We thank the reviewer for the positive evaluation and valuable comments. We provide a point-by-point response to each comment, with reviewer's comments in black, and author's responses in purple. The modified manuscript text is shown in quotation marks and italic, with additions in bold.

General remarks

GR1 Intrinsic uncertainties:
The reported uncertainties from the individual data sets are assumed to be uncorrelated. Therefore, the trends are subsequently estimated using ordinary least squares with the uncertainties on the diagonal of the co- variance matrix. I don't think that this is the right approach to estimate the trend uncertainties due to intrinsic errors. For many estimates the uncertainties will be serially correlated, for example due to uncertainties that affect the trend. Like if the uncertainty in a GRACE time series is fully due to GIA uncertainties that only affect the trend, the aforementioned assumption doesn't hold, and the resulting errors are an underestimation. For estimates where the rates and their uncertainties are available, an approximation that often works well is to assume that the rate errors are uncorrelated, which is equal to assuming random walk. Then you can generate an ensemble of time series by perturbing the rate with random normal noise, and then integrate the rates to obtain the time series. A good way to verify the results is to compare the barystatic trend uncertainties in Gt/yr or mm/yr with those reported in the papers where the data sets came from.

Thank you for pointing this out. This was also noted by Reviewer #1. Indeed, we assumed intrinsic uncertainties to be uncorrelated, but we agree with the reviewers that this assumption may not be valid in this case. We have therefore modified the intrinsic uncertainty computation by perturbing each time series with normal noise for a 1000-member ensemble. We then take the trend for each ensemble member, and compute the 95% confidence interval of the trend distribution. We use the half width of the 95% confidence interval as the rate uncertainty. An example of the new rates are shown in Figure 1 for the GMSL contribution from the AIS and the GIS based on the IMBIE datasets. We note, however, that these uncertainties are still smaller than the ones reported by IMBIE (Shepherd et al., 2018, 2020), as the reported uncertainties include both the intrinsic and temporal components.

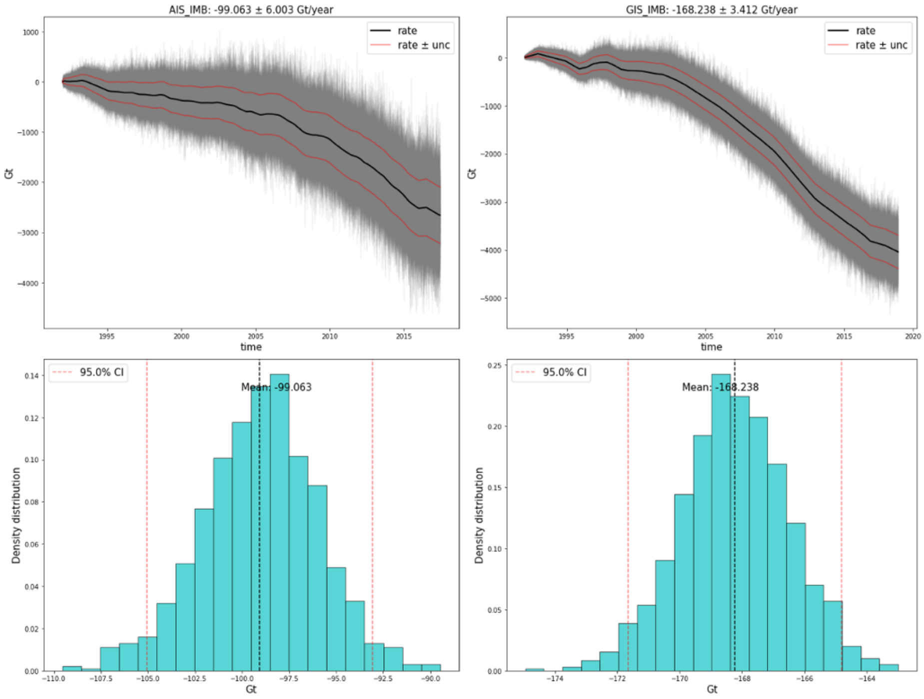

Figure 1. Mass change rates and improved intrinsic uncertainties. Gray lines on the top panels represent the 1000 ensemble members of the original time series (black) perturbed with random noise and the uncertainty time series (red). Histograms on the lower panels represent the trends of the 1000 ensemble members. We take the 95% confidence interval of the trend distribution, and use the largest difference between the mean and the CI as the rate uncertainty.

GR2 Trend uncertainties:
I think the paper could use some more discussion on the meaning of the trend uncertainties, because their meaning is not trivial and explaining the meaning of these trend uncertainties is important for data users to correctly apply them. This is a bit of a philosophical point, but the auto-correlated residuals after estimating the trend are not per se due to measurement errors, but they could represent a real signal. An example is the drop in GMSL during the 2010/2011 La Nina event, and the acceleration in ice-sheet mass loss. Let's assume now that someone downloads the regional data as well as some altimetry data of regional sea level. Then the uncertainty in the unexplained residual (Local altimetry – local ocean mass) should not contain the trend uncertainty given here. Altimetry will also see the acceleration and La Nina-like bumps and throughs and the difference probably shows much less interannual variations and thus has a lower trend uncertainty. However, when this user just uses the provided trend uncertainty and adds it in quadrature to some other errors, he or she will overestimate the uncertainties of the just computed difference. Some guidance could help here.

We agree that the residuals could actually represent a real signal, hence the importance of using the noise models to better represent these uncertainties. As noted by the reviewer, depending on the source of this uncertainty, the signal will be present in both the observed mass contributions as well as in altimetry (and also in other components of the sea-level budget). Consequently, summing up the uncertainties of different sources can lead to an overestimation of the uncertainty. We have added a comment about this in the discussion:

"In this manuscript we investigate the barystatic contribution to regional sea-level trends over 1993-2016 and 2003-2016, focusing on improving the understanding of the uncertainty budget. We show how mass changes of glaciers, land water storage, and the Greenland and Antarctic ice sheets influence regional SLC by computing sea-level fingerprints. We consider three types of uncertainties in our budget: the determination of a linear trend (temporal); the spread around a central estimate as influenced by the distribution of mass change sources (spatial); and the uncertainty from the data/model itself (intrinsic). The uncertainty budget is dominated by the temporal uncertainty, followed by a significant contribution of the spatial-structural uncertainty, while the contribution of the intrinsic uncertainty is relatively small. ***Regarding the temporal uncertainties associated with the trend, we note that they could partially represent real climatic signals in addition to measurement errors. For example, the variability due to climatic oscillations, such as El Niño Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO), may be reflected in the residuals of the time series, affecting the trend and its temporal uncertainties (Royston et al., 2018). As such climatic events influence not only mass change, but also other drivers of sea-level change (e.g., thermal expansion), caution must be taken when using and comparing these uncertainties with those from other sea level observations.****"*

GR3 Barystatic sea level:
How do the global-mean time series and uncertainties look like? A simple plot with the global-mean time series from each component and the total might be a nice addition. That could also help verifying the 1993-2016 time series from models: do they show similar trends and variability as GRACE? For TWS, Scanlon et al. (2018) show some discrepancies between models and GRACE for TWS. Might be interesting to see whether estimates from WaterGAP and PCR-GLOBWB now perform better.

We have added a figure of the global-mean time series in the main text as Figure 1, and have included a table with global mean barystatic trends and uncertainties in the appendix (Table A1), as the focus of this study is on regional variations.

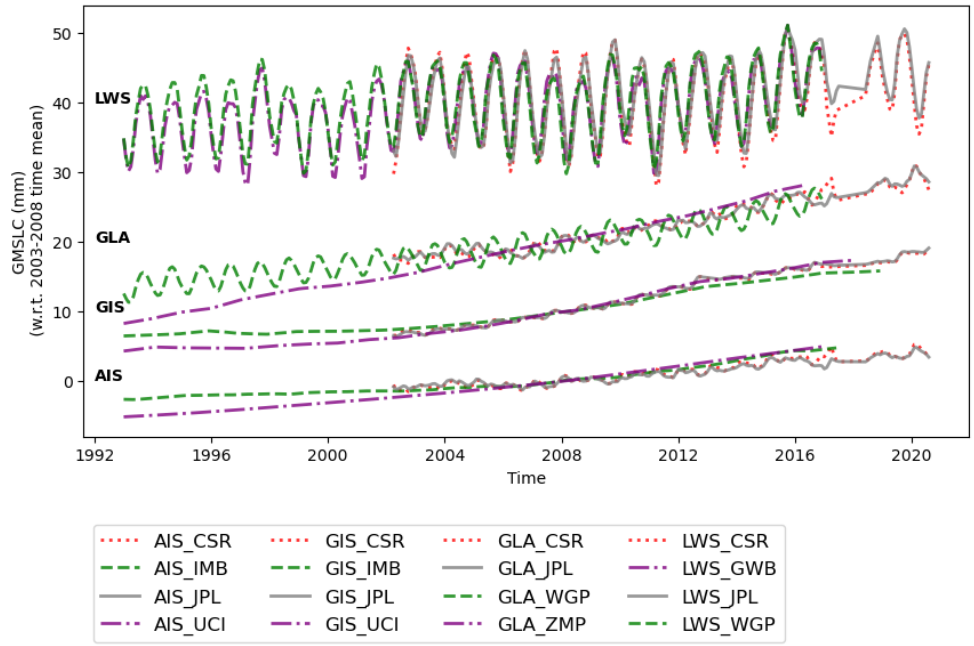

Figure 2. Barystatic contributions to the GMSL time series. Time series are offset by contribution. (included in main text as Figure 1)

Table A1. Table with global mean barystatic sea-level changes and uncertainties from the original global mean timeseries. Note that these numbers may be different compared to the histograms of Figure 7, which represent the spatial average of the regional trend and uncertainty. The difference between the trends is due to the use of noise-models for the regional trend, against an ordinary least-squares fit for the global mean trend.

	2003-2016						**1993-2016**					
	trend	±	σ_{total}	$\sigma_{temporall}$	$\sigma_{spatial}$	$\sigma_{intrinsic}$	**trend**	±	σ_{total}	$\sigma_{temporall}$	$\sigma_{spatial}$	$\sigma_{intrinsic}$
AIS												
AIS_CSR	0,32	±	0,09	0,03	0,09							
AIS_JPL	0,27	±	0,1	0,04	0,09	0,04						
AIS_IMB	0,37	±	0,13	0,05	0,09	0,07	0,19	±	0,15	0,04	0,14	0,03
AIS_UCI	0,48	±	0,09	0,01	0,09		0,4	±	0,14	0,01	0,14	
GIS												
GIS_CSR	0,72	±	0,32	0,03	0,31							
GIS_JPL	0,73	±	0,32	0,03	0,31	0,01						
GIS_IMB	0,53	±	0,32	0,03	0,31	0,07	0,36	±	0,12	0,03	0,11	0,03
GIS_UCI	0,06	±	0,32	0,08	0,31		0,52	±	0,12	0,03	0,11	
GLA												
GLA_CSR	0,68	±	0,16	0,06	0,15							
GLA_JPL	0,64	±	0,16	0,07	0,15	0,01						
GLA_WGP	0,58	±	0,15	0,03	0,15		0,51	±	0,16	0,03	0,16	
GLA_ZMP	0,92	±	0,15	0,03	0,15		0,74	±	0,17	0,04	0,16	
LWS												
LWS_CSR	0,09	±	0,14	0,12	0,06							
LWS_JPL	0,22	±	0,33	0,12	0,06	0,3						
LWS_WGP	0,2	±	0,12	0,1	0,06			±	0,07	0,04	0,06	
LWS_GWB	0,18	±	0,12	0,1	0,06			±	0,07	0,04	0,06	
Combination												
CSR	1,81	±	0,39	0,14	0,36							
JPL	1,86	±	0,49	0,15	0,36	0,3						
IMB+WGP	1,68	±	0,39	0,12	0,36	0,1	1,27	±	0,26	0,07	0,25	0,04
IMB+GWB+ZMP	2,00	±	0,39	0,12	0,36	0,1	1,58	±	0,26	0,08	0,25	0,04
UCI+WGP	1,32	±	0,38	0,13	0,36		1,64	±	0,25	0,06	0,25	
UCI+GWB+ZMP	1,64	±	0,38	0,13	0,36		1,95	±	0,26	0,06	0,25	

GR4 The term ‘regional barystatic’:
After Gregory et al. (2019), barystatic sea level should only refer to global-mean sea-level changes, and not to regional patterns. I’d remove the term ‘regional barystatic’ and replace it with ‘Barystatic sea level and associated GRD patterns’ or something like that.

For brevity, we replace ‘regional GRD-induced patterns associated with barystatic sea-level change’ by ‘GRD-induced sea-level change’. We define the term at the end of the introduction:

”The aim of this work is to provide a comprehensive overview of regional GRD-induced patterns associated with barystatic SLC with a focus on the global and regional uncertainty budget. ***Throughout this paper, we use ‘GRD-induced SLC’ when referring to the GRD-induced pattern associated with barystatic SLC.”***

GR5 Glaciers and ice sheets:
A nasty problem when working with GRACE data for glaciers is that the GRACE resolution is pretty coarse compared to the size of some glaciers. Therefore, it’s hard to separate the mass loss from peripheral glaciers in Greenland and Antarctica from the nearby ice sheets. The same goes for small glaciers in for example Asia, where mass changes from nearby TWS changes leak into the glacier mass change estimates. Did the authors take this into account? A possible way out is the method described in the supporting information of Reager et al. (2016): for the RGI regions where glacier mass loss dominates the GRACE mass change estimates, use GRACE, for the ice sheets, treat the glaciers as part of the ice sheets, and for the other regions, use another dataset (for example Malles & Marzeion, 2021 or Hugonnet et al. 2021) to separate glaciers from TWS.

This is a good point. Up to now, we used the RGI regions to isolate the signals of glaciers from GRACE, and peripheral glaciers to Greenland and Antarctica were included with the ice sheets. However, we had not explicitly considered the LWS leakage into glacier mass change of other regions. Following the suggestion of the reviewer, we have now used the method described in Reager et al. (2016) and Fredekerikse et al. (2019), to separate glaciated areas from LWS: (1) Peripheral glaciers to Greenland and Antarctica are included with the ice sheets mass changes; (2) Regions where glaciers dominate the mass changes are considered ‘full’ glaciers, that is, the land signal in those regions are purely denoted as glacier mass change. These include the RGI regions of Alaska, Arctic Canada North, Arctica Canada South, Iceland, Svalbard, Russian Arctic Islands and Southern Andes; (3) for the remaining RGI regions, we assume that the mass change is partly due to glacier mass change, and partly due to LWS (‘split’ glaciers). This method results in the mask in Figure 3

For the ‘split’ Glaciers, the glacier mass changes are known to be small and land mass changes are dominated by terrestrial water storage variations. To isolate the glacier to the LWS signal, we use the GRACE glacier estimates of Wouters et al. (2019), which have already been corrected for the hydrological signal. We decided to use the estimates of Wouters et al (2019) instead of the geodetic and glaciological measurements from Zemp et al. (2019) to ensure that the glacier estimates between the 4 datasets used here remain as independent as possible. Another possibility would have been to use the model glacier estimates of Malles & Marzeion (2021), however this is an updated glacier model version of the one incorporated in WaterGap, which would introduce some circularity.

By applying this new method to isolate the glacier and LWS signals in the CSR and JPL mascons, we find small differences in the trends and (spatial and temporal) uncertainties of the Glaciers and LWS Figure 4 highlights the differences in the trend and temporal uncertainty of the GRACE datasets before using this method (a-h) and after (i-p).

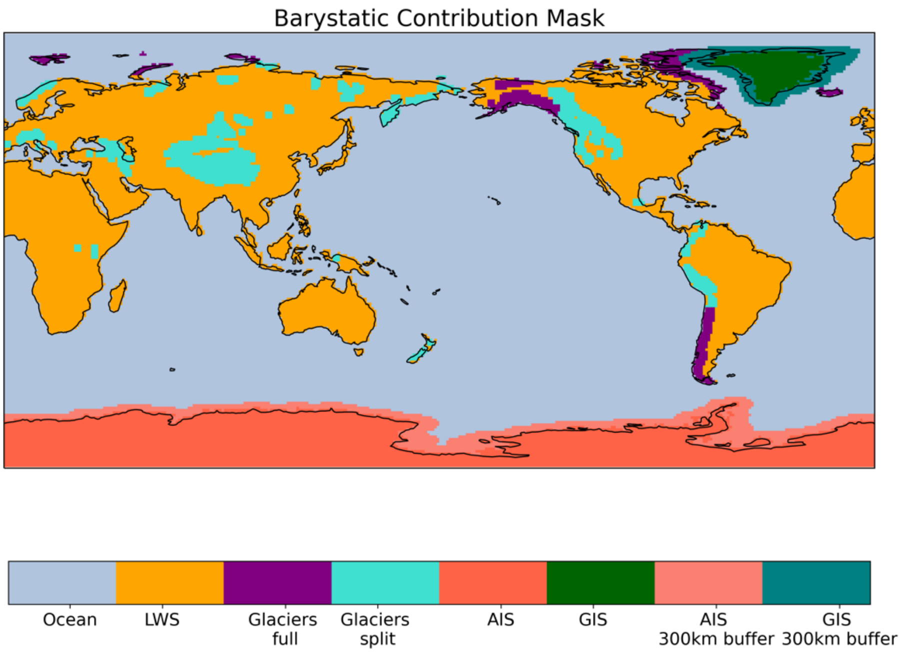

Figure 3. Barystatic contributions mask.

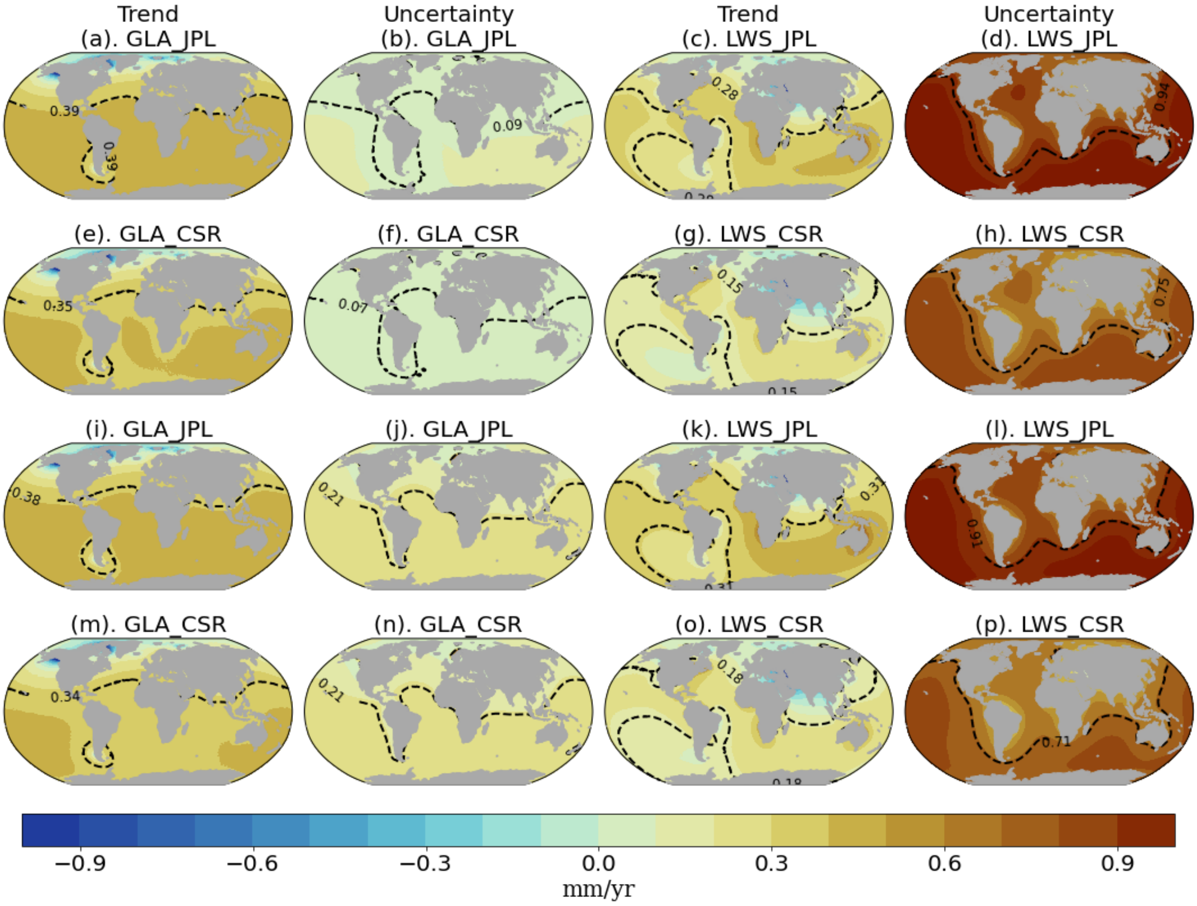

Figure 4. Difference between previous and new method of splitting up the signal between glaciers and LWS. ***Panels i-p are included in the manuscript in Figure 4.***

GR6 Used datasets.
The authors have collected a large and diverse set of sources for their barystatic estimates. I've listed below a few other data sets that could be added as well. Since new data sets appear all the time, this list isn't exhaustive and should be seen more as an idea rather than a demand to incorporate them in this manuscript.

Thank you for the suggestions of new datasets. Most of these were not available at the time of preparing the manuscript and could therefore not be included at the time, while others were available but were not suited for the purpose of this study. As mentioned by the reviewer, new datasets become available all the time, so this will always be a moving field. At the moment, four datasets are used for each of the contributions, which encompass a wide range of possibilities giving a robust estimate. We have therefore decided to not expand the number of datasets for now.

Line-by-line comments

L10: the trend ranges, do they refer to the 95th percentile of the gridded field? I'd think the minimum trend will be lower very close to the ice sheet edges

Yes, they represent the 95th percentile of the ocean grids. The minimum values close to the ice sheet are much lower indeed. For example, from 2003-2016 period the minimum values are around -4.5 mm/yr. We have clarified it in the text that we are citing the 95th percentile of the ocean grids.

L63-L64: "The structural uncertainty is related to the use of different datasets of the same process". The structural and intrinsic uncertainties, are they independent? I can imagine that for example in GRACE, there's an uncertainty in some atmospheric correction, and product A uses estimate A and product B uses estimate B for that process. Then parts of the intrinsic uncertainties also end up in the structural uncertainties.

Indeed, depending on the source of the intrinsic uncertainty it can reflect the structural uncertainty We have added a comment about this in the introduction and also in the methodology (section 2.2.3).

"Errors in the measurement system, known as intrinsic uncertainties (Palmer et al., 2021), describe the sensitivities of choices within a methodology (Thorne, 2021). The intrinsic uncertainties, also referred as observational (Ablain et al., 2019; Prandi et al., 2021) or parametric (Thorne, 2021), need to be determined during the low-level data processing and are usually provided with higher level (ready-to-use) products. Another class of uncertainties originates from the use of different methodologies to describe the same physical system, known as structural uncertainty (Thorne et al., 2005; Palmer et al., 2021). This can be defined as the spread around a central (ensemble) estimate. The structural uncertainty is related to the use of different datasets of the same process. ***Note that, depending on the products used in the processing chain, the intrinsic and structural uncertainties could be partially correlated****."*

"Whereas the trends are added together linearly, we add the uncertainties in quadrature, assuming they are independent and normally distributed. ***We acknowledge that this is an important assumption, as it is possible that the intrinsic uncertainty will be reflected in the temporal and structural uncertainties.*** *For each contribution, we first combine the different types of uncertainty following Equation (3)."*

L131: More of an idea than a comment: there's a lot of people looking for fingerprints to analyze altimetry data, so there might be quite some interest in complementary geocentric sea-level fingerprints.

Thanks for the suggestion. We will make the geocentric fingerprints available with the dataset on 4TU (https://doi.org/10.4121/16778794, currently reserved).

L166 Average – typo

Corrected

L179 The JPL mascon uncertainties do not represent the uncertainties due to the GIA correction. This uncertainty is actually pretty large, but a bit cumbersome to propagate into the final GRD patterns. It can be done by using uncertainty estimates from for example Caron et al. (2018) and Simon & Riva (2020, I'm sure some of the authors are aware of this study). Propagating the full GIA uncertainties into the fingerprints might be a bit too far-fetched for the current manuscript, but it's a good idea to mention that there's additional uncertainty related to GIA in these GRACE estimates.

Agreed. We have added a comment about this in the manuscript, when describing the intrinsic uncertainties of JPL mascons (Section 2.2.2), and also a comment in the discussion (Section 4).

"The final type of uncertainty considered in our assessment is the intrinsic uncertainty, which represents the formal errors and sensitivities in the measurement system and needs to be provided with the observations/models by the data processor/distribution center. The intrinsic uncertainty was only provided with the JPL and IMBIE datasets. For all other cases, the uncertainty budget does not include the intrinsic uncertainty. The uncertainties provided with the JPL Mascons represent the scaling and leakage errors from the mascon approach (Wiese et al., 2016), and, over land, are scaled to roughly match the formal GRACE uncertainty of Wahr et al. (2006). The latter represent errors in monthly GRACE gravity solutions, encompassing measurement, processing and aliasing errors (Wahr et al., 2006). ***Note that, while the mascons have been corrected for mass changes due to the glacial isostatic adjustment (GIA) with the ICE6G-D model (Peltier et al., 2018), the intrinsic uncertainties of JPL mascons do not represent the uncertainties from the GIA correction, which can be large depending on the region (Reager et al., 2016; Wouters et al., 2019). For example, the choice of the GIA model used for the correction could lead to uncertainties representing 19% of the signal in Antarctica, but less than 1% in Greenland (Blazquez et al., 2018). Since estimating GIA uncertainties is in itself an open issue (Caron et al., 2018; Simon and Riva, 2020***), ***we could not propagate full GIA uncertainties into the fingerprints***. *"*

"Compared to previous studies (e.g., Horwarth et al., 2021), we tend to find larger uncertainties, thus our approach seems to be conservative. Nonetheless, we did assume independence of the different types of uncertainty, and did not propagate GIA uncertainties into our fingerprints, which could lead to even larger uncertainties. ."

Figure 2 It looks like the glacier mass balance from the CSR and JPL mascons has been estimated by splitting up some of the mascons. This is a bit tricky: for some regions, the mass changes of the whole mascon are dominated by small glaciers, and taking a part of the mascon induces an error. The opposite also happens. I'd recommend to not split mascons into smaller pieces. See also GR5 for a possible way out.

We followed the reviewer's suggestion in GR5 for splitting up the mascons (see Author Response for GR5). We acknowledge that there might be errors introduced to the contributions by splitting up the mascons, but this is a known limitation inherent to GRACE resolution.

L255: Just out of curiosity: does the UCI dataset show any mass gains in East Antarctica?

Yes, the UCI dataset shows mass gains in East Antarctica, but they are very small. For details, the reviewer is referred to Rignot et al. (2019).

L264: as a rule of thumb, the individual mascons from the JPL solution are all independent and agree more-or- less with the spatial resolution of the GRACE measurements. For other mascons, like GSFC and CSR ones that have a much higher resolution, the individual mascons are not fully independent of each other.

Indeed, the JPL mascons are defined on an equal-area of 3x3 degrees, while CSR and GSFC are defined o a 1x1 degree cap. Considering the native resolution of GRACE observations of about 300km half-width at the equator, the JPL mascons will have independent solutions at each mascon centers, with uncorrelated errors, while the mascons with higher resolution will not be fully independent and is expected to contain spatially correlated errors. We have added a comment about the mascons resolution in section 2.1, when introducing the datasets used.

In this specific line where the reviewer made the comment, we actually wanted to highlight the spatial difference between GRACE observations and the IMBIE and UCI ones, despite the resolution of the mascon solution. Thus, we have rewritten as follows:

"The regional SLC fingerprints directly reflect the differences in the spatial distribution of the mass change sources of the datasets (Mitrovica et al., 2011). Over the ice sheets, for instance, IMBIE provides one time series for the entire Greenland Ice Sheet, which is subdivided into dynamic and surface mass balance changes, and the Antarctic Ice Sheet is divided into three drainage basins. ***GRACE products, on the other hand, have a native resolution of about 300 km at the equator (Tapley et al., 2004).*** *To account for the uncertainties arising from the differences in location of the mass change between datasets, we first normalize the fingerprints and then combine them into estimates of the spatial-structural uncertainty (Figure 4)."*

Figure 4: This is a very interesting figure! I discovered a lot of intriguing phenomena when looking at it.

Thanks

Figure 5: also related to GR1. If you check the uncertainties listed in Table 1 from the IMBIE Antarctic paper, the reported uncertainties, which are about 50 Gt yr-1 for 5-year periods, seem to be much higher than reported here. This is probably related to the assumption of uncorrelated uncertainties. Using the rates+uncertainties procedure from GR1 might solve this difference.

Using the 'ensemble perturbation' method, as suggested by the reviewer in GR1, we obtained higher intrinsic uncertainties than before, but they are still smaller than the ones reported in the IMBIE reports. This is because their reported uncertainties represent not only the intrinsic uncertainty, but also the temporal uncertainties. We have added a comment about this in the manuscript:

" The IMBIE datasets (Figure 6e,f) show larger intrinsic uncertainty than the ice sheet uncertainties from JPL (Figure 6c,d), which is expected as the IMBIE time series is an ensemble of several datasets and methods. ***Note that these uncertainties are smaller than those reported in the IMBIE studies (Shepherd et al., 2018, 2020), because the reported uncertainties represent not only the use of the uncertainty time series (intrinsic), but also the errors due to the linear fit of the trend (temporal uncertainties).****"*

L375: Check the paper from Humphrey and Gudmundsson (2019), who provide some centennial estimates of TWS changes.

Thank you for the literature suggestion. Humphery and Gudmudsson (2019) discuss deseasonalized and detrended time series, and their work focuses on the validation of their variability dataset instead of the discussion of the results, so it actually can't be used in our discussion of trends. However your suggestion did lead to another work by the same authors which was useful for the discussion here and is added to Section 4.

"The main source of uncertainty in the barystatic-GRD SLC is the temporal uncertainty from the land water storage (LWS) contribution. This is likely related to the (climate-driven) natural variability of LWS (Vishwakarma et al., 2021; Hamlington et al., 2017; Nerem et al., 2018), which is mainly driven by seasonal and interannual cycles (Cáceres et al., 2020). A method to deal with the LWS natural variability would be to use different metrics than linear trends (Vishwakarma et al., 2021), such as the use time varying trends based on a state space model (Frederikse et al., 2016; Vishwakarma et al., 2021). However, we choose to use linear trends in this study for sake of accuracy, reproducibility and discussion. It has also been suggested that a more appropriate way of computing a meaningful linear trend from LWS is to incorporate this variability in the analysis (Vishwakarma et al., 2021), as we did by including the seasonal components in the functional model. Nonetheless, the LWS uncertainties related to the trend were still

very high, suggesting that a period of 25 years (1993-2016) might still be too short to solve the low frequency natural variability of LWS, particularly on (multi)-decadal timescales. ***Indeed, Humphrey et al. (2017) showed that removing the short-term climate-driven variability of the LWS signal yields in a more robust long-term (>10 years) trend, with reduced uncertainties*** *"*

L381: Antarctica Ice Sheet typo

Corrected

L429 Individuals typo

Corrected