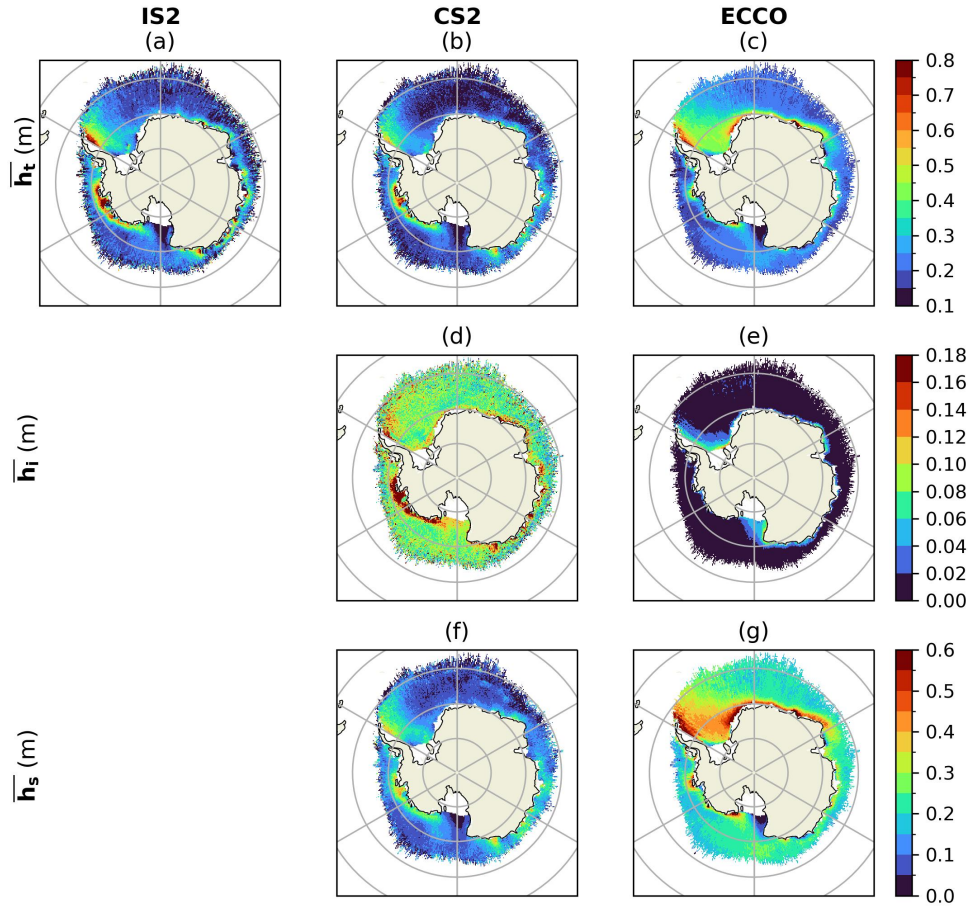


Figure 3. Same as Figure 2 but for the Antarctic.

These negative biases are compensated by the overestimates of $\overline{h_s}$ in v5sim, contributing to the closer v5sim-CS2 agreement
 175 in $\overline{h_t}$ seen in Figure 3b,c.

3.2 Seasonal evolution

The short records of freeboard data in a given grid in IS2 do not allow for a meaningful examination of the mean seasonal
 cycle on the grid scale. Therefore, we examine the seasonal cycles over the entire Arctic and Antarctic domains. Specifically,
 for each month in a given polar region, we first compute the regional-averaged freeboard. After removing the mean values and
 180 linear trends from these time series, the mean seasonal cycle is calculated as the averaged value across all years for each month
 ($\widetilde{h_t}$, $\widetilde{h_i}$, and $\widetilde{h_s}$ hereafter). IS2-derived $\widetilde{h_s}$ is estimated as the difference between IS2's $\widetilde{h_t}$ and CS2's $\widetilde{h_i}$ for comparison with $\widetilde{h_s}$
 provided by CS2. For all three products (IS2, CS2, v5sim), we assess the mean seasonal cycle in freeboard in the Arctic over
 October 2018–December 2023 and in the Antarctic over October 2018–August 2021. We also examined the seasonal cycle

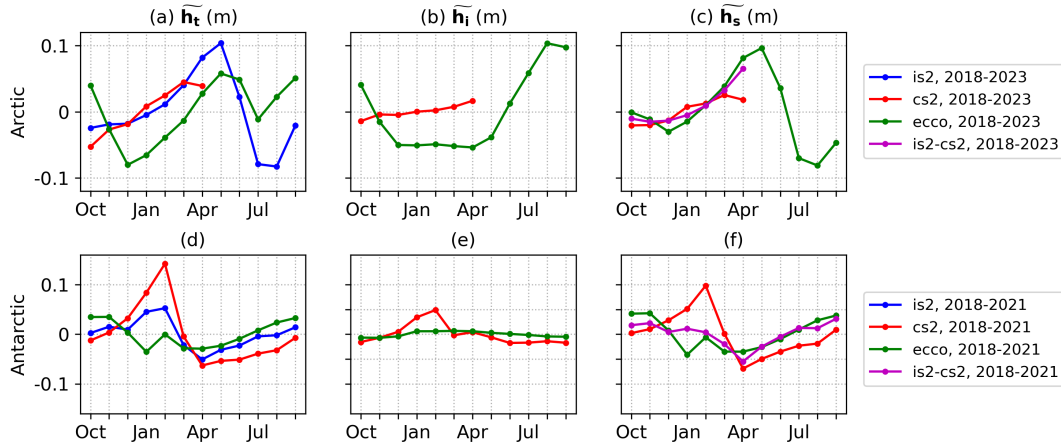


Figure 4. Mean seasonal cycle of (a,d) $\tilde{h}_t$, (b,e) $\tilde{h}_i$, and (c,f) $\tilde{h}_s$ in (a-c) the Arctic and (d-f) the Antarctic. Units are meters.

from CS2 and v5sim over their longer overlapping periods with very similar results (not shown), indicating that the few years
 185 of IS2 record analyzed in Figure 4 roughly capture seasonal variations representative of the past decade.

In the Arctic, during the ice growing season when CS2 data are available (October to April), $\tilde{h}_t$ increases are observed in both IS2 and CS2, with comparable range of magnitudes (Figure 4a, blue versus red). However, while IS2-derived $\tilde{h}_t$ increases more rapidly after January, increase in CS2 is more rapid from October to January followed by a gradual slowdown. This behavior is mostly due to the different evolution in $\tilde{h}_s$ fields (Figure 4c, purple versus red).

190 The v5sim run captures the Arctic-wide $\tilde{h}_t$ thickening of ~ 0.12 m from December to May (Figure 4a), when seasonal maximum value is found in both IS2 and v5sim. The thickening is dominated by $\tilde{h}_s$ (Figure 4c, purple versus green). Values of $\tilde{h}_i$ stay almost the same during this period (Figure 4b). More inconsistencies are found in the beginning of the ice growth season, October to December, when v5sim-derived $\tilde{h}_t$ decreases in contrast with the observed slight increase (Figure 4a, green versus blue and red). The decrease in $\tilde{h}_t$ is driven by $\tilde{h}_i$ (Figure 4b versus 4c, green). In the melting season, while v5sim reproduces
 195 the increase in $\tilde{h}_t$ from July-August to September-October, it underestimates the thinning of $\tilde{h}_t$ from May to July, when ice starts to melt, by ~ 0.1 m (Figure 4a, green versus blue), originating from the thickening of $\tilde{h}_i$ in v5sim (Figure 4b, green).

Over the Antarctic, observed $\tilde{h}_t$ shows reasonable agreement in phase, but CS2 exhibits much larger peak value in February when Antarctic sea ice concentration minimum occurs (Figure 4d, red versus blue). The large CS2-derived peak value can be attributed to $\tilde{h}_s$ (Figure 4e versus 4f, red), which is missing from IS2-derived $\tilde{h}_s$ (Figure 4f, red versus purple). During the ice
 200 growing season from April to November, the thickening of $\tilde{h}_t$ is consistent in both phase and magnitude among the two data sets and v5sim (Figure 4d), dominated by $\tilde{h}_s$ (Figure 4e versus 4f, red). Like CS2, modeled $\tilde{h}_s$ contributes more to $\tilde{h}_t$ than $\tilde{h}_i$, leading to seasonal variations similar to those of $\tilde{h}_t$ (Figure 4d-f), including a second minimum in January that is not seen in the observations. The seasonal cycle of $\tilde{h}_i$ in v5sim has a very weak amplitude (~ 0.02 m) compared to ~ 0.06 m for CS2.



3.3 Temporal variability

205 An assessment of time-varying freeboard sheds light on the consistency among the two data sets and v5sim on monthly timescales. We compare the standard deviation of the monthly freeboard from the three products, after removing their time mean and the linear trend (h'_t , h'_i and h'_s hereafter). The seasonal cycle is retained, as the limited data availability at the grid scale aliases a representative seasonal cycle. We focus on comparing h'_t between IS2 and v5sim, and h'_i between CS2 and v5sim, as each sensor directly measures its respective variable (h_t for IS2, h_i for CS2) without reliance on auxiliary data. The interpretation is complemented by IS2-CS2 comparison in h'_t .
 210

3.3.1 Arctic

Variations in IS2-derived h'_t on the monthly timescale are more pronounced in MYI, especially along the old ice belt (>0.2 m). IS2's h'_t exhibits the weakest variability in the Barents Sea and the East Siberian Sea, generally smaller than 0.06 m (Figure 5a). When only considering ice growing season, h'_t becomes weaker by ~ 0.02 m across the Arctic (Figure 5c), suggesting more
 215 intense variations during the ice melting season, possibly due to the onset of surface and basal melting and ice deformation during the spring and summer months.

The v5sim-derived h'_t values are more variable than IS2 almost everywhere across the Arctic (Figure 5a,d). The v5sim-IS2 differences in h'_t are larger in most of the western Arctic (>0.12 m) relative to the eastern Arctic (<0.08 m), peaking at >0.25 m in the old ice belt (Figure 5g). IS2-derived h'_t is well correlated with v5sim where their differences are small, with correlation
 220 coefficients exceeding 0.6 (Figure 5j).

Differences in h'_t variability are smaller between the two observations, on the order of 0.03–0.06 m in general, and up to 0.1 m along the edge of the MYI and along the coast (Figure 5c,f,i). While the spatial distribution of h'_t variability appears inconsistent between IS2 and CS2, correlations are above 0.6 in most of the Arctic (Figure 5l).

The CS2 data allow us to examine consistency of h'_i estimates with v5sim, to further understand the role of h'_i and h'_s in h'_t (Figure 5b,e,h,k). Observed h'_i variations are largest in MYI (>0.05 m). Modeled h'_i variability is >0.05 m everywhere except from the eastern Fram Strait to the Laptev Sea, where positive correlations between CS2 and v5sim are found. In the MYI, observed and modeled h'_i are negatively correlated (Figure 5k), consistent with behaviors in $\tilde{h}_i$. The better agreement in h'_t between observations and v5sim, but poor consistency in h'_i between CS2 and v5sim suggests that h'_i and h'_s in ECCO could benefit from separate constraints.
 225

3.3.2 Antarctic

Both IS2 and v5sim show greater variability in h'_t along the Antarctic coast in October 2018–December 2023 (Figure 6a,d), though IS2 exhibits consistently larger variations than v5sim across the Antarctic, except the southern Weddell Sea. Offshore, standard deviations range from 0.04–0.10 m in IS2 and 0.02–0.08 m in v5sim, while along the coast they exceed 0.16 m and 0.12 m, respectively. Standard deviations of the difference (IS2–v5sim) in h'_t are greatest along the coast (Figure 6g). The
 235 h'_t field in v5sim is significantly correlated with IS2 in the Weddell Sea, and several scattered locations along the coasts, with

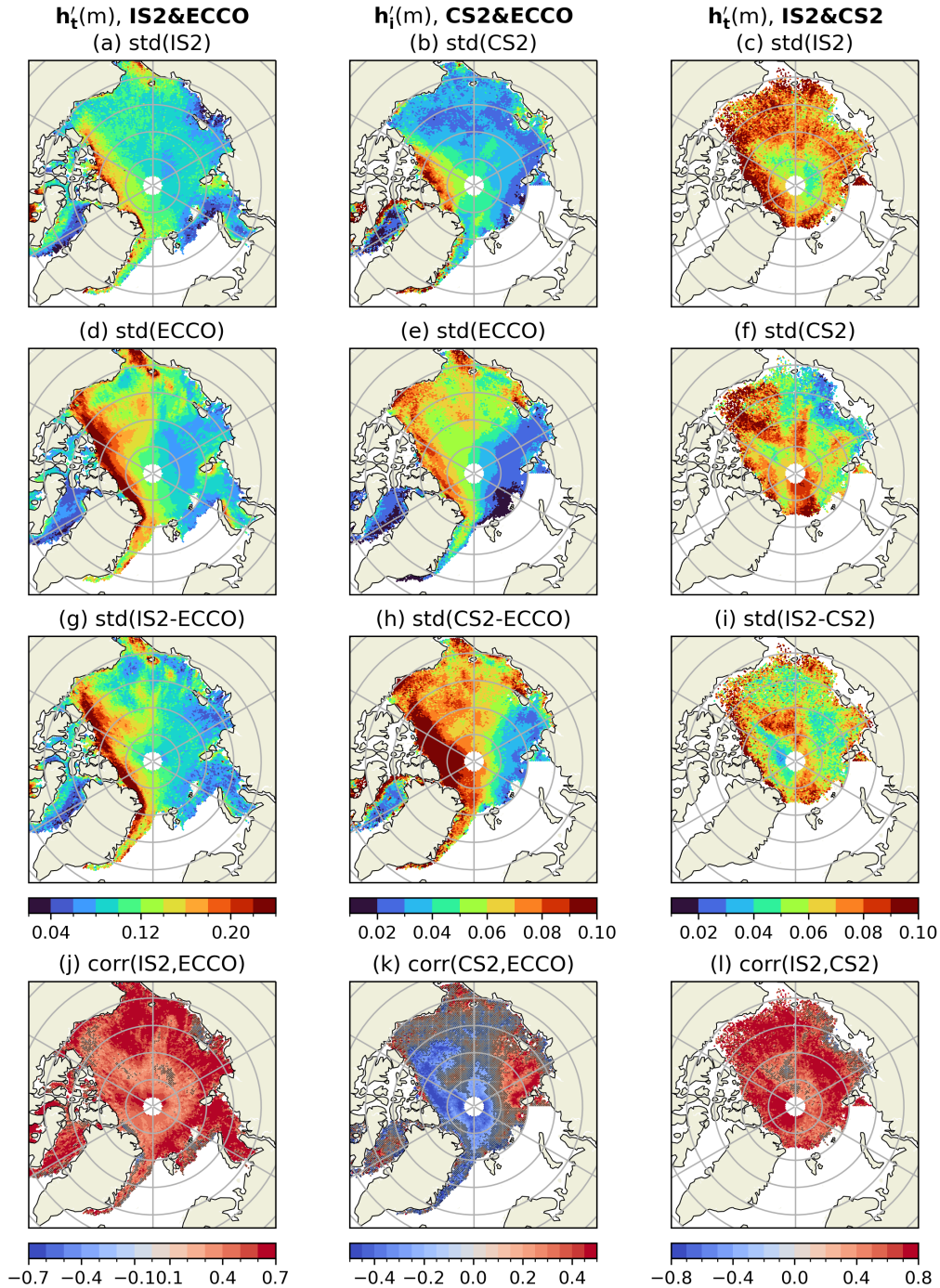


Figure 5. Statistics computed in grid cells where more than 12 months of data are available: (a-f) standard deviation, (g-i) standard deviation of differences, and (j-l) correlation coefficient. Comparisons of h'_t are shown for the IS2-v5sim and IS2-CS2 pairs (left and right columns), and h'_i for the CS2-v5sim pair (middle column). Based on periods (a,d,g,j) October 2018–December 2023, (b,e,h,k) October 2010–December 2023, and (c,f,i,l) October 2018–February 2024. Stippling areas in j-l indicate locations where the correlation is insignificant (95% confidence level). Note the different color bars in several panels.



correlation coefficient >0.6 (Figure 6j). Over a shorter period (October 2018–August 2021), h'_t variability in IS2 is comparable to that over the longer period (Figure 6a versus 6c), implying that h'_t variability remains stable in 2018–2023.

240 Variability in CS2-derived h'_t mirrors that in IS2, but with weaker amplitude (Figure 6f). The standard deviation of the difference (IS2–CS2) range from a few centimeters offshore to more than 0.16 m along the coast (Figure 6i), and the correlations are insignificant almost across nearly the entire Antarctic except the along-coast region between $\sim 60^\circ\text{W}$ – 170°W , from the Bellingshausen Sea to the eastern Ross Sea (Figure 6l).

Similar to h'_t , variability in h'_i shows consistent spatial distribution between CS2 and v5sim, but v5sim exhibits near zero variations offshore and 0.02–0.12 m along the coast, whereas CS2's h'_i varies by 0.02–0.08 m offshore and more than 0.12 m along the coast (Figure 6b,e). The large magnitude differences between CS2 and v5sim are clear in the standard deviation of
 245 the difference (CS2–v5sim) in Figure 6h. Moreover, h'_i in v5sim and CS2 are not significantly correlated over most of the domain (Figure 6k).

4 Constraining ECCO freeboard to observations

The previous section shows relatively large model-data differences in both time-mean and time-varying freeboard, along with better agreement between the IS2 and CS2 observations in the Arctic than in the Antarctic. The differences among
 250 the v5sim and data products, including their poor correlations in extensive regions, raise the question of whether observations could effectively constrain ECCO freeboard estimates in both polar regions. An assessment of this issue is attempted here using estimates of data errors and respective cost values as discussed in section 2.4.

4.1 Errors and cost for time-mean freeboard

We restrict our analysis to $\overline{h_t}$, as $\overline{h_i}$ cannot be unambiguously separated from $\overline{h_s}$ in IS2 measurements, and all three products
 255 are required for the error and cost calculation. As previously described in section 2.4, we estimate errors of $\overline{h_t}$ (i.e., $\varepsilon_{\overline{D}}$) as the absolute difference between IS2- and CS2-derived $\overline{h_t}$.

Errors are on the order of a few centimeters over most of the Arctic, with higher values (>0.11 m) in the East Siberian Sea shelf and northern MYI (Figure 7a). Maps of cost are comparable for both observations: larger cost (>3) is found throughout large parts of the Arctic, except north of the Fram Strait and the Laptev Sea, where cost is smaller than 1 (Figure 7c,e). The
 260 large cost across the domain suggests that constraining ECCO solutions to either IS2 or CS2 data could lead to substantial changes in estimated $\overline{h_t}$.

Errors over the Antarctic are more spatially variable but generally larger near a few coastal regions (>0.12 m; Figure 7b). Offshore, errors range from 0.01–0.09 m. Cost values for both observations exceed 4 along the coast of the Weddell Sea, the Amundsen Sea and Ross Sea, as well as some discrete locations offshore (Figure 7d,f). Areas with higher costs are
 265 more prevalent in CS2, suggesting the latter product would provide a stronger constraint on the representation of $\overline{h_t}$ in ECCO optimizations.

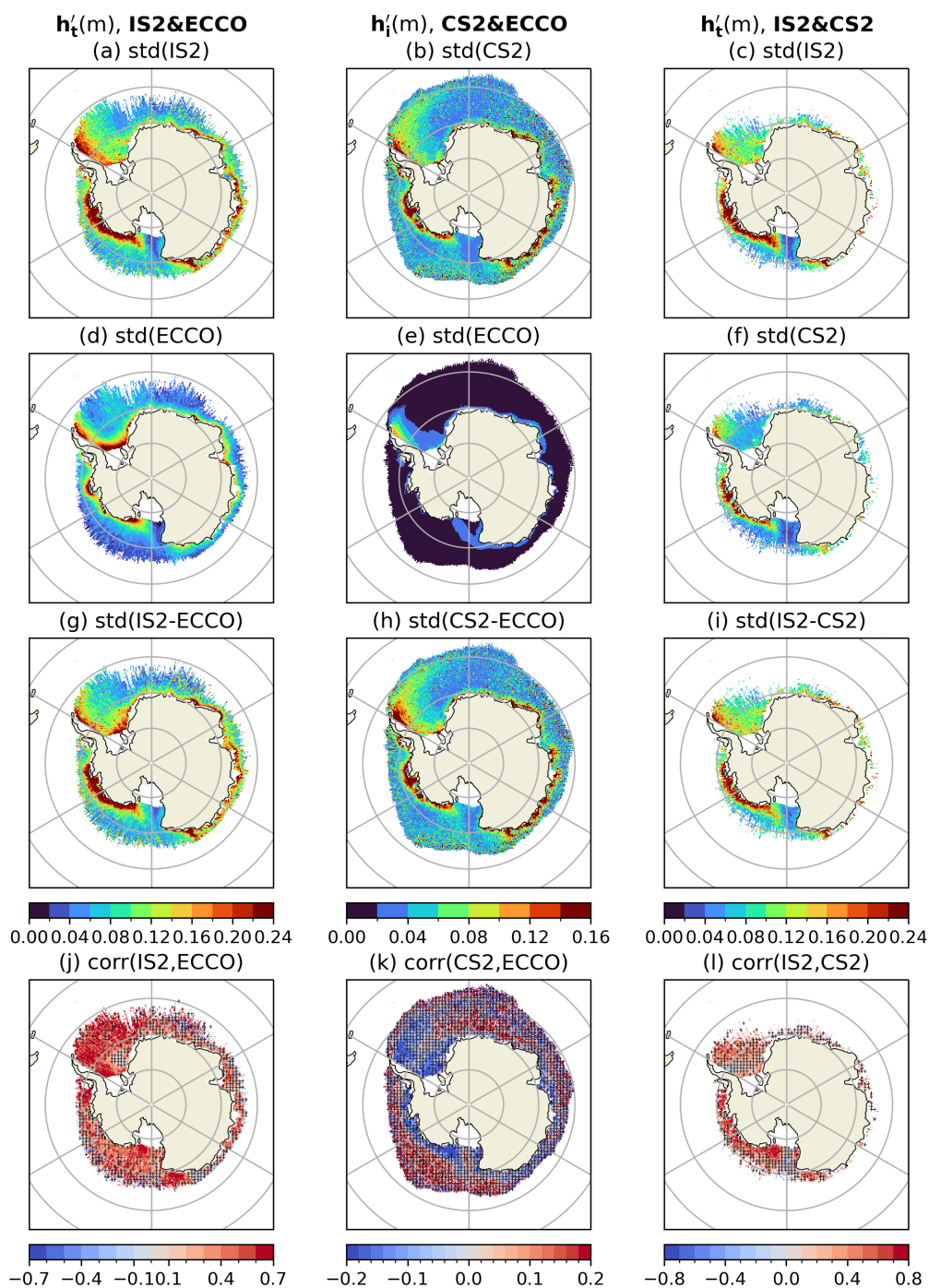


Figure 6. Same as Fig. 5 but for the Antarctic. Based on periods (a,d,g,j) October 2018–December 2023, (b,e,h,k) July 2010–August 2021, and (c,f,i,l) October 2018–August 2021.

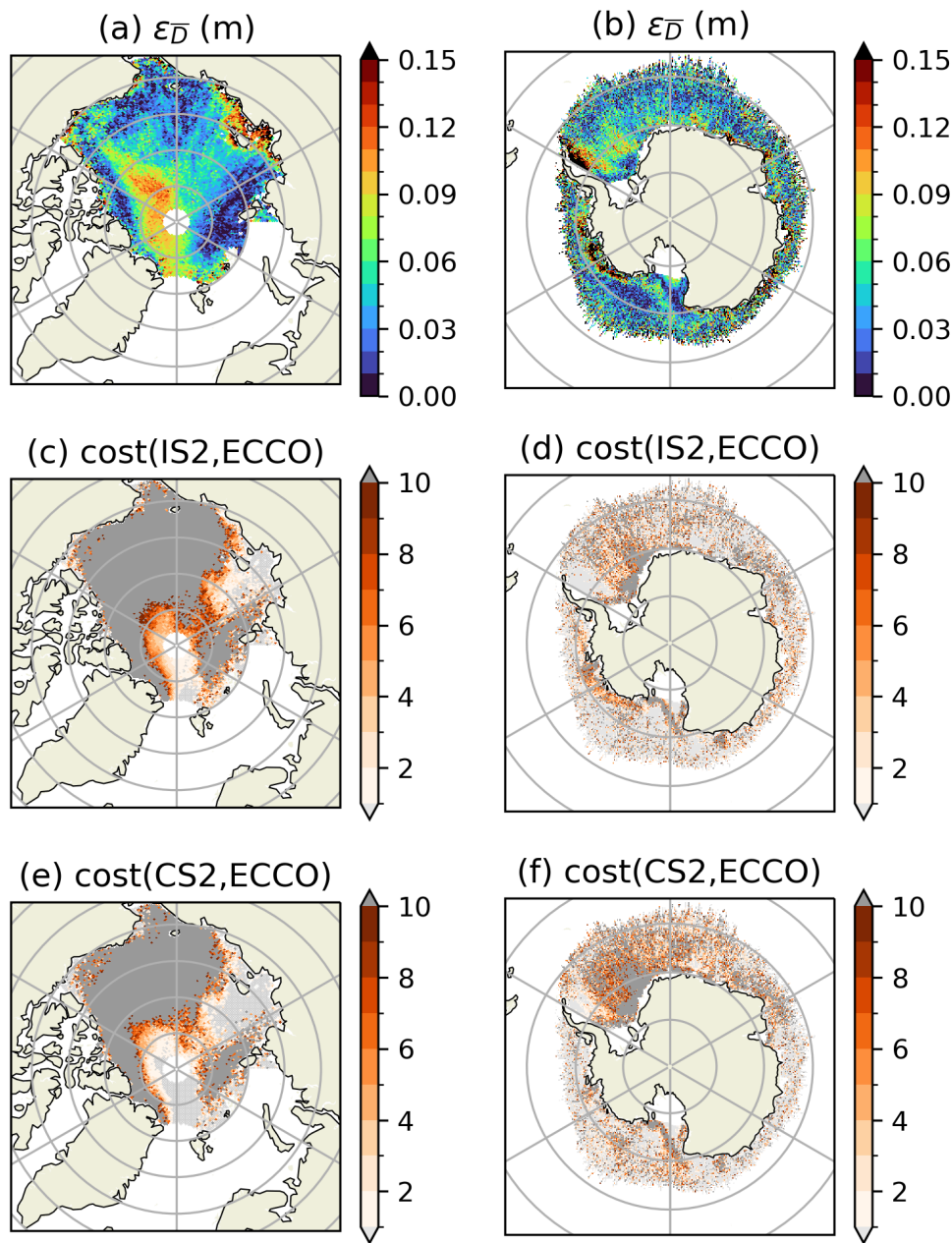


Figure 7. (a,b): $\overline{\varepsilon_D}$ (m) over the (a) Arctic and (b) Antarctic. (c-f): Cost values calculated with (c,d) IS2 and (e,f) CS2 $\overline{h_t}$. Light and dark grey denote cost values < 1 and > 10, respectively. Both errors and costs are computed on each grid cell over their common period (generally between October 2018 and December 2023 from October to April in the Arctic, and between October 2018 and August 2021 in the Antarctic).



4.2 Errors and cost for time-varying freeboard

We estimate standard deviation of time-varying errors based on equation (4) in section 2.4 ($\sigma_{\varepsilon'} = \sqrt{\text{var}(\varepsilon_{D'})}$), using freeboard anomalies after removing the time-mean values (h'_t, h'_i). Unlike the analyses in section 3.3, we retain all temporal variability including the linear trends in the derivation of error estimates and assessment of costs, since we envision the use of the full time series when implementing freeboard data constraints in future ECCO optimizations. In the cost calculations, following previous practices (e.g., Vinogradova et al., 2014) as mentioned in Section 2.4, we set minimum values of $\text{var}(\varepsilon_{D'})$ to be 10% of $\text{var}(D - M)$, which results in maximum cost values of 10.

In the Arctic, estimates of $\sigma_{\varepsilon'}$ for IS2-derived h'_t exhibit higher values in MYI (>0.1 m). Largest errors (>0.16 m) are found along the old ice belt (Figure 8a). Lower values, including some areas with unphysical negative numbers, are found in regions along the coast and west of the Beaufort Gyre. Cost values are larger than 1 across the entire Arctic domain (Figure 8c). Higher costs (>3) are found in the western Arctic, and along the coasts of the eastern Arctic. Antarctic $\sigma_{\varepsilon'}$ values are largest along the coasts, especially in the Amundsen-Bellingshausen Sea and the Indian Ocean sector, where $\sigma_{\varepsilon'}$ exceeds 0.2 m (Figure 8b). Large costs are found in only a few locations (Figure 8d), including the eastern and southern parts of the Weddell Sea, southern part of the Ross Sea, and a few scattered places. In the remainder of the Antarctic, cost values are close to 1.

We also examine the potential of CS2-derived h'_i for constraining the same field in ECCO, given the relatively bigger v5sim-data disagreement. In the Arctic, errors in CS2's h'_i are largest in MYI (>0.08 m) and a few centimeters in the rest of the Arctic (Figure 9a). Respective cost values are larger than 5 in extensive areas from the Beaufort Gyre to the East Siberian Sea, but < 2 over the remainder of the Arctic (Figure 9c). Errors in h'_i for the Antarctic are highest along the coast (>0.1 m), including the northern part of the Weddell Sea (Figure 9b). Cost values are overall around 1 but slightly higher in the western and southern Weddell Sea and the Ross Sea (Figure 9d).

5 Summary and discussion of results

In this study, we compare observed freeboards from the IS2 and CS2 missions with v5sim—a preliminary forward model run of the ECCO version 5 setup done without data constraints—and assess the potential for improving the latter sea ice freeboard fields through assimilation of the IS2 and CS2 data. We find a broad consistency between the two observational data sets on time-mean, seasonal, and monthly timescales, but substantial model-data differences in total freeboard h_t arising from misrepresentations in both ice freeboard h_i and snow depth h_s , particularly h_i .

In the Arctic, $\bar{h}_t$ from both satellites exhibits the largest values (>0.4 m) in MYI. In contrast, v5sim overestimates $\bar{h}_t$ relative to both IS2 and CS2 across the entire domain and displays a different spatial structure, characterized by a secondary maximum exceeding 0.7 m in the Beaufort Gyre region. Unlike CS2, for which $\bar{h}_i$ and $\bar{h}_s$ contribute comparably to $\bar{h}_t$, v5sim attributes more than 75% of $\bar{h}_t$ to $\bar{h}_s$ over most of the Arctic. The seasonal evolution of v5sim-derived $\tilde{h}_t$ generally agrees with observations, peaking in May and reaching a minimum in July-August, with variability dominated by $\tilde{h}_s$. Besides its smaller contribution to $\tilde{h}_t$, $\tilde{h}_i$ in v5sim differs from the observations during the early ice-growth and melt seasons, as evidenced by a decrease from October to December, and a less pronounced minimum in July. Observed monthly anomalies h'_t

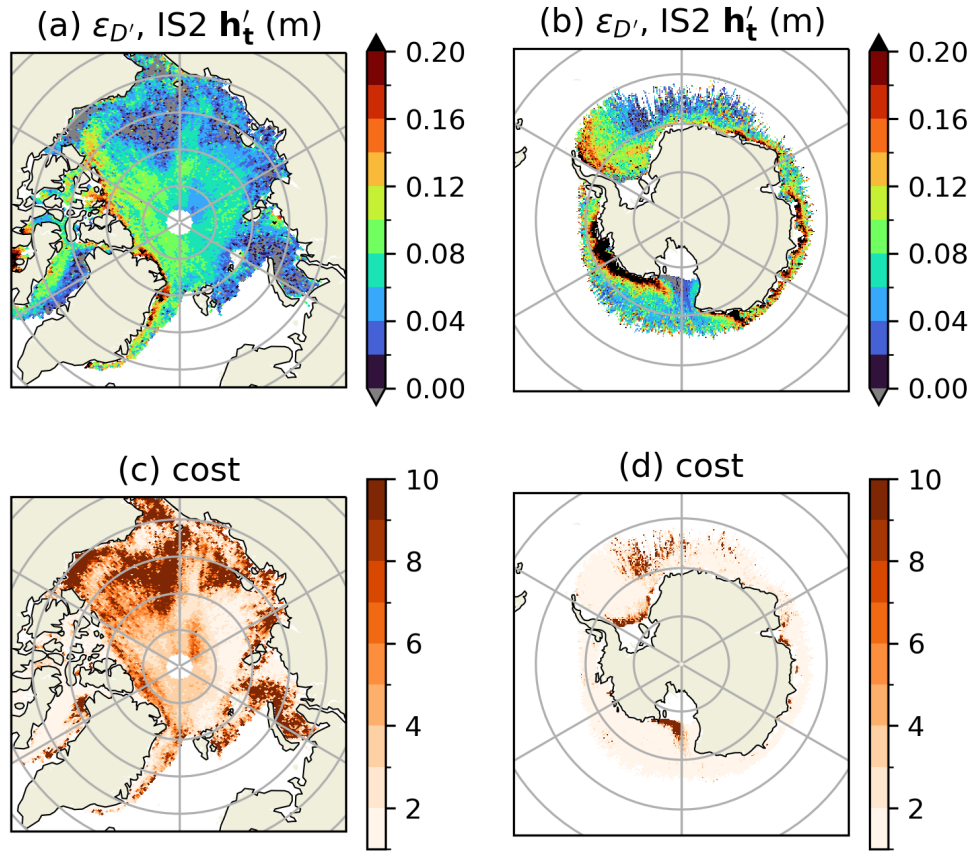


Figure 8. (a,b): Standard deviation of errors $\sigma_{\epsilon'}$ (m) for h'_t in (a) Arctic and (b) Antarctic, based on IS2 data. Grey area shows where $\sigma_{\epsilon'}$ values are not available. Errors are calculated on grids where more than 12 months of data are available. (c,d): Cost values in the (c) Arctic and the (d) Antarctic. Maximum values are set to 10 as explained in the text. Both errors and costs are computed on each grid cell over their common period (generally between October 2018 and December 2023 in October to April in the Arctic, and between October 2018 and August 2021 in the Antarctic).

300 and h'_i exhibit pronounced variability in MYI, while in v5sim, elevated h'_t variability extends over a broader area that includes the Beaufort Gyre region and the East Siberian Sea. The positive correlation of h'_t among IS2, CS2, and v5sim, together with anticorrelation between CS2-derived and v5sim h'_i in the western Arctic, highlights the potential value of constraining modeled h'_i and h'_s separately.

305 In the Antarctic, while v5sim fields capture well the observed spatial patterns of time-mean and time-variable freeboards, with larger values along coasts, their magnitude exhibits considerable departures from observations. Specifically, $\overline{h_i}$ in v5sim is substantially underestimated by ~ 0.12 m, but offset by an overestimated $\overline{h_s}$. A similar behavior is also seen in $\tilde{h}_i$ and h'_i , with near zero variations offshore. As a result, modeled $\tilde{h}_s$ dominates $\tilde{h}_t$, mapping its notable discrepancies with observations during

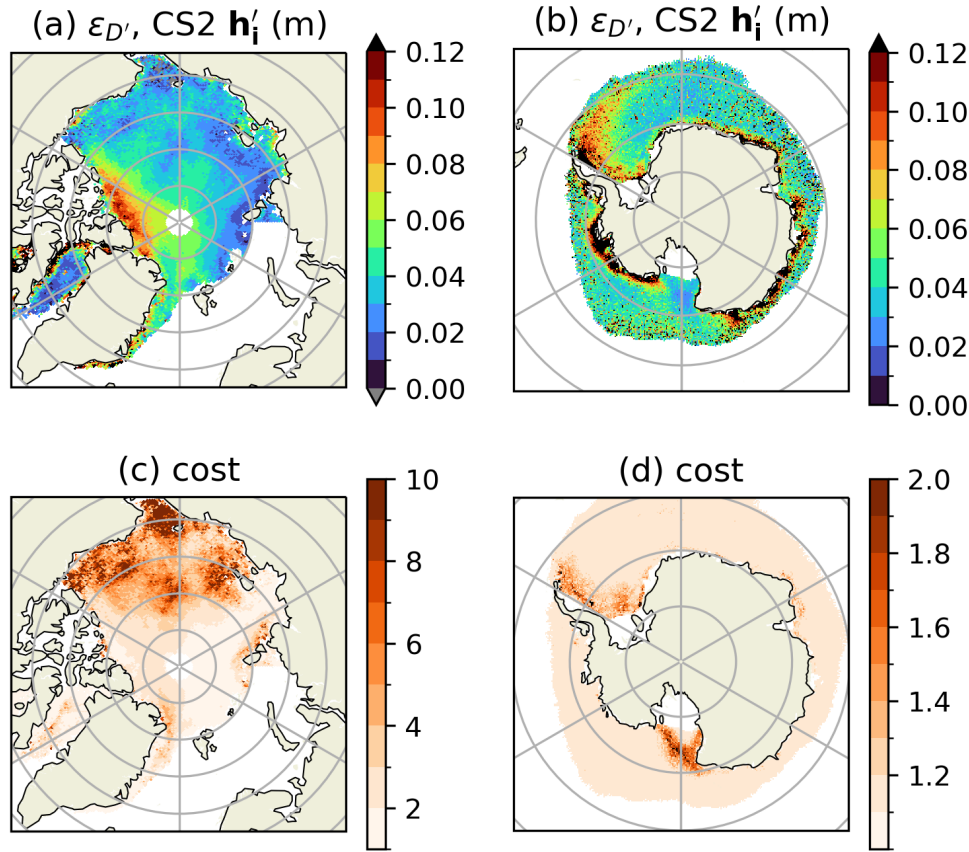


Figure 9. Same as Figure 8 but for CS2-derived h'_i .

the ice growth season onto $\tilde{h}_t$. Unlike the Arctic, we find higher disagreements in h_t between IS2 and CS2 across all examined timescales.

310 Based on observed and modeled freeboards, we estimate errors in observed $\bar{h}_t$, IS2-derived h'_t and CS2-derived h'_i to evaluate the potential for improving ECCO's freeboard fields through data assimilation. Over the Arctic, $\bar{h}_t$ data uncertainties are higher (>0.1 m) in the northern part of MYI and the Siberian shelf, but are generally a few centimeters elsewhere. The small errors alongside the large model-data differences results in high cost values over most of the Arctic. Over the Antarctic, errors are spatially noisy, but generally larger (>0.1 m) along the coasts. Regions along the coast of the Weddell Sea and the Ross Sea, as
 315 well as several scattered locations, would benefit substantially from constraints provided by $\bar{h}_t$ observations, especially from CS2.

Errors in time-varying h'_t and h'_i largely mirror the spatial patterns of the corresponding standard deviations, but with slightly smaller magnitude. Cost estimates indicate that v5sim-derived h'_t could be improved in the western Arctic and along the eastern Arctic coasts, as well as portions of the southern Weddell and Ross Sea and a few other isolated locations. Similarly,



320 CS2-derived h'_i could provide valuable constraints in the Arctic from the Beaufort Gyre to the East Siberian Sea, and in the Antarctic over the western and southern Weddell Sea and the Ross Sea.

Our analyses have focused on the IS2-CS2 overlap period, but results and methodologies can be readily applied to other periods. In particular, use of CS2 data prior to 2018 seems warranted for future ECCO releases. The weak dependence of time-mean freeboard on the selected averaging period in 2012–2023 (not shown) opens the possibility of optimizing ECCO-
 325 derived mean-state freeboard using the whole CS2 data, even though our estimated time-mean errors are based on IS2-CS2 overlap period. Such use may be particularly beneficial because time-mean discrepancies in $\bar{h}_i$ in Figures 2d,e and 3d,e persist throughout the entire CS2 record (not shown). Similar considerations apply to constraining time-variable freeboard with the full CS2 record.

A more realistic representation of the sea ice seasonal cycle could have far-reaching impacts, given that sea ice growth and
 330 melt strongly influence the seasonal evolution of the upper ocean through a range of coupled thermodynamic and dynamic processes. In both hemispheres, v5sim-derived $\tilde{h}_i$ exhibits substantial differences from CS2, which are likely related to the different characteristics of multi-year ice (thick, relatively high freeboard, present every year) versus first-year ice (thin with low freeboard, variable from year to year). In the Arctic, during the ice growth season, the nearly constant $\tilde{h}_i$ from CS2 likely results from the thickening of the multi-year ice balanced by the emerging thin first-year ice. In contrast, the rapid decrease in
 335 v5sim's $\tilde{h}_i$ during the early ice growing season indicates extensive formation of thin first-year ice, causing the Arctic-averaged ice thickness to shift toward lower values despite concurrent thickening of multi-year ice. Similarly, during the early ice-melting months, a rapid diminishing of first-year ice occurs in v5sim, leading to the large increase in $\tilde{h}_i$. The disagreement between v5sim and observations in these critical times implies the possible misrepresentation of ice growth speed and/or the ice age distribution across the Arctic. Similar misrepresentation may also occur over the Antarctic, given the substantially
 340 underestimated $\tilde{h}_i$ variations and $\bar{h}_i$ compared to observations. The larger inconsistencies in $\tilde{h}_s$ between estimates derived from IS2-CS2 and those provided directly in the CS2 products suggest greater uncertainties in h_s from the latter. Such uncertainties are consistent with the reliance on an older climatological snow depth dataset used in the Arctic CS2 product, as well as the greater snow depths in the Antarctic, which increase the complexity of interpreting Ku-band returns (Fons et al., 2023).

As elaborated in section 2.4, errors shown in Figures 8a,b and 9a,b include both data noise and representation errors. To
 345 explore their relative importance, one can derive data noise from equation (4) using h'_t from both IS2 and CS2 (Figure 10). The standard deviations for IS2 data noise are smaller than those calculated against v5sim (Figure 8a) across most of the Arctic except coasts along the eastern Arctic, suggesting that representation errors make substantial contributions to the h'_t error estimates in Figure 8a. In contrast, over the Antarctic IS2 data noise in Figure 10b is comparable to values in Figure 8b, suggesting the dominance of data issues, likely associated with the smaller number of IS2 freeboard measurements in a given
 350 25-km grid cell in the Antarctic (Figure 1a-b). Possibly because of its denser data coverage, estimated CS2 noise is smaller than that for IS2 over the Antarctic (cf. Figure 10b,d). Data noise is of comparable magnitude between IS2 and CS2 across the Arctic, but of different spatial distribution: smaller for IS2 towards the central Arctic and opposite pattern for CS2 (cf. Figure 10a,c). Such difference is consistent with the different IS2 and CS2 h'_t variabilities in Figure 5c,f, which might in turn be partly

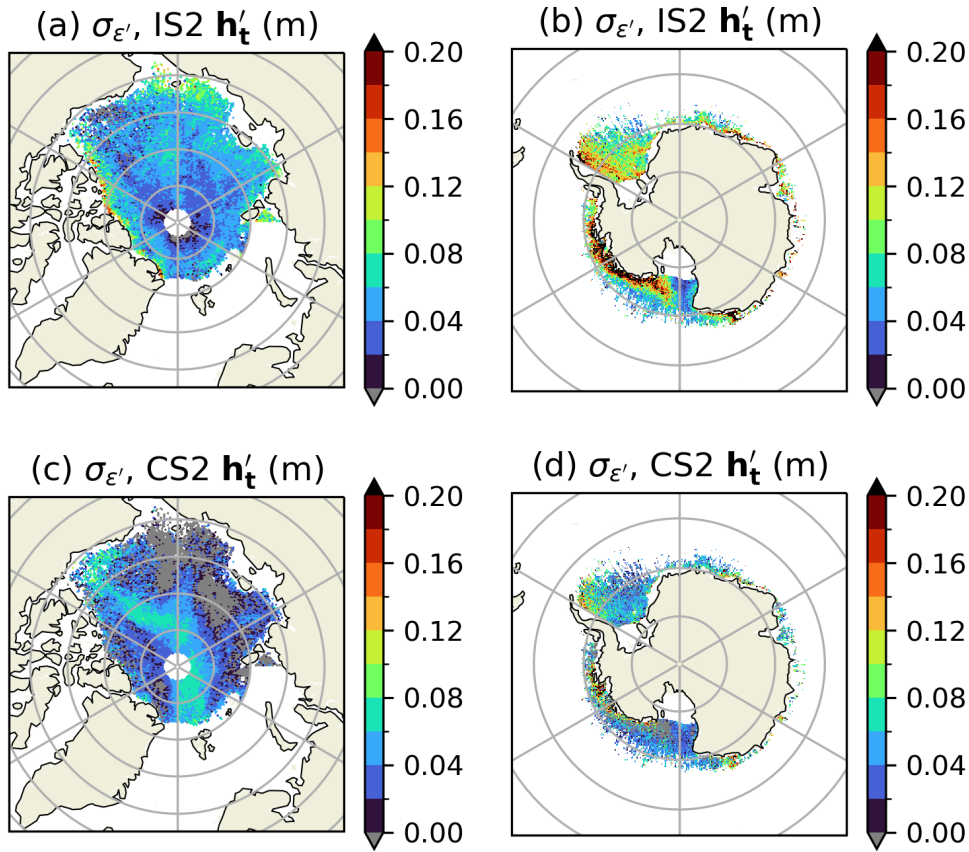


Figure 10. Standard deviations for (a,b) IS2 and (c,d) CS2 data noises. Units are meters.

related to the use of climatological h_s values in CS2, whereas IS2 measures h'_t directly without need for a separate estimate of h_s .

The forthcoming release of ECCO v5 release 1 assumes a spatially uniform error of 0.5 m for time-varying total freeboard, and ~ 0.16 m for mean-state freeboard, both much larger than the errors we derived in Section 4, implying that the total freeboard in ECCO v5 release 1 is not strongly constrained. Our work provides spatially varying, ECCO-specific errors for both mean-state and time-varying total freeboards. We also develop error estimates for ice freeboard, facilitating the use of both total and ice freeboard as complementary constraints in future ECCO optimizations. These constraints have the potential to improve the representation of sea ice and snow, thereby enhancing the simulation of associated thermodynamic and dynamic processes and influencing broader aspects of the climate system beyond the cryosphere.

In the development of future ECCO v5 releases, constraints based on spatially averaged freeboard over larger grid cells and respective data errors could be implemented. This approach can reduce spatial noise, potentially increasing the signal-to-noise ratio, and eventually enhancing the value of these satellite measurements in the ECCO optimization process. Moreover, including initial conditions for h_t and h_i in the control vector might help in the optimization. The initial condition for sea ice



state (including concentration, thickness and velocity fields) used in ECCO v5 release 1 is identical to the v5sim run analyzed here. Although the sea ice state has evolved substantially since 1 January 1992, the start date of ECCO solutions, and no basin-scale freeboard observations are available back then, deficiencies in the initial freeboard state are apparent (not shown).
370 Employing a more realistic initial freeboard, such as that from the Arctic sea ice reanalyses described in Zhang and Rothrock (2003), could improve the representation of sea ice in the data assimilation efforts.

Data availability. ICESat-2 ATL20 product used in this study are available at <https://nsidc.org/data/atl20/versions/5>, accessed on 02 March 2026. Arctic freeboard data from CryoSat-2 are distributed by the National Snow and Ice Data Center from <https://nsidc.org/data/rdf4/versions/1>, accessed on 04 June 2024. Antarctic freeboard data derived from CryoSat-2 are available at <https://zenodo.org/records/7327711>,
375 accessed on 04 June 2024. Freeboard fields from ECCO preliminary simulation for version 5 analysis were generated by Ou Wang and were acquired on 13 May 2024, available at <https://zenodo.org/records/21709083> (Zhao et al., 2026).

Author contributions. MZ and RMP came up with concept and methodology for the study, with help from OW, IFu and IFe, and wrote the first draft. MZ performed all calculations and created the figures. OW, IFu and IFe provided support on ECCO-related analyses. All authors participated in the writing of the final version of the manuscript.

380 *Competing interests.* The contact author has declared that none of the authors has any competing interests.

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