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Key Points:

- Spatial patterns of the sum of Argo steric and GRACE ocean mass sea level trends do not fully match those from satellite altimetry
- This mismatch is due to missing short-wavelength information in Argo data and observation processing differences at the hemisphere scale
- Omitting eddy rich regions does not resolve the SLB with large sensitivities to GIA correction and altimetry orbital altitude remaining

Supporting Information:

- Supporting Information S1

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Can We Resolve the Basin-Scale Sea Level Trend Budget From GRACE Ocean Mass?

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Abstract Understanding sea level changes at a regional scale is important for improving local sea level projections and coastal management planning. Sea level budget (SLB) estimates derived from the sum of observation of each component close for the global mean. The sum of steric and Gravity Recovery and Climate Experiment (GRACE) ocean mass contributions to sea level calculated from measurements does not match the spatial patterns of sea surface height trends from satellite altimetry at 1° grid resolution over the period 2005–2015. We investigate potential drivers of this mismatch aggregating to subbasin regions and find that the steric plus GRACE ocean mass observations do not represent the small-scale features seen in the satellite altimetry. In addition, there are discrepancies with large variance apparent at the global and hemispheric scale. Thus, the SLB closure on the global scale to some extent represents a cancelation of errors. The SLB is also sensitive to the glacial isostatic adjustment correction for GRACE and to altimetry orbital altitude. Discrepancies in the SLB are largest for the Indian-South Pacific Ocean region. Taking the spread of plausible sea level trends, the SLB closes at the ocean-basin scale (2σ) but with large spread of magnitude, one third or more of the trend signal. Using the most up-to-date observation products, our ocean-region SLB does not close everywhere, and consideration of systematic uncertainties diminishes what information can be gained from the SLB about sea level processes, quantifying contributions, and validating Earth observation systems.

Plain Language Summary An important check on the accuracy of our global measurement systems and understanding of the processes driving sea level rise is the sea level budget. This describes the comparison of measured sea surface height change from satellite radar altimetry with the sum of its component parts, due to density and mass changes. With over 11 years of very high quality density and mass observations at good spatial scale, the sum of the parts matches the total within some uncertainty at a global scale. If, however, we examine the sea level budget at the ocean basin scale, we find significant discrepancies that are difficult to explain. We investigate different processing and averaging methods and find the density measurements do not include small spatial scales that are recorded by sea surface height measurements. Rather than this mismatch averaging out over basin scales, which we would expect if the errors are random, it instead leads to differences in the ocean basin average. Also, there is a mismatch at the hemispheric and global scale, which we believe comes from the way the satellite measurements are processed.

1. Introduction

Closure of a regional to local-scale sea level budget (SLB; e.g., Church et al., 2011) is important to understand the accuracy of observational systems at their operational resolution. It also improves understanding and projections of sea level change and its impacts at the coast, which is the most critical location in terms of human population.

At the global scale, the SLB closes to within the uncertainty of the observations during the satellite era (WCRP Global Sea Level Budget Group, 2018). It should also be possible to reconstruct sea surface height anomalies (SSHAs), derived from satellite altimetry, from the sum of steric and mass observations over a specified area. Steric data are provided by the Argo float array, but there are large uncertainties outside of their coverage in time (pre-2005) and space (deeper than 2,000 m and in sparsely monitored regions such as the polar oceans). Different processing choices in standard gridded products also have an impact at the

sub-ocean-basin scale (Storto et al., 2017). Sea level changes due to ocean mass changes can be determined from the land mass exchange (from land ice and hydrology) applied to the sea level equation (Farrell & Clark, 1976), or they can be directly determined from gravimetry data such as from the Gravity Recovery and Climate Experiment (GRACE) mission. Hereafter, we refer to the former method as mass changes via the sea level equation and the latter as ocean-mass changes observed by GRACE. Note that these two methods should give the same global mean mass change (because of global conservation of mass) but there are large spatial variations between the different GRACE products (e.g., Blazquez et al., 2018; Chen et al., 2018; Dieng et al., 2015; WCRP Global Sea Level Budget Group, 2018). There are additionally systematic biases and hence uncertainties not accounted for in each of the observational products' formal error estimates. Using the terminology established by Gregory et al. (2019), ocean mass changes directly observed by GRACE include both manometric changes in sea level, the change in the local mass of the ocean that incorporates the barystatic change and ocean circulation and redistribution, and the gravitational, rotational, and solid-Earth deformation (gravitational, rotational, and deformation [GRD]) response.

At the basin scale, Frederikse et al. (2018) were able to close the SLB in most but not all basins. Their sea level anomalies (SLAs) were defined using tide gauge data, corrected for vertical land movement by GNSS or altimetry (Wöppelmann & Marcos, 2016), and their ocean mass contribution was determined from the observed land mass change via the sea level equation. Similarly, a regional study looking specifically at the North-East Atlantic and North Sea coastlines (Frederikse et al., 2016) was able to determine a statistical relationship between tide-gauge-observed SLAs and steric SLAs in the open ocean, by removing the component due to mass. Because these studies determine ocean mass sea level change from the sea level equation, this term represents gravitational and rotational changes but does not include changes due to ocean circulation and redistribution (manometric sea level changes). Yet sea level as observed by tide gauges does include ocean circulation impacts, so there is a mismatch in the contributors to the SLB that may be averaging out over the regions chosen.

A number of studies have investigated the variability of the steric and mass terms in the SLB at the basin scale, finding interannual variability in the seasonal signal (although the studies use short periods of data; see, e.g., Llovel et al., 2010, 2011; Marcos et al., 2011). Attempts to use ocean mass changes observed by GRACE in the SLB to understand basin-scale ocean circulation have also been made using short periods of data (e.g., Chambers & Willis, 2009, 2010). There have been a small number of regional studies successfully comparing changes in ocean mass, steric SLAs, and SSHAs from satellite altimetry (Kleinherenbrink et al., 2016, 2017). These studies use GRACE products to determine the mass SLA and match subbasin-scale sea level variability through the authors' choice of products and a statistical optimization. Purkey et al. (2014) demonstrated that basin-scale observed ocean-mass trends mostly match steric-corrected sea level changes calculated from repeat hydrographic sections supplemented by observed SSHAs from satellite altimetry. Due to the limited spatial and temporal coverage of the hydrographic sections, the method matches the broad scale (long wavelength and longer period) trends.

To date, we are unaware of work that has successfully resolved the SLB at the regional scale using ocean-mass changes observed from GRACE.

Subjective choices regarding, for example, the data center processing methodology, filtering, signal leakage correction, glacial isostatic adjustment (GIA) correction, geocenter motion correction, Earth oblateness correction, and pole tide correction, all have a substantial impact on ocean-mass estimates (e.g., Blazquez et al., 2018; Chen et al., 2018; Dieng et al., 2015; Jeon et al., 2018; Wahr et al., 2015). Many of these corrections affect the spatial patterns in the estimated ocean-mass trends. Of course, these systematic uncertainties in the data processing are expected to have a larger impact, proportionally, on local to regional scale observations than on the global mean. Here, we investigate the SLB at the resolution of the observational systems, using SSHA from satellite altimetry, ocean-mass changes observed by GRACE, and changes in in situ steric observation products. With full spatial coverage and formal errors provided by satellite altimetry, gravimetry, and the Argo float program, it should in theory be possible to close the SLB at each point on the Earth's surface.

In developing the regional SLB at the ocean subbasin scale, we investigate the effect of different processing center products, postprocessing, and correction choices. We make comparisons of the trend spatially (i.e., on a latitude-longitude grid) and for basin-scale averages. Comparing the SSH trend observed by satellite

altimetry with GRACE ocean-mass and steric components, we decompose the residual spatially and discuss systematic spatial uncertainties.

2. Data

In this work, we focus on the comparison of the sum of ocean-mass changes observed by GRACE and steric SLAs derived from in situ measurements, with SSHA from satellite altimetry. Therefore, we focus on the era of highest quality observations from all systems from January 2005 to December 2015 inclusive.

2.1. Satellite Altimetry

The observed SSHA is determined from satellite altimetry, using the ESA SLCCI v2.0 product (Ablain et al., 2015; ESA, 2018; Legeais et al., 2018). This is a multimission gridded product, with high-latitude coverage and the most up-to-date instrumental and geophysical corrections applied. The SSHA is corrected for instrument and atmospheric corrections, ocean tides including long-period, solid Earth, and pole tides (including the linear pole tide correction of Desai et al., 2015), and is provided as an anomaly from the DTU15 mean sea surface. In the ESA SLCCI product, a correction of -0.3 mm/year is applied to account for the effect of GIA (Argus et al., 2014; Peltier et al., 2015) on the global scale. The GIA correction is discussed further in section 2.4. The ESA SLCCI satellite altimetry product is chosen because it is a multimission gridded product, therefore with good spatial coverage including into the polar oceans, and has the lowest difference in trend and root mean square (RMS) to the ensemble mean of the major data center products (Legeais et al., 2018, Table 1). (Rougier, 2016 shows that the ensemble mean can be better fitting than any ensemble member and also be nonphysical, both for mathematical reasons connected with the use of RMS error as the discrepancy measure. Therefore, where we have an ensemble of models, we choose the single ensemble member which has the smallest RMS error to the ensemble mean.) The ESA SLCCI product includes recent processing corrections that minimize variance (Quartly et al., 2017) and includes the linear pole tide correction (Desai et al., 2015) required for consistency with Release 6 (RL06) GRACE mass data products. A comparison is made with three alternative gridded satellite altimetry SSHA products, from AVISO (AVISO, 2018), MeASURES (Zlotnicki et al., 2019), and CSIRO (CSIRO, 2019).

2.2. Steric Sea Level

The shallow ($<2,000$ m) steric SLA is determined from four gridded, subsurface temperature and salinity data sets: Scripps Institution of Oceanography (hereafter SIO, updated from Roemmich & Gilson, 2009; Scripps Oceanographic Institute, 2018); JAMSTEC (Hosoda et al., 2008; JAMSTEC, 2018); UK Met Office EN4.2.1 (Good et al., 2013; UKMO, 2018) with the Gouretski and Reseghetti (2010) corrections; and ISAS15 from IFREMER (Gaillard et al., 2016; IFREMER, 2018). These data sets use Argo profile measurements supplemented with other subsurface measurements from casts and profiles and are all optimal-interpolation products. Hereafter, Argo data refer to these shallow steric SLA data that also incorporate other in situ measurements. The steric SLA is calculated using the Thermodynamic Equation of Sea Water (TEOS-10; Millero et al., 2008; TEOS-10, 2008) as the equation of state. We have removed a monthly climatology defined as the time mean for each calendar month. The uncertainty of each measurement in temperature and salinity is propagated through the TEOS-10 calculation of steric SLA to give an uncertainty for each measurement of steric SLA in each grid point time series. An ensemble mean time series of the four products is calculated as the weighted mean, with weights proportional to the inverse of the steric SLA measurement error squared. The IFREMER ISAS15 product has the lowest RMS difference to the ensemble mean and is therefore used to represent shallow steric SLA in section 3.

Deep steric sea level change is added separately. The global-mean deep steric sea level contribution from 2005.0–2016.0 is 0.1 ± 0.1 mm/year (WCRP Global Sea Level Budget Group, 2018). To investigate its spatial distribution, we additionally determine the deep ($>2,000$ m) steric sea level from temperature and salinity values through the TEOS-10 equation of state from (1) the EN4.2.1 optimal interpolation (Good et al., 2013) and (2) from ECCO-V4r3 state space estimate at 1° resolution (LLC90; Forget et al., 2015; Fukumori et al., 2017). The EN4.2.1 data are an optimal interpolation from subsurface profiles. Therefore, it considers only observations and suffers from sample sparsity, leading to “bulls-eye” changes associated with profile locations. We therefore additionally include a deep steric sea level change estimate from a numerical model that incorporates independent observations. The ECCO model solves an adjoint problem to incorporate observations within a space estimate that is physically consistent with continuity equations. Therefore, the model provides a best estimate of changes in the deep ocean that are consistent with observations with full spatial

coverage. We calculate the steric sea level change deeper than 2,000 m using the TEOS-10 equation of state from differences between model monthly mean and model climatological temperature and salinity values, on an interpolated latitude-longitude-depth grid.

2.3. GRACE Ocean Mass

For mass SLAs we use ocean mass observed by GRACE. The choice of data center processing and corrections applied leads to quite different global-mean trends. In this study we compare the ocean-mass equivalent water height changes from GRACE processed by two different data centers, which cover the range of global-mean sea level trends for the 2005.0–2016.0 period (between 2.0 and 2.6 mm/year global-mean mass sea level equivalent; WCRP Global Sea Level Budget Group, 2018, Table 11). We compare JPL mass concentration (mascon) release 05 and 06 (RL05 and RL06; JPL, 2018; Watkins et al., 2015; Weise et al., 2016; Wiese et al., 2018) and GSFC mascon RL05 (Goddard Space Flight Center, 2017; Luthke et al., 2013) products. The JPL RL06 mascon product is used in Section 3 because it represents the most up-to-date processing and corrections including an improved atmosphere-ocean dealiasing model (AOD1B) and the linear pole tide correction (Wahr et al., 2015) that is consistent with the ESA SLCCI satellite altimetry processing. The mascon products are regularized mass change estimates over predefined equal-area regions on the Earth's surface and therefore do not require additional filtering compared to the unconstrained spherical harmonic GRACE products. Furthermore, mascons have a better signal separation at the land-ocean boundary. The JPL mascon product is defined on an equal-area grid that is 3° by 3° longitude-latitude at the equator, whereas the GSFC mascon product is defined on an equal-area grid that is 1° by 1° longitude-latitude at the equator. The native resolution of the monthly GRACE product is around 300-km half width at the equator (Tapley et al., 2004; Vishwakarma et al., 2018). Therefore, the JPL mascon product should have uncorrelated errors at the given mascon centers, whereas the GSFC product, which is provided at a finer posting, is expected to contain spatially correlated errors. Since we are interested in the ocean-mass sea level signal, we use the GRACE products with the AOD1B atmosphere-ocean dealiasing model restored, but with the spatial-mean atmospheric signal at each time step removed. A correction for the effect of GIA on the GRACE mass anomalies is made and discussed in section 2.4. For all basin-scale calculations, we mask and ignore spatial areas where seismic deformation after the 2004 Sumatra and 2011 Tokohu earthquakes clearly affect the ocean-mass equivalent water height observation. We omit the same mask from all observations when calculating basin-scale averages.

2.4. GIA and Ocean Bottom Deformation

GRACE gravity measurements observe the gravitational change due to solid Earth redistribution from GIA (in the upper mantle and lithosphere) as well as the resulting GRD changes in the fluid envelope due to GIA. For the RL05 products, the Geruo A GIA model (A et al., 2013) is removed as standard whereas for the RL06 product, the ICE-6G_D VM5a GIA model (Argus et al., 2014; Peltier et al., 2015) is removed as standard. We test the sensitivity of basin-scale-mean sea level trends to the GIA solution chosen by adding the GIA correction back to each grid point and subtracting different GIA forward-model corrections. We note that this approach ignores the processing steps that the data centers would make in changing GIA product and is a much simplified approach.

In the satellite altimetry measurement, GIA has two effects, one on the shape of the geoid or gravitational equipotential with mass redistribution, self-attraction, and loading and one due to the changing shape of the ocean bottom that leads to a shift in the sea surface for a given ocean volume (see Tamisiea, 2011, equation 2). Because we are interested in the local spatial scale, we quantify the difference in treating the GIA correction spatially rather than taking a global mean. We add the altimetry GIA geoid correction (a constant in space) from the ICE-6G_D VM5a model back to each ocean grid point and reapply it at each latitude-longitude grid location (spatially varying GIA) from the Stokes coefficients provided by Peltier (2018) and add the global-ocean-mean shift in the gravitational equipotential (as discussed by Tamisiea, 2011). Additionally, Frederikse et al. (2017a) have identified and quantified the difference between SSHA measured by altimetry and mass-driven equivalent water height changes measured by GRACE due to ocean bottom deformation (OBD). Present-day land-ocean mass exchanges lead to an elastic component of OBD on the annual to decadal scale. If the spatial extent of the oceans is unchanged, the changing shape of the ocean bottom would lead to a global-mean shift in the gravitational equipotential that the mean sea surface sits on and a smaller magnitude shift in the geoid, like the GIA altimetry correction. Both absolute sea level measured by satellite altimetry and relative sea level change measured by GRACE observe the changing geoid due to present-day mass redistribution, but satellite altimetry does not measure the crustal deformation in its center of mass

reference frame whereas GRACE does measure the mass change of the full water column. Therefore, the global-ocean-mean trend in crustal deformation due to present-day mass loss, which we term OBD, needs to be additionally accounted for in a SLB, and we choose to add it to the satellite altimetry. We obtain the total crustal deformation from Frederikse et al. (2017b) and calculate the ocean-mean trend for our period of interest.

2.5. Geocenter Motion, Earth Oblateness, and Orbital Altitude

GRACE measures gravitational changes, the solution to which is determined in spherical harmonics in a nonrotating frame. As such, the lower degree spherical harmonics (from Degree 0 to 3) are either not measured or can be contaminated by long wavelength signals such as errors in the tidal correction. There have been incremental improvements in the treatment of these values, in particular determination from alternative sources (e.g., Swenson et al., 2008). Mass trends from GRACE are affected by Degree 1 (Earth geocenter motion) and C_{20} (Earth oblateness) corrections (e.g., Chambers et al., 2004; Chen et al., 2005; Swenson et al., 2008), and Blazquez et al. (2018) quantified the sensitivity of global-mean ocean-mass trends from GRACE products to these and other corrections. We investigate subbasin-scale mean sensitivity at Degree 1 by comparing the correction provided with the JPL RL06 data product to those provided by CSR and GFZ each determined from the Sun et al. (2016) method, and by comparing C_{20} corrections by Loomis et al. (2019) and Cheng and Ries (2017), all of which are provided by the JPL data center (PO.DAAC, 2018). We note that these comparisons do not and cannot cover all sources of uncertainty, in particular methodological systematic errors for the C_{20} corrections, but they indicate a lower bound for the uncertainty on the subbasin-mean.

The satellite altimetry orbital altitude has a significant effect on ocean-basin-scale SSHA trends (e.g., Quartly et al., 2017; Rudenko et al., 2016, 2019). The sensitivity of subbasin-scale SSHA trend to orbital altitude is quantified by determining the spatial-mean difference in orbit for the sea level reference missions Jason-1 and Jason-2 between the GFZ VER11 product used in the ESA SLCCI SSHA product and three major recent alternatives: JPL/NASA GDR-D, JPL/NASA GDR-E, and GSFC Std1404. The orbital altitude is compared using the RADS database to download and process the data (Scharroo, 2019; Scharroo et al., 2013).

3. The SLB at 1 Degree Resolution

3.1. Method

For the era of good quality, spatially dense observations from 2005.0 to 2016.0, the SSHA trend from satellite altimetry is compared to the sum of steric and GRACE equivalent sea level trends. Each data set is interpolated onto a 1° resolution latitude-longitude grid to enable direct comparison. Ocean-mass trends are calculated from GRACE observations and deep steric change is added as a global-mean trend of 0.1 mm/year.

A linear trend in time is calculated by generalized least squares regression applied to each grid point time series, weighted by the inverse of the measurement error squared at each time point, giving a standard error on the trend related to the measurement errors at each grid point in time. The regression includes an autoregressive error term to account for colored noise in each time series. We assume an autoregressive model of order 1 (AR1) is sufficient to describe the noise in this short time series of 132 months (Bos et al., 2014; Royston et al., 2018). The data are deseasoned as part of the trend analysis by including an annual and semiannual periodic in the design matrix, except for the steric SLA where the calculation from temperature and salinity measurements to SLA accounts for the climatological monthly mean.

The variety of different combinations of data center products and processings leads to a large range of possible trend values and hence SLB. Selecting those products that provide a best match may result in SLB closure for the wrong reasons. We discuss in section 2 our selection of the most up-to-date products and corrections available that minimize the mean square error from an ensemble mean of alternative products and use consistent GIA and linear pole tide corrections. At the resolution of the data products, interpolated onto a 1° latitude-longitude grid, we compare the ESA SLCCI satellite altimetry product with shallow steric SLA from ISAS15, deep steric at a global constant 0.1 mm/year (WCRP Global Sea Level Budget Group, 2018) and mass sea level from the JPL RL06 GRACE mascon product.

We investigate the power spectral density by wavelength of the contributors to, and discrepancy in, the SLB using a 2-D Fourier transform applied to each data set interpolated onto the same $1^\circ \times 1^\circ$ latitude-longitude grid to make a fair comparison, using Generic Mapping Tools (Wessel et al., 2013) gridfft function by spherical distance. Additionally, in the supporting information, we apply spherical harmonic decomposition to the latitude-longitude gridded data.

Figure 1. Trend in observed SSH (mm/year; 2005–2015 inclusive): (a) shallow steric SSH from ISAS15 objective analysis of Argo and other in situ data plus an estimated deep steric signal of 0.1 mm/year, (b) mass SSH from JPL RL06 GRACE mascon product (which uses the ICE6G GIA correction), (c) altimetry observed SSH from the ESA SLCCI product, (d) sum of Argo, deep steric and GRACE SSH, (e) discrepancy between observed SSH trend from satellite altimetry (ESA SLCCI product) and the sum of Argo (ISAS15), deep steric and GRACE SSH trends (JPL RL06 with ICE-6G GIA), and (f) discrepancy smoothed with a 500-km Gaussian filter for visualization.

3.2. Results

The spatial variability in the sea level trend is dominated by the Argo plus deep steric signal rather than the GRACE signal as expected and previously reported (Leuliette & Willis, 2011; Figure 1). For the study period, 2005.0–2016.0, the steric sea level trend is dominated by a large La Niña event in 2011 and the beginning of a large El Niño event toward the end of 2015, which give rise to the “see-saw” of trends across the Pacific (Zhang & Church, 2012). There is also a broad rise in steric sea level trends across the Indian Ocean and South Pacific, driven by changes in wind circulation and strength over the Pacific (see, e.g., Roemmich et al., 2016; Thompson et al., 2016).

Visually the sum of the Argo, deep steric, and GRACE sea level trend shows largely similar patterns to the altimetry SSH trend (Figure 1c compared with Figure 1d), but there are clear areas of discrepancy (Figures 1e and 1f). There is an apparent basin-scale component to the discrepancy with the altimetry SSH trend change being larger than the sum of components in the North Indian and South Pacific Oceans and smaller than the sum in the South Indian and North Atlantic Oceans. There are large differences at a small scale that mostly cancel out with smoothing, as well as specific areas of large difference such as the Agulhas Current and Gulf Stream. Qualitatively, the smoothed spatial pattern of the discrepancy (Figure 1f) has a similar magnitude but different spatial pattern to the uncertainty introduced by processing choices, for example, the difference between different GIA forward-model corrections for GRACE (Figure S1).

Figure 2. The wavelength spectra of altimetry observed SSH (black), shallow steric SSH (red) and GRACE SSH (blue) trends, and the sum of steric plus GRACE SSH trends (gray).

The sum of GRACE, Argo, and deep steric SSH trend has similar power to altimetry observed SSHA trend between wavelengths of approximately 3,000 and 10,000 km, at the hemispheric scale (Figure 2; see Figure S2 for all data sets). GRACE has a native resolution of 300 km (latitude dependant; Vishwakarma et al., 2018) that is subsequently processed and filtered resulting in a longer wavelength effective resolution, whereas satellite altimetry has a minimum native resolution of 7 km along track, which once filtered and processed to the multimission product has an effective resolution of between 100 and 800 km (latitude dependant; Ballarotta et al., 2019). The spatial coherency of the Argo SSHA products is also latitude dependant. The original target distribution for Argo floats was $3^\circ \times 3^\circ$ globally. So with an ideal distribution of Argo floats, we could expect at best a spatial sampling resolution around 600 km at the equator reducing at high latitudes. The effective resolution of the optimal interpolation methods of the steric data products used here is usually set by correlation spatial scale parameters. Spatial correlation of ocean heat content data using similar mapping methods to the data products used here is high ($r > 0.5$) on the order of 300–500 km at mid-latitudes, although along the equator high correlations occur over 1,000 km (Cheng et al., 2017). We might expect that the steric sea level trend signal will capture the shorter wavelengths in the observed SSHA trend data but that is not the case for the ISAS15 shallow steric sea level trend data set (Figure 2). As a consequence the sum of GRACE and Argo SSH trend has significantly less power than the altimetry SSHA trend at wavelength less than around 700 km (Figure 2). This means that the satellite altimetry product contains information not observed by the Argo and GRACE products.

Between approximately 900- and 3,000-km wavelengths the sum of Argo and GRACE SSH trend consistently has more power than altimetry observed SSH trend. It is plausible that there is an aliasing of power or variance from the true shorter wavelengths to these midwavelengths due to the sampling bias of the steric data products and due to the constrained regularization in the GRACE mascon product used here. But there are several possible reasons for this discrepancy, which requires further investigation.

There is also a notable discrepancy around 20,000-km wavelength or at Degrees 1 to 2 in spherical harmonics (Figure S3). Since sea level trend displays the largest power at these spatial scales, systematic errors in orbit determination, geocenter motion (Degree 1 spherical harmonics), and other low degree harmonics are also contributing to the difference.

Therefore, it appears that the sampling bias of the steric observations combined with the native resolution of the GRACE observations, means the observations of steric and GRACE sea-level trend cannot provide any further information at this time toward the spatial SLB at small scales with 1° grid posting.

4. Basin-Scale-Mean SLB

Given the spatial variability of the discrepancy, we aggregate the observations onto regional means to compare basin-scale SLBs and quantify the effect of some potential sources of error and uncertainty.

4.1. Method

The spread in plausible basin-scale-mean SSHA trends is demonstrated by varying the data center products used, processing steps, and the spatial criteria for retaining data in the calculation. Here, the sea level

trends are aggregated by regions, as defined by coherency in SSHAs observed by satellite altimetry (following Thompson & Merrifield, 2014; Figure 3a). The areas of these coherent regions varies from 7.3 to 91.4 million km².

The time series of each of the altimetry SSHA, Argo SLA, and GRACE observed mass SLA in each region is determined by the area-weighted mean of latitude-longitude grid point time series. The uncertainties in each of these time series are propagated as area-weighted measurement error at each time point. The region's linear trend in time is calculated in the same manner as the grid point trend, in a generalized, weighted least squares regression with weights equal to the inverse of the measurement error squared and including autoregressive noise and annual and semiannual periodic signals in the least squares design matrix. Therefore, the trend standard error for each region-mean time series incorporates the area-weighted measurement error that changes in time.

We compare the region-mean sea level trends from a range of data center products from satellite altimetry, shallow steric (Argo), deep steric and GRACE sea level change, as described in section 2, to quantify the spread of plausible region means. We calculate additional uncertainty bounds incorporating the spread (standard deviation) of region-mean trend estimates from differing data center product and processing choices and combine each source of uncertainty in quadrature with the trend standard error.

Sources of uncertainty on the long-wavelength scale are investigated by determining differences in the region-mean trends resulting from the following long-wavelength processing and/or corrections: (1) the choice of GIA correction for GRACE, (2) the application of global or spatial GIA correction for altimetry and the influence of OBD, (3) GRACE Degree 1 (geocenter motion) correction, (4) GRACE C_{20} (Earth oblateness) correction, and (5) satellite altimetry orbital altitude. It is noted that new versions of these corrections are incremental improvements; hence, in section 3 we use the most up-to-date data products to make comparisons. Here, we compare to some older or alternative processing and/or corrections to quantify the order of magnitude difference that occurs in the region-mean.

It is often stated that a significant contribution to the SLB discrepancy is due to the different sampling characteristics of steric and altimetry sea level variations in eddy rich areas, where the reference track of the satellite altimeter may overpass more cold than warm eddies (or vice versa) and/or the Argo float may become trapped in an eddy for sufficient time to bias observations low (or high; von Schuckmann et al., 2014). This is expected to be a particular issue when using a linear trend to characterise the SLB, since the step in sea level between cold and warm eddy centers causes a spurious trend (see Hughes & Williams, 2010, for a discussion of the high kurtosis in SSHA time series in eddy rich regions). Our analysis further confirms that the Argo sea level trend lacks information (power) at short wavelengths (Figure 2). It might be assumed that the spatial coherency of these eddies should be “white” such that taking a subbasin-scale average of the discrepancy between Argo and altimetry measurements over a large enough area should zero mean. To test the influence of eddy rich areas, rather than hemispheric scale observation processing, on the region-mean SLB, we have applied two different masks to the data sets: a 300-km buffer from land typically applied to GRACE data (Chambers, 2006, 2009; WCRP Global Sea Level Budget Group, 2018; Figure 5a) and a mask that removes data points that are poorly sampled by Argo or by satellite altimetry or exhibit high variance typical of eddy rich regions (Figure 5b). It is noted that the buffer approach removes shallow sea areas where steric changes are poorly sampled and observed SSHA from altimetry can contain larger errors. The latter “high-quality” mask is defined by data points where the standard deviation of the satellite altimetry SSHA or Argo SLA monthly time series is greater than 150 mm or where the Argo gridded time series have less than 50% of time with a temperature and salinity profile located within 3° longitude or latitude.

4.2. Results

The difference in region-mean trends between data center products can be as large a magnitude as the trend signal itself (Figure 3). This is particularly true for Argo products and is the case for both small (e.g., North Atlantic) and far larger regions used in this study. This is partly due to the choice in data sources, for both Argo floats and many other in situ temperature and salinity measurement platforms, and data quality control that is far broader than between the data products for GRACE and altimetry. There is also a clear sensitivity of GRACE products in the North Atlantic, where the ocean mass response to present-day mass loss and the GIA correction for GRACE are largest.

Figure 3. Sensitivity of SSH trend (mm/year) to data center product and processing. (a) Ocean regions defined by Thompson and Merrifield (2014); (b–g) SSH trend of shallow steric, deep steric, GRACE, and satellite altimetry. Error bars in (b)–(g) represent 2σ trend standard error. The region-mean trends are ordered as (b) South Atlantic, (c) Indian-South Pacific, (d) East Pacific, (e) Subpolar North Atlantic, (f) Subtropical North Atlantic, and (g) North-West Pacific.

The SLB discrepancy on a longitude-latitude grid displays subbasin scale coherency (Figure 1f). However, the spread in GRACE Degree 1 and C_{20} estimates is smaller than the discrepancy, generally on the order of 0.1 mm/year and up to 0.5 mm/year in the region mean (Figure 4). Larger sensitivity is determined for the choice of GIA correction in GRACE (up to 1.4 mm/year) and the satellite altimetry orbital altitude (up to 1 mm/year). Although in most regions the sensitivity of long wavelength processing and corrections are of the order of 0.1 mm/year, for those regions with the largest GIA signal (e.g., the North Atlantic), the sensitivity in GRACE GIA correction dominates. Whereas the satellite orbital altitude dominates uncertainty in the larger area South Atlantic, East and North-West Pacific, and in the Indian-South Pacific regions.

The region-mean SLB closes (2σ trend standard error) in several regions when taking a time series mean (Figure 5) but fails to close within the trend standard error estimates for the Indian-South Pacific Ocean region. We find that masking those eddy rich or poorly sampled regions worsens the SLB for the South Atlantic, Indian-South Pacific, and Sub-Tropical North Atlantic regions but does marginally improve the SLB for the North-West Pacific (Figure 5d). We calculate the region-mean SLB using the most up-to-date data sets that minimize the difference to an ensemble mean of data products. The plausible spread in the SLB

Figure 4. Sensitivity of SSH trend (mm/year) to long wavelength processing choices. (a) Ocean regions defined by Thompson and Merrifield (2014); (b–g) difference in SSH trend by region due to choice of GIA correction in GRACE, global or spatial GIA correction and OBD correction in altimetry, Degree 1 and C_{20} correction in GRACE, and satellite altimetry orbital altitude. Error bars in (b)–(g) represent 2σ trend standard error. The region trends are ordered as (b) South Atlantic, (c) Indian-South Pacific, (d) East Pacific, (e) Subpolar North Atlantic, (f) Subtropical North Atlantic, and (g) North-West Pacific.

derived from the spread of data products and data processing is shown by the gray error bars and shading in Figure 5. By allowing for the ensemble spread of products and processing, the uncertainty estimate at 2σ overlaps in the SLB for all regions. However, the uncertainty is large, of a similar magnitude to the trend signal in many regions, such that the value of using the SLB as a method of observation validation could be called into question. We provide details of the region-mean SLB with product used in Table S1.

5. Discussion

Analysis of the discrepancy in the trend signal spatially suggests that both the Argo and GRACE derived sea level provide good estimates of the SSHA trend processes and the spatial discrepancy in the SLB appears to be due to (1) the effective spatial resolution of the Argo and GRACE observations being too coarse; (2) a mismatch between the trend from Argo plus GRACE and the trend from altimetry in the 900- to 3,000-km wavelength; and (3) differences between the GRACE and altimetry products due to processing choices that generate hemispherical scale discrepancies with wavelength of the order of 20,000 km.

Figure 5. Sensitivity of SSH trend (mm/year) to spatial masking. (a) Ocean regions defined by Thompson and Merrifield (2014) with the 300-km land buffer masked in gray, (b) ocean regions with the 300-km buffer from land and poor data coverage or high variability masked in gray, (c) observed SSH trend from ESA SLCCI satellite altimetry (colored by region), and (d) trend anomaly between the sum of ISAS15 shallow steric, deep steric and JPL RL06 GRACE SSH trend, and ESA SLCCI satellite altimetry SSH trend. Colored error bars and shaded regions in (c) and (d) represent 1 σ (dark) and 2 σ (light) trend standard error for the satellite altimetry and quadratic sum of GRACE and steric trend standard error. Gray error bars and shaded regions in (c) and (d) represent the 2 σ sum in quadrature of trend standard error, spread in data products shown in Figure 3, and spread in other data processing shown in Figure 4.

It is apparent that the largest discrepancy between the power in the satellite altimetry trend and the sum of Argo, deep steric, and GRACE SSHA trend is at wavelengths less than 700 km (Figure 2). The spatial resolution of the altimetry, Argo, and GRACE observation systems is limiting on these scales, and this is well known. The lower power of the steric trend implies that the steric SLA products are missing information compared with altimetry. One line of reason for the difference is that large SSHA within larger or more persistent mesoscale eddies are observed by altimetry but not by the Argo network or that Argo floats get caught in eddies causing a warm or cold bias over large spatial extent in the interpolated products. Yet we find masking those eddy-rich regions does not improve the SLB closure at the regional scale (Figure 5). If the SSHA variability were spatially random, we might expect the errors on these small scales to cancel over the region mean, but we observe discrepancy in the SLB at midwavelengths (Figure 1f), which may be due to aliasing of sampling bias or aggregation of sampling and mapping inadequacies into longer wavelengths or may be due to other processing issues at those wavelengths. This requires further investigation. Similar results are found for simple Atlantic, Pacific, and Indian Ocean basins (as defined by Chambers & Willis, 2009), and hence, we conclude our results are robust to the basins chosen (Figure S4).

Deep steric contributions are estimated to be between 0.0 and 0.3 mm/year at the global scale (Dieng et al., 2015; Llovel et al., 2013; Legeais et al., 2016), but there is thought to be considerable regional variability

Table 1
Region-Mean and Global-Mean Sea Level Trend and Uncertainties

		Region mean												Global mean			
		S. Atl.		Ind.-S. Pac.		E. Pac.		S-P. N. Atl.		S-T. N. Atl.		N.W. Pac.					
Altimetry																	
ESA SLCCI	± s.e.	2.70	± 0.17	4.05	± 0.12	4.69	± 0.85	1.12	± 0.21	5.56	± 0.51	0.36	± 0.42	3.14	± 0.13		
	± ensemble spread		± 0.21		± 0.12		± 0.38		± 0.43		± 0.42		± 0.40		± 0.11		
	± orbital altitude		± 0.37		± 0.20		± 0.42		± 0.14		± 0.15		± 0.66		± 0.13		
	± GIA spread		± 0.03		± 0.04		± 0.05		± 0.22		± 0.35		± 0.01		± 0.00		
	± OBD		+ 0.16		+ 0.16		+ 0.16		+ 0.16		+ 0.16		+ 0.16		+ 0.16		
Quadratic sum of uncertainties		2.70	± 0.62	4.05	± 0.43	4.69	± 1.18	1.12	± 0.70	5.56	± 0.92	0.36	± 1.04	3.14	± 0.37		
GRACE																	
JPL RL06	± s.e.	1.78	± 0.22	1.09	± 0.15	2.34	± 0.18	1.11	± 0.17	2.50	± 0.21	2.20	± 0.21	1.75	± 0.10		
	± ensemble spread		± 0.29		± 0.53		± 0.42		± 1.51		± 0.66		± 0.57		± 0.28		
	± degree 1 spread		± 0.09		± 0.03		± 0.13		± 0.11		± 0.21		± 0.13		± 0.16		
	±C ₂₀ spread		± 0.03		± 0.02		± 0.47		± 0.41		± 0.03		± 0.28		± 0.03		
	± GIA spread		± 0.03		± 0.12		± 0.14		± 1.44		± 0.86		± 0.05		± 0.04		
Shallow steric (Argo)																	
ISAS15	± s.e.	0.82	± 0.11	1.66	± 0.11	2.18	± 0.71	-0.38	± 0.17	2.95	± 0.46	-2.16	± 0.45	0.96	± 0.06		
	± ensemble spread		± 0.28		± 0.26		± 0.48		± 0.91		± 1.01		± 0.50		± 0.08		
Deep steric																	
WCRP	± ensemble spread	0.10	± 0.39	0.10	± 0.02	0.10	± 0.08	0.10	± 0.24	0.10	± 0.38	0.10	± 0.08	0.10	± 0.14		
GRACE + full depth steric± s.e.		2.70	± 0.46	2.85	± 0.19	4.62	± 0.74	0.83	± 0.34	5.55	± 0.63	0.14	± 0.50	2.81	± 0.18		
Quadratic sum of uncertainties		2.70	± 0.62	2.85	± 0.63	4.62	± 1.10	0.83	± 2.34	5.55	± 1.62	0.14	± 0.96	2.81	± 0.38		
Alt. - GRACE - full depth steric		0.00		1.20		0.07		0.29		0.01		0.22		0.33			

(Storto et al., 2017), with the most prominent impact probably in the Southern Ocean (Legeais et al., 2016). We attempt to account for the spatial variability in the deep steric trend and its large uncertainties by calculating region-mean trends from one observational product and from the ECCO state space model. The regional variation in deep steric sea level trends is of the order of 0.1 mm/year with a small spread between those data used here (Figure 3). There are however difficulties in the applicability of the observational product (EN4.2.1) that uses optimal interpolation from a very small spatial coverage of profiles. Purkey and Johnson (2010) develop subbasin-scale deep steric trends from repeat profile data accounting for oceanographic processes and spatial coherency, enhanced with specific analysis for the Southern Ocean southward of 30° S in Purkey and Johnson (2013). In both studies, there is a strong deep steric signal of up to 1 mm/year around Antarctica, and a strong signal in the South Pacific up to 0.2 mm/year. The trend magnitude generally decreases northward, particularly in the Indian Ocean. The average deep steric signal southwards of 30° S was calculated to be 0.34 ± 0.16 mm/year (Purkey & Johnson, 2013), which could account for some of the Indian-South Pacific SLB misclosure but would increase SLB misclosure for the South Atlantic region. This plausible high trend in the Southern Ocean is somewhat offset in our Indian-South Pacific region (which has approximately 47% of its area northward of 30° S) by a negative deep steric trend in the Indian Ocean of around -0.2 mm/year (Purkey & Johnson, 2013). Thus, although our final SLB includes an assessment of data product spread, there may be additional uncertainty in the deep steric that has not been quantified. However, given the large areas covered by the regions chosen, we do not anticipate the error in the deep steric SSH trend to close the SLB gap.

It is well understood that the choice of data center, processing choices, and GIA forward-model can significantly affect the basin-scale SSH trend, particularly in those areas where the GIA signal has a large amplitude (e.g., Marcos et al., 2011). It is also clear that the choice of GRACE processing produces significant variations in the trend, which corresponds with long-wavelength or low-degree spherical harmonic coefficient differences (similarly shown by Blazquez et al., 2018, Uebbing et al., 2019, and others). In our analysis, the subpolar and subtropical North Atlantic region means are most affected by the choice of GRACE prod-

uct and GIA correction. While we caution against cherry-picking data products to obtain SLB closure, it is encouraging that the “best” match is given by the most recent GRACE product: the JPL RL06 product and ICE-6G_D VM5 GIA forward model. The difference between the GIA forward-model trends has a clear hemispheric Degree 2, Order 1 spherical harmonic pattern although the difference between the models chosen in this study does not have the same spatial pattern as the discrepancy in the SLB (Figures 1f and S1). Jeon et al. (2018) discuss the impact of different GRACE processing methods on the consistency of ocean mass estimates when compared to mass changes from the sea level equation. They suggest that improvements can be made to the RL05 standard GRACE corrections for geocenter motion, Earth oblateness, and pole tide corrections but that there remains an inconsistency in the trend when looking at the ocean-basin scale. Our analysis, which includes the atmosphere-ocean mass variability, suggests that the changes made in RL06 of the JPL GRACE product have improved the SLB on the ocean-basin scale.

The ESA SLCCI orbital altitude (from GFZ VER11) uses more up-to-date corrections than the alternative products we compare against and, therefore, offer the best product choice of those compared. However, the comparison highlights the sensitivity of region-mean SLB to altimetry orbits, and, given recent improvements to orbital altitude estimates referenced to ITRF2014 rather than ITRF2008 (Rudenko et al., 2019), a strong conclusion from this comparison is the need for the ESA SLCCI and other multimission altimetry SSHA products to adopt the latest orbital altitude estimates.

Several studies have shown estimating ocean mass from GRACE data to be problematic for some ocean basins. Marcos et al. (2011) found the correlation of steric-corrected SSHA and GRACE ocean mass deseasoned sea level residual (2004–2009) was particularly poor for the Indian Ocean and equatorial oceans. The signal-to-noise ratio of GRACE ocean mass is low in the equatorial oceans (von Schuckmann et al., 2014). Purkey et al. (2014) compared GRACE ocean mass with steric-corrected SSH at hydrographic sections and aggregated into subbasin means and concluded that the GRACE ocean mass overestimates in the North Pacific and underestimates in the Indian and South Pacific Oceans, outwith the 90% confidence intervals. These studies all used earlier releases of the GRACE data. Here, we find that the RL06 JPL mascon product shows a significant improvement over the RL05 by region (Figure 3) but there remains a discrepancy outside of the 95% confidence limits for the Indian-South Pacific Ocean. Masking (and hence omitting from analysis) the most poorly sampled and high variability regions, which includes large parts of the Southern Ocean, makes little difference (Figure 5). Therefore, the discrepancy is not simply due to random errors in the sampling between the different observation systems.

6. Conclusions

While the global-mean sea level trend budget closes over the era of good quality spatially broad observations (2005–2016 inclusive; WCRP Global Sea Level Budget Group, 2018), interrogating the SLB on the local to regional (subbasin) scale reveals a mismatch between altimetry and the sum of GRACE, Argo, and deep steric SSHA trend.

In particular, the SLB does not close in the Indian-South Pacific region within 2σ trend standard error using the most up-to-date data center products, processing, and corrections in this study. Although a large mismatch in the wavelength power comes from the lack of small-scale resolution in the Argo data products, masking out eddy rich regions does not improve the SLB over all regions, pointing to the potential that the errors in the Argo data products are not random in space and aggregate up to regional scale. A wider assessment of the observation uncertainty, allowing for the spatial variability in the spread of data center products and of GIA, GRACE geocenter motion, and Earth oblateness corrections and altimetry orbital altitude products, significantly increases the uncertainty bounds. While this wider uncertainty assessment allows the region-mean SLB to close (2σ), the uncertainty constitutes around one third of the global-mean sea level trend signal and in several region means is of the same magnitude as the observed trend (Figure 5). Acknowledging and quantifying this uncertainty at the regional scale is important in validating the Earth observation systems, since these uncertainties highlight possible large trend bias drifts in the Earth observations systems at the regional scale. Furthermore, wider uncertainties diminish the fidelity to which the SLB can monitor changes in SLR contributions by different processes (e.g., mass and steric).

While the SLB closes on the global scale, it is entirely plausible that by taking the spatial mean time series, the global-mean averages out subbasin-scale systematic errors. Spatially, uncertainties in the altimetry and GRACE observation systems at the hemispheric scale and a lack of effective spatial resolution at scales less

than 1,000 km in the Argo and GRACE observation systems appear to dominate the discrepancy in the SLB. Therefore, a combination of sampling bias between the observation systems and systematic errors persist. At the length scales for which the observation systems were designed, the sum of Argo, deep steric, and GRACE sea-level trend matches that measured by altimetry well for all regions except the Indian-South Pacific region. The design of the observational systems therefore limits the usefulness of the SLB at spatial scales less than 1,000 km but also raises the question of systematic errors of the order of 1 mm/year remaining at ocean-basin scales in one or more of the observation systems, even with recent improvements to the processing methods. The largest power (or degree-variance) corrections that require attention include the choice of GIA correction, particularly for GRACE, and the altimetry orbital altitude, in particular to incorporate the most up-to-date product referenced to the ITRF2014 (Rudenko et al., 2019).

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