Reviewer 1 comments and *our response*

This manuscript presents monthly GrIS elevation changes from a long-term series using multi-sources satellite and airborne altimeter data. The authors improved the previous annual elevation change method to detect monthly elevation changes. They also separated the seasonal surface variation from the time series of surface elevation observations. This method seems to be effective; however, I still have some concerns about this paper.

Authors: *Thank you very much for your time and for reviewing this paper. In light of the insightful feedback from you and the other reviewers, we have made several changes that have greatly improved the revised manuscript. A detailed response to your comments, addressing all the identified issues, is listed below.*

Major comments:

1. This paper resembles more a technical report than a scientific paper because it lacks careful organization of original data and a logical description of the methods.

Authors: We follow the guidelines from ESSD regarding the organization of the paper. We agree that the paper provides no new science and is structured more like a technical report.

2. The authors use the seasonal terms derived from ICESat or ICESat-2 to represent the seasonal surface elevation changes observed in other satellite altimeters. The rationale and the associated uncertainties should be discussed further.

Authors: correct, the rationale behind this selection is Figure 12 and Figure 13.

While ICESat and ICESat-2-derived seasonal amplitude maps show the same spatial pattern (Fig. 12a and 12b), CryoSat-2-derived seasonal amplitude maps show some differences, likely caused by radar signals penetrating through surface snowfall.

Figure 8 shows the seasonal signal from CryoSat-2 and ICESat/ICESat-2 for the exact same location. We note that CryoSat-2 shows a smaller amplitude than ICESat/ICESat-2, likely due to radar signal penetration through surface snowfall.

In addition, ICESat (2003–2009) and ICESat-2 (2018–2023) show almost the same spatial pattern of the amplitude (new Figure 13).

However, the multiannual variations in surface elevations from ICESat-2 and CryoSat-2 are consistent. Similar findings have recently been published by Ravinder et al. (2024); see their Figure 2b.

3. The validation and cross-comparison with other monthly GrIS elevation change methods should be discussed, such as the method developed by Lai et al. R. Lai and L. Wang, Monthly Surface Elevation Changes of the Greenland Ice Sheet From ICESat-1, CryoSat-2, and ICESat-2 Altimetry Missions, IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, doi: 10.1109/LGRS.2021.3058956

Authors: Thanks for this paper. We mention the method from Lai et al. in the introduction. In addition, we also list the recent paper Ravinder, N., Shepherd, A., Otosaka, I., Slater, T., Muir, A.,

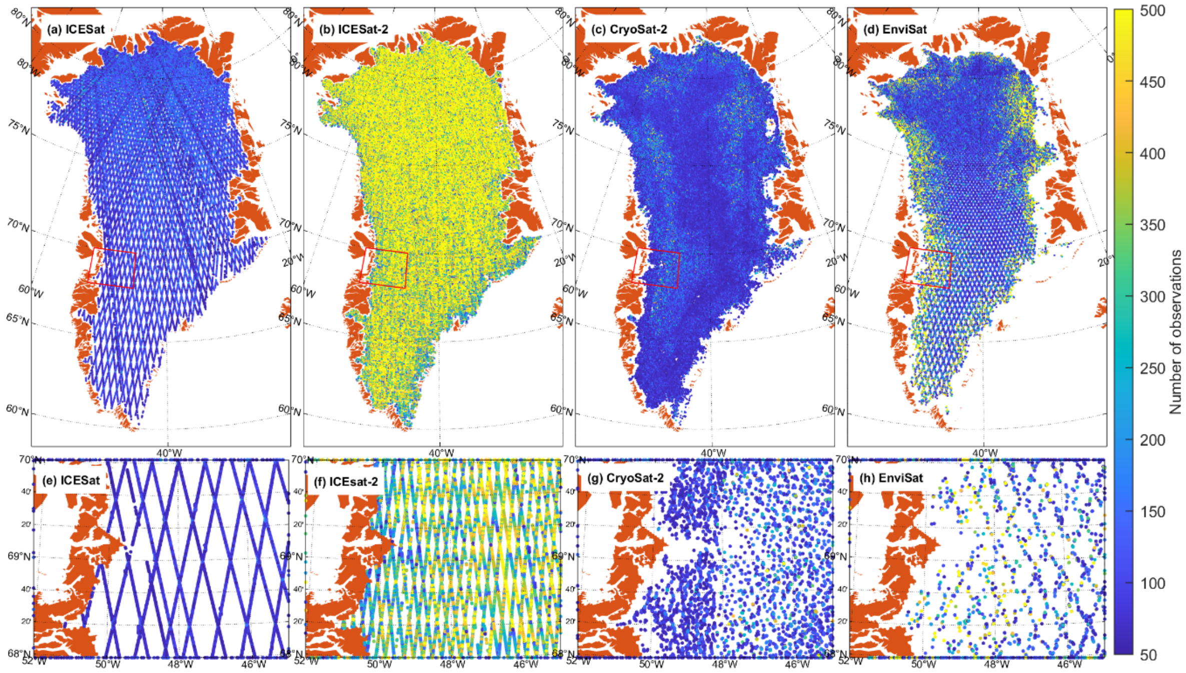
& Gilbert, L. (2024). Greenland Ice Sheet elevation change from CryoSat-2 and ICESat-2. *Geophysical Research Letters*, 51, e2024GL110822. https://doi.org/10.1029/2024GL110822

4. The accuracy of the time series elevation change detection method depends on the validity of observations in a specific grid. With higher resolution grids, there are fewer observations. Did the authors analyze the distribution of valid observations at 1 km resolution across the whole GrIS on a monthly scale? If so, please add this distribution.

Authors: Yes, we did. We have now added a figure that shows the number of observations used in each single-point time series from each sensor.

Note that for our method, it is not necessary to consider the distribution of valid observations on a monthly scale. However, the distribution of valid observations over the entire length of the dataset is relevant. This is shown, for example, in Figure 6, which presents a surface elevation change time series derived from ICESat data for a single point. The error bars denote observed elevations, but the best-fitting 7th-order polynomial is used to estimate monthly elevation changes for this particular point.

The number of observations used in each single-point time series is shown in the figure below.



Minor comments:

1. In Section 2, please add a table to summarize the data and its characteristics, such as time span and original accuracy.

Authors: Done, table added.

2. Line 155: "For each grid point with the center at (x_0, y_0), we identify the nearest data point within a 1000 m radius (x_i, y_i, h_i, t_i)......". Since the resolution of the grid is 1000 m, why not use a 500 m radius instead?

Authors: Very good question. A 500 m radius compared to a 1 km radius will result in fewer observations to fit a 7th-order polynomial for characterizing temporal elevation changes and a 3rd-order polynomial for describing the surface shape and seasonal signal. This also means that a 2 km radius will provide even more observations. However, as the radius increases, we need to increase the order of the polynomial that describes the surface shape.

Note that in our method, using a 1 km radius, we allow "observations" to be included in the time series at more than one grid point. In principle, this means that we spatially smooth elevation changes. The goal of this paper is to provide smoothed elevation changes.

3. Line 185: "Using the above equation, we only need to estimate two unknowns, A and φ." In fact, Equation 5 has three parameters.

Authors: No, only two unknowns a_{18} and a_{19}.

4. Line 250: "For the 2009-2018 period, (when data from both missions is available), we derive the seasonal signal averaged from ICESat and ICESat-2." The ICESat spans 2003–2009, while ICESat-2 spans 2018–2023. How can the seasonal signal be averaged over these periods?

Authors: By averaged seasonal signal we mean, average of a_{18} and a_{19} for each grid point estimated from ICESat and ICESat-2, respectively. This is now clarified in the text. As show in new figure 13a, the amplitude is more less the same for ICESat and ICESat-2.

5. Line 380: The ice loss from other methods should be listed here.

Authors: Many studies have estimated ice loss, and we mention them in the introduction based on temporal and spatial resolution. In general, our results agree with those of previous studies. The main goal of this paper is to provide data useful for solid Earth deformation and ice flow modeling.

6. Line 395 and Figure 15(a): "with R values ranging from 0.88 to 0.92". The R value should be referred to as the coefficient of determination (R^2).

Authors: corrected.

7. I suggest listing the data in the appendix.

Authors: we follow ESSD guideline for manuscript structure and list data in the section entitled "Data and code Availability". All data is already available through the link for download.

Review report

Manuscript Number/DOI: https://doi.org/10.5194/essd-2024-348

Full Title: Smoothed monthly Greenland ice sheet elevation changes during 2003-2023

Authors: Shfaqat A. Khan et al. Submitted to ***Earth System Science Data***

Recommendation: Major/Moderate revision

Overall Evaluation

This manuscript presents a comprehensive analysis of Greenland Ice Sheet elevation changes from 2003 to 2023, integrating multiple satellite and airborne altimetry datasets. The methodology demonstrates considerable rigor in data processing and uncertainty assessment, particularly in combining diverse data sources to produce a consistent long-term record. The approach to data integration and uncertainty quantification shows careful attention to detail. However, several aspects of the analysis require additional clarification and enhancement to strengthen the scientific contribution of this work. These concerns primarily relate to the physical basis of the seasonal model, methodology justification, and validation approaches.

Authors: Thank you very much for your time and for reviewing this paper. In light of the insightful feedback from you and the other reviewers, we have made several changes that have greatly improved the revised manuscript. A detailed response to your comments, addressing all the identified issues, is listed below.

Major Scientific Concerns and Suggested Improvements

Seasonal Signal Modeling and Physical Basis

The seasonal signal modeling presented in Section 3.2 (pages 7-8) requires substantial revision. The authors propose a new seasonal model in equation (4) that assumes 8 months of mass gain and 4 months of mass loss. While Figure 5 illustrates this seasonal pattern, the physical basis for this temporal distribution needs more rigorous justification. Specifically, the manuscript should explain how this seasonal pattern relates to known atmospheric circulation patterns and seasonal precipitation variability across Greenland. The relationship with regional climate dynamics, including the influence of the North Atlantic Oscillation on seasonal mass balance patterns, should be addressed. The authors should also demonstrate why their model performs better than the conventional cosine function described in equation (5), particularly in capturing the asymmetric nature of accumulation and ablation processes.

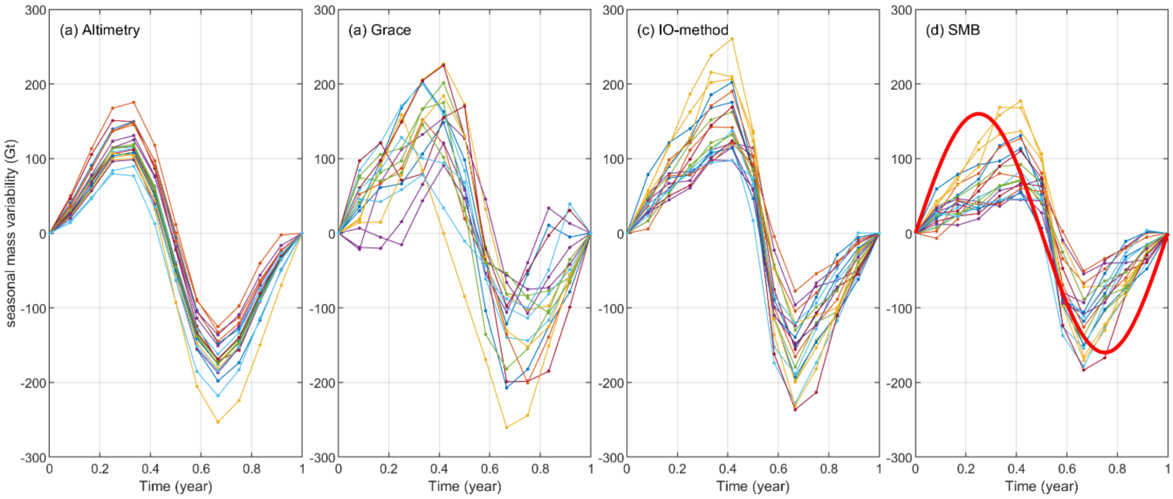
Authors:

Please note that this is primarily a "data" paper. We utilize GRACE, IOM, and SMB data to demonstrate the structure of the seasonal signal, which consists of 8 months of mass gain and 4 months of mass loss. Explaining the underlying causes of this behavior falls outside the scope of this study, as ESSD focuses solely on data presentation rather than scientific interpretation.

However, we acknowledge the reviewer's point that the North Atlantic Oscillation significantly influences the structure of the signal.

In response, we have added a new figure displaying seasonal mass variability from Altimetry, GRACE, IOM, and SMB data. For each method, we plot the seasonal signal for each year on the same graph, stacking them together. To ensure consistency, we detrend the data and remove the mean for each year, setting the seasonal mass to 0 at time = 0 and 1 year. In panel (d), we show the seasonal signal from SMB alongside a conventional cosine function (red curve), which represents a mass increase over 6 months and a decrease over the following 6 months.

Our results show that GRACE and IOM, which are based on direct mass change observations, align better with our seasonal model than a conventional cosine function. While the cosine function commonly used in many studies provides a useful first-order approximation for describing the seasonal signal, our model is more consistent with the observed data. The SMB model, which incorporates accumulation, runoff, and evaporation processes. Previous studies have highlighted the correlation between accumulation and melting with the North Atlantic Oscillation.

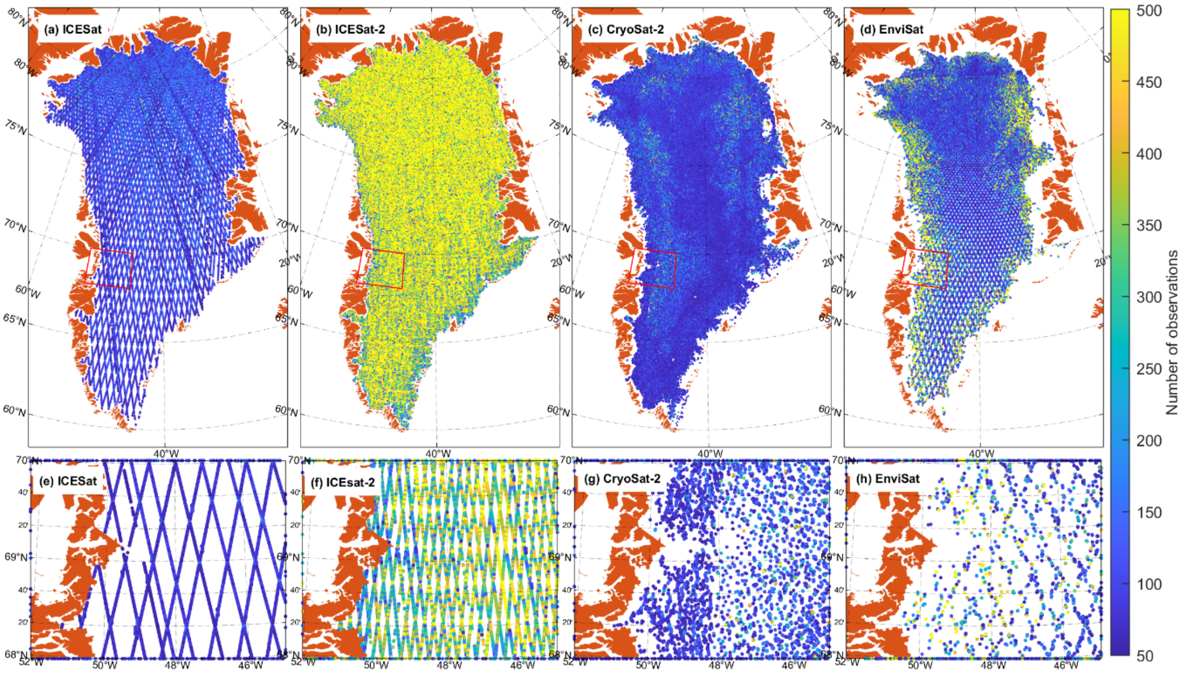


We have added a new section entitled “5.3 Seasonal signal”.

Methodology and Parameter Selection

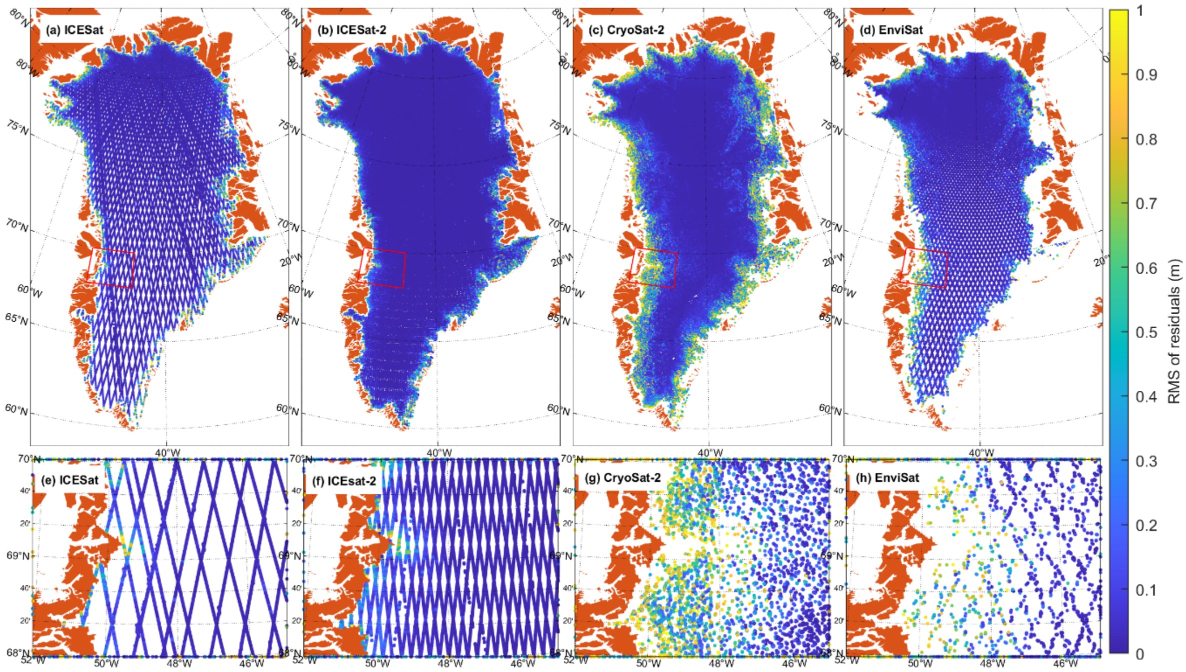
The methodology section (Section 3.2-3.4) should better justify key analytical choices. The use of a 7th-order polynomial for fitting elevation changes (equation 2, page 7) lacks sufficient justification. The authors should demonstrate why this order is optimal by comparing residuals across different polynomial orders and discussing potential overfitting issues. A systematic analysis of model performance with different polynomial orders would strengthen this choice. Additionally, the kriging interpolation parameters described on page 17 (lines 334-335) need more detailed explanation, particularly regarding the choice of the 65 km range parameter. The spatial correlation structure of elevation changes and its influence on interpolation parameters should be more thoroughly discussed.

Authors: The Greenland ice sheet exhibits complex spatial and temporal elevation change with rapid thinning e.g. in 2012 and 2019. For example, Jakobshavn Isbræ show thinning until 2016, followed by thickening during 2016–2018, and return to thinning from 2019 to 2023. In addition, thinning was extraordinary large in 2012, and 2019. *To capture these events higher order* polynomial is required. As show in figure 7, polynomials of order of 5-7 seems to capture changes very well. Figure 7b shows residual for different polynomials. However, the selection of polynomials is a compromise on data availability. We have 19 unknows parameters, and using a 1x1 km grid we set a threshold of 50 observations, excluding any time series with fewer data points. We have added a new figure displaying the total number of observations per grid point for each sensor.



To estimate parameters, we incorporate all observations within a 1 km radius of the center grid point. While a 500 m radius could be used, it would lead to large areas with insufficient observations and potential overfitting issues. We use a 3rd-order polynomial to represent surface topography, with the choice of polynomial order dependent on the selected radius. A larger radius (e.g., 5 km) requires a higher-order polynomial to capture complex topographic variations, whereas a smaller radius (e.g., 500 m) allows for a simpler 1st- or 2nd-order polynomial.

Our selection of polynomials for describing both surface changes and topography is a balance between ensuring sufficient observations and reliably estimating all parameters (19 in total). To assess parameter reliability, we have introduced a new figure (Figure 9) displaying the RMS of residuals from point time series for each sensor. Notably, RMS values are highest near the margin, where surface topography is more complex and may require higher-order polynomials. Alternatively, integrating high-resolution (100×100 m) Digital Elevation Model (DEM) data could improve complex topographic representation.



The kriging interpolator's weights are determined by the modeled variogram, making it highly sensitive to any mis-specification of the variogram model. Its interpolation accuracy is limited when the number of sampled observations is small, the data has a restricted spatial extent, or there is insufficient spatial correlation. In such cases, constructing a reliable sample variogram becomes challenging. Using data from a single sensor—such as CryoSat-2 or EnviSat—near the ice margin (see Fig. 8g and 8h) where data gaps are large can lead to significant large uncertainty. However, our approach, which integrates multiple data sources, particularly the inclusion of ATM data concentrated along glacier flow lines, helps to reduce uncertainty. However, ATM data does not provide complete coverage of all glaciers in Greenland. In particular, elevation changes in small glaciers, especially those 1–2 km wide in southeast Greenland, may not be well captured.

Validation and Comparison

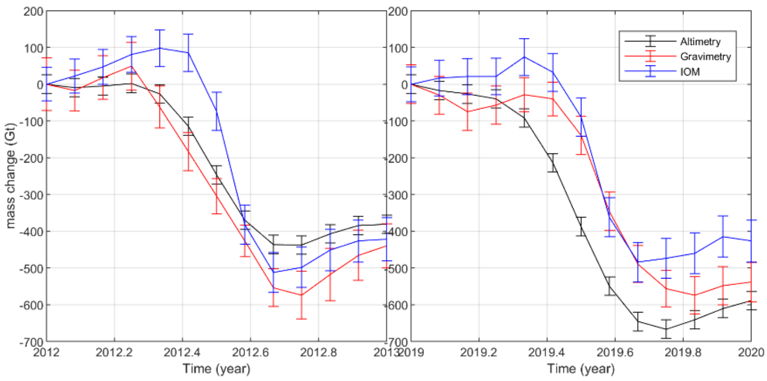
The validation approach presented in Section 5 (pages 20-23) should be expanded. While the comparison with GRACE data and the Input-Output method provides valuable insight, the analysis should include:

- Quantitative metrics for agreement between different methods, including correlation coefficients and root-mean-square differences
- Analysis of spatial patterns in the differences between methods, particularly in regions with complex topography
- Discussion of temporal variations in the agreement between different approaches, especially during periods of rapid change
- Assessment of seasonal cycle differences between methods and their implications for mass balance estimates

Authors:

It is very difficult to asses spatial patterns in the differences between methods. IOM total mass loss of a whole glacier basin. No basin wide elevation change is provided. GRACE has spatial resolution of about 200 km, and cannot separate ice loss from the different glaciers. However, we do provide elevation change in figure 18 from altimetry and GRACE. GRACE show thickening in the interior, altimetry does not. We do observe inconsistently between altimetry and GRACE, likely do to the poor resolution of GRACE.

we have added a new "5.3 Seasonal signal" where we justify of choice of seasonal signal. However, the choice of seasonal signal has less or no implications for long term mass balance estimates (trends).



In 2012 and 2019, the Greenland Ice Sheet experienced record-high ice loss during the summer months, as observed by satellite altimetry, GRACE, and the input-output method. In both years, extreme melt events were driven by anomalously warm atmospheric conditions, leading to significant surface mass loss (Bevis et al., 2019). Satellite altimetry recorded a rapid decline in ice surface elevation, while GRACE data detected substantial reductions in gravitational mass, confirming extensive ice loss. The input-output method further confirmed the ice mass loss. New Figure 21 illustrates the level of agreement between the three methods during the rapid ice losses in 2012 and 2019. All three methods detected ice loss ranging from 381 to 439 Gt in 2012 and 426 to 589 Gt in 2019.

Discussion and Implications

The discussion section (Section 6, pages 24-25) should be expanded to address methodological limitations more comprehensively. The authors should discuss:

- The implications of combining data from sensors with different spatial footprints, particularly for capturing small-scale elevation changes
- The challenges in detecting rapid elevation changes and their impact on mass balance estimates
- The potential impact of these limitations on ice sheet modeling applications, especially for initialization and validation
- Future improvements that could address current limitations, including upcoming satellite missions and methodological advances

- The broader implications for understanding ice sheet response to climate change

Our main motivation behind this study is to make critical data available for ice sheet and solid earth models. We have added the following text to the discussion section:

Recent studies using high-resolution modeling of Greenland's major outlet glaciers has shown that short-term changes in terminus position, ice thickness, and basal conditions significantly influence ice velocity (Cheng 2022, Lippert 2024, Lu 2025). For example, studies on Helheim Glacier (100–1,500 m resolution), Kangerlussuaq Glacier (350 m–12 km), and Jakobshavn Isbræ (100–1,500 m) have all demonstrated that ice front retreat and thickness variations drive substantial seasonal and multi-annual ice velocity fluctuation. These studies emphasize that annual elevation changes at a 5 km or higher resolution risk averaging out critical seasonal dynamics, leading to inaccuracies in modeling ice dynamics and underestimating short-term variations that are essential for projecting future changes of the ice sheet. Ultimately, the incorporation of observed high-resolution data into ice sheet models is essential for improving the fidelity of simulations and enhancing our ability to assess the implications of climate change on ice sheet stability and sea-level rise *(Choi et al.*, 2023).

In addition, a 1×1 km grid resolution of ice surface elevation data is essential for accurately modeling elastic land deformation of the crust because it captures the spatial variability of ice load changes at a fine enough scale to resolve localized flexural responses. Ice mass variations exert pressure on the Earth's crust, causing it to deform elastically, but these deformations are not uniform across the ice sheet. In regions with steep ice surface gradients, such as outlet glaciers and ice sheet margins, coarse-resolution data may smooth out critical variations in ice load, leading to inaccuracies in predicted uplift and subsidence patterns (Khan et al., 2022). A high-resolution grid allows for more precise calculations of surface mass redistribution, improving estimates of bedrock displacement. This level of detail is particularly crucial when observing Glacial Isostatic Adjustment with GPS observations, where corrections for elastic deformation need to be applied.

Combining data from sensors with different spatial footprints presents challenges in accurately capturing small-scale elevation changes. Sensors with coarse spatial resolution tend to smooth out localized ice surface variations, potentially underestimating rapid or heterogeneous changes. In contrast, higher-resolution sensors provide more detail but often have limited coverage or increased noise. Merging datasets requires careful interpolation to reconcile differences in sampling density, measurement techniques, and error characteristics. Discrepancies in spatial footprints can also result in mismatches when detecting localized thinning, particularly at glacier termini or steep ice sheet margins, which may affect estimates of mass loss and ice dynamics at finer scales.

A key limitation in detecting rapid ice sheet elevation changes using satellite altimetry is the temporal resolution of the data. Many altimetry satellites have repeat cycles spanning months, making it difficult to capture short-lived or sudden elevation changes, such as those driven by extreme melt events or rapid ice flow acceleration. Gaps between observations can lead to underestimation or misinterpretation of transient changes, especially in highly dynamic regions where ice loss occurs on short timescales. Additionally, seasonal variations in surface conditions, such as snowfall accumulation or meltwater refreezing, introduce further uncertainties when interpolating between measurement periods.

Since most ice loss occurs at the ice sheet margin, where the terrain is rough and data coverage is sparse, an alternative approach may be necessary. One method involves fitting a third-order polynomial equation to describe the surface shape using observations within a 1 km radius.

While this approach works well for much of the ice sheet, it may be insufficient in fast-flowing regions with rugged terrain. Using a higher-order polynomial is not feasible due to the limited number of observations relative to the unknown parameters in Equation 1. Additionally, we assume that surface topography remains constant over time intervals of 4–7 years. While this is a reasonable approximation for most of the ice sheet, near the termini of outlet glaciers, topography can change significantly from year to year. To address these challenges, integrating high-resolution (10×10 m) annual Digital Elevation Model (DEM) data with altimetry observations may improve topographic representation (Winstrup et al., 2024).

Technical Corrections and Presentation

Figures and Visualization

Several figures require improvement:

- Figure 5 (page 8): Add more detailed axis labels and improve legend readability, and if possible, include error bounds on the seasonal signals to better represent uncertainty in the temporal patterns
- Figures 13-14 (pages 20-21): Consider adding difference maps to better illustrate spatial patterns and include quantitative measures of uncertainty in the spatial comparisons

Authors: The primary purpose of Figure 5 is to illustrate the difference between the two seasonal signals. It represents an artificial signal rather than an observed one. However, we have added a new figure (Figure 20) based on actual observations.

Regarding Figures 13–14, we have already included five additional figures in the updated version, and adding more subpanels would make the figures overly complex. Uncertainty data is provided in the uploaded files accompanying this manuscript.

Recommendation

Major/Moderate Revision. The manuscript requires substantial revisions before it can be considered for publication. The authors should:

1. Provide a thorough physical justification for their seasonal model, including regional analysis and comparison with known climate patterns

- Strengthen the methodology section with quantitative justification for key parameter choices
- Expand the validation analysis with comprehensive statistical metrics and spatial comparisons
- Enhance the discussion of limitations and implications

These revisions are essential to ensure that this valuable dataset can be effectively utilized by the broader scientific community. Upon addressing these concerns, this work will make a significant contribution to our understanding of Greenland Ice Sheet mass changes and provide an important resource for future research in glaciology and climate science.

Authors: Thanks, we have Strengthen the methodology, Expand the validation analysis, Enhance the discussion of limitations and implications with 6 new figures and new sections.

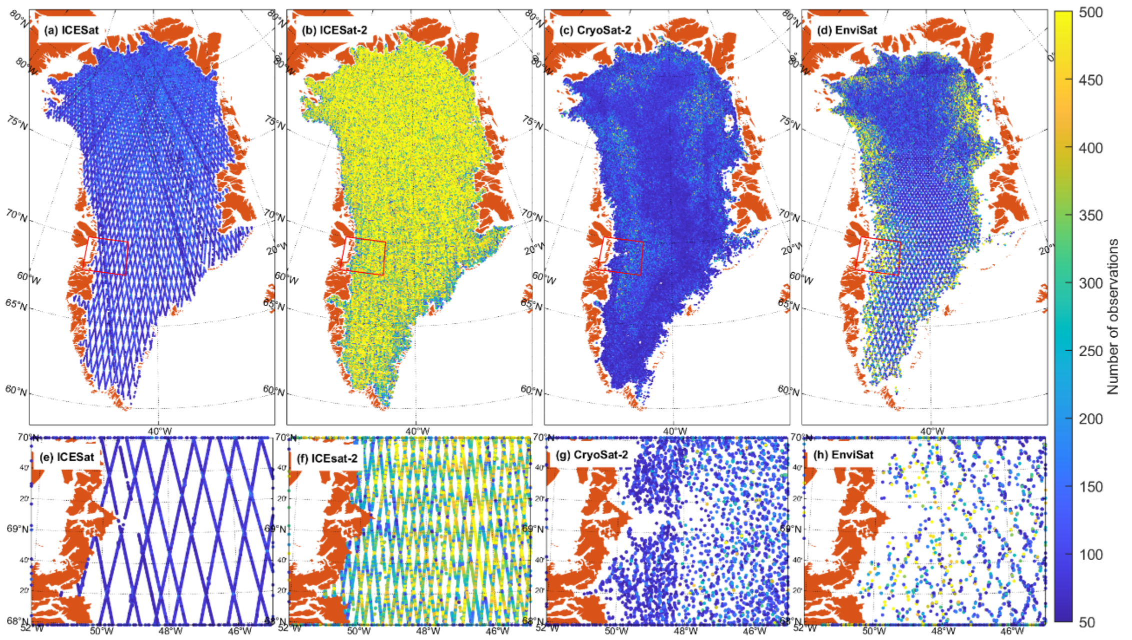
This paper presents a valuable new altimetric dataset of the Greenland Ice Sheet (GIS), derived from satellite and airborne altimetry data. The authors describe the processing steps for generating gridded (1 km × 1 km) monthly time series of surface elevation change for the GIS. The dataset was created using altimetry data from Envisat, ICESat, CryoSat-2, ICESat-2, and Operation IceBridge ATM. The authors also validate their monthly GIS elevation products against results from satellite gravimetry and the Input-Output method. However, I have a few suggestions and points of clarification before the manuscript is finalized. Detailed comments are outlined below.

Authors: *Thank you very much for your time and for reviewing this paper. In light of the insightful feedback from you and the other reviewers, we have made several changes that have greatly improved the revised manuscript. A detailed response to your comments, addressing all the identified issues, is listed below.*

Major Comments:

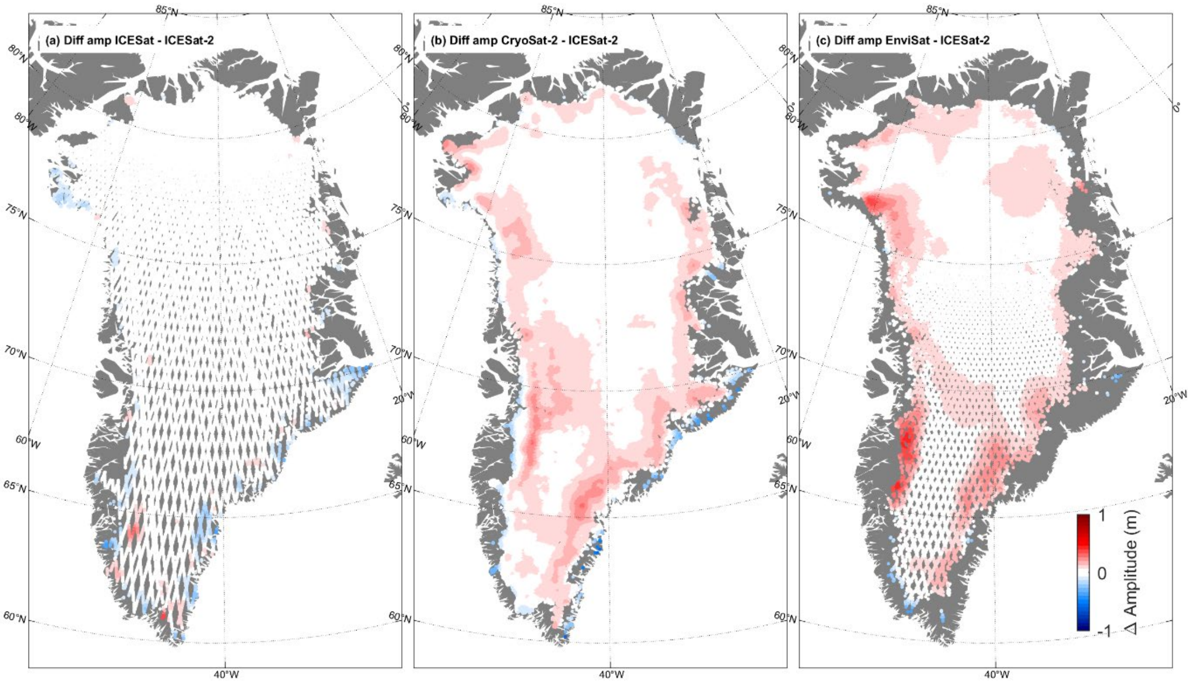
1. Section 3.2: I notice the spatial resolution of ICESat is much lower than 1 km, especially in lower-latitude regions of the GIS. Given this, ICESat data points within 1 km of grid nodes are typically located along repeat tracks from different cycles. How can the authors ensure the stability of the multi-parameter solution (7th-order polynomial, 3rd-order surface topography, seasonal term, and 21 parameters in total) with such sparse data points? If the number of height observations is smaller than the number of parameters to be solved, could the authors clarify how this issue is addressed?

Authors: This is not an issue. We have added a new figure (Figure 8) displaying the total number of observations per grid point for each sensor. A threshold of 50 observations is applied, excluding any time series with fewer data points. To estimate parameters, we incorporate all observations within a 1 km radius of the center grid point. This ensures a sufficient number of observations to reliably estimate all parameters (in total 19), including the 7th-order polynomial, 3rd-order surface topography, and seasonal term.



2. Lines 240-253: In this step, the radar seasonal signal is removed and replaced with the laser seasonal signal. ICESat/GLAS data covers only 18 discontinuous cycles between 2003 and 2010. How much will this substitution improve the estimate of the seasonal term, especially during the period between 2009 and 2017, when laser altimeter data is missing? Could the authors elaborate on this aspect?

Authors: We have added a new figure (figure 13) illustrating the difference in seasonal amplitude between icesat-2 and the various sensors. Notably, the amplitude difference between ICESat and ICESat-2 is minimal. This discrepancy may stem from the fact that amplitudes are estimated over different time periods using data from two sensors with varying spatial and temporal resolutions. Given the strong overall agreement between the two sensors, we propose that the mean amplitude from ICESat and ICESat-2 serves as a reasonable approximation for filling the gap from 2009 to 2018. The figure suggests that Envisat and Cryosat-2 yields larger amplitude compared to icesat-2.



3. Please double check the following references:

Nilsson, J. and Gardner, A. S.: Elevation Change of the Greenland Ice Sheet and its Peripheral Glaciers: 1992–2023, Earth Syst. Sci. Data Discuss. [preprint], https://doi.org/10.5194/essd-2024-311, in review, 2024.

Nilsson, J., Gardner, A. S., and Paolo, F. S.: Elevation change of the Antarctic Ice Sheet: 1985 to 2020, Earth Syst. Sci. Data, 14, 3573–3598, https://doi.org/10.5194/essd-14-3573-2022, 2022.

Authors: *Both are now included.*

Minor Comments:

1. **Line 234**: "Furthermore, we detect and remove outliers from each time series." How are outliers removed? Please provide more detail on the method used.

Authors: Outliers are identified based on residuals, which represent the difference between the observed elevation and the polynomial fit. Any values falling outside the 2-σ range are excluded.

2. **Lines 255-262**: The processing steps for Envisat and CryoSat-2 are similar, except for two individual time sub-intervals for CryoSat-2. I suggest the authors separately introduce the separate processing steps for radar and laser altimeter data to make this section clearer.

Authors: we fit and remove the seasonal signal from Envisat and CryoSat-2, and replace with and ICESat/ICESat-2 derived seasonal signal. We have added a new figure 13 that shows the difference in seasonal amplitude between the difference sensors.

3. **Section 3.7**: When creating the multi-sensor monthly grid, how are the estimated monthly change rates for the same month and grid cell merged? Did the authors consider the potential inconsistency in reference frames between different altimetry missions? Please specify.

Authors: we do not merge elevation time series estimates from the different sensors. Instead, we merge estimated elevation changes. We have not detected any inconsistency due to reference frames.

4. **Line 296 and Figure 11**: The merged data also contains many NaN grids. The interpolation method used is crucial in such cases. Could the authors provide the average percentage of effective raw grids used each month?

Authors: Good point. We now present the average percentage of effective raw grids for each month from 2003 to 2023. While we acknowledge that the "average percentage" is important for interpolation, the spatial distribution of the data is equally crucial. For instance, if all observations are concentrated in the north while the south remains unrepresented, the ice sheet-wide interpolation would be poorly estimated.

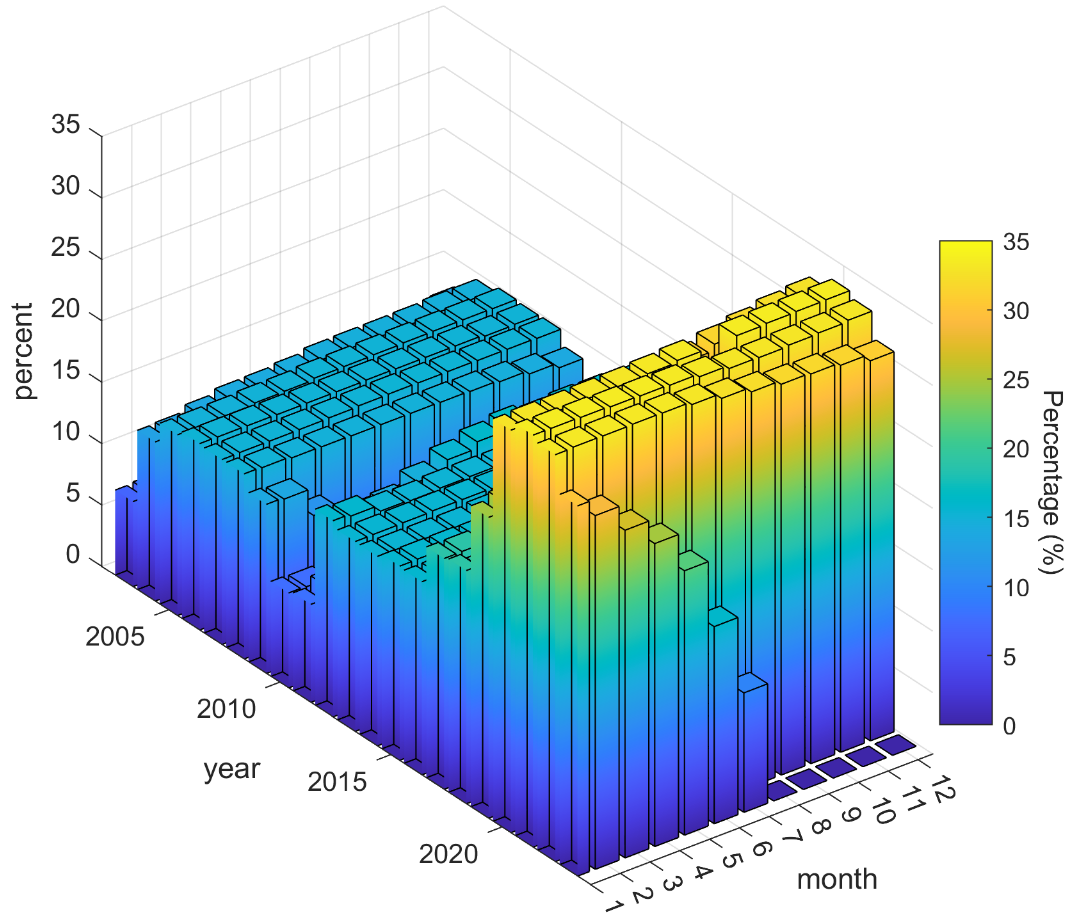


Figure of average percentage of effective raw grids for each month from 2003 to 2023

5. **Figure 12**: The time series of cumulative monthly ice mass change is presented, but it would be helpful to include the average annual rate of mass change in the same period calculated by different methods. This would provide additional context and comparison.

Authors: we find average annual rates from the three methods unnecessary here, since we already compare the 3 methods in figures 16.

6. **Line 180**: SMB -> Surface Mass Balance (SMB).

Authors: *changed accordingly.*

7. **Section 3.8.3**: How did the authors account for the impact of SMB in the step of converting volume to mass?

Authors: Elevation changes caused by firn compaction are simulated using a simple firn model that accounts for melt and refreezing (Khan et al., 2022b). Our approach incorporates temperature, accumulation, melt, and refreezing data from the regional climate model RACMO2.3p2. In this study, we provide estimates of ice volume and ice mass changes. Thus, users can easily substitute the firn compaction model with one of their choice.