Satellite- and Reanalysis-Based Mass Balance Estimates of Global Continental Discharge (1993–2015)[Ⓐ]

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ABSTRACT

Total continental freshwater discharge into the oceans is a key feature of the global water cycle, but it is currently impossible to observe using ground-based methods alone. To characterize the uncertainty across existing modeling and satellite approaches, the authors present ensembles of historic monthly global continental discharge estimates that enforce water mass balance over land and ocean. The authors combine independent measurements of ocean–landmass change from altimetry and GRACE with multiple estimates of evaporation minus precipitation ($E - P$) from remote sensing and reanalysis data to compute 28 time series of global discharge. Results reveal agreement in mass budget across approaches but a large spread in global $E - P$ estimates that propagates into the discharge estimates. It is found that discharges with reanalysis-based $E - P$ provide a closer comparison with current observation-based estimates. After combining GRACE- and altimetry-based mass change estimates with moisture convergences from reanalysis, the total annual mean continental discharge into the oceans is $38\,550 \pm 4800 \text{ km}^3 \text{ yr}^{-1}$. Last, the authors provide continent-wise discharge estimates from GRACE and moisture convergences over land, compare them to other studies, and discuss implications for ocean modeling.

1. Introduction and background

Continental discharge (i.e., freshwater discharge from all landmasses including Greenland and Antarctica, also referred to as continental runoff in some studies) is the

primary mechanism of freshwater transport from global land to the global oceans and is the largest freshwater input to the oceans after precipitation (Trenberth et al. 2007; Oki and Kanae 2006; Rodell et al. 2015). Yet, our ability to measure discharge globally and continuously is limited by traditional ground-based instrumentation and methodologies (Syed et al. 2005; Clark et al. 2015). River discharge is typically measured using streamflow gauging stations (e.g., de Couet and Maurier 2009). Gauged observations are regarded as highly accurate at the scale of measurement and are used as benchmark for calibration and validation of modeled estimates.

However, while in situ observations of continental discharge are an essential component of a terrestrial

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hydrologic observation system, they have several limitations. Gauging stations measuring river discharge to the oceans have inconsistent records owing to variations in management practices (Syed et al. 2005), have sparse density near river mouths (Dai and Trenberth 2002; Dai et al. 2009), and are often inadequate to correctly record basin-wide flooding events in floodplains and other flows that bypass the location of observation (Syed et al. 2005). Also, while several countries continue to observe river discharge and share it with the global research community, there has been a decline in discharge observations in public domain over the recent decades. For example, the Global Runoff Data Centre (GRDC; <http://www.bafg.de/GRDC/EN/>) hosts the world's largest database of gauging stations' observations. The number of gauging stations providing data to GRDC has reduced from about 7500 in 1980 to about 1000 in 2015 (GRDC 2015). Major reasons for this decline include declining budgets, skilled-labor-intensive nature of the monitoring, increased privatization of the monitoring stations, and lack of public sharing of hydrologic data by several countries (Garcia et al. 2016). These factors make retrieval of in situ hydrologic data challenging.

Land surface models (LSMs) are sometimes used to simulate continental discharge for global water cycle studies (e.g., Milly et al. 2005) and for gap-filling (e.g., Dai et al. 2009) and extrapolation of inconsistent and sparse in situ observations and in some basins are the only available estimates of discharge. Considerable advancements are being made in hydrologic modeling with respect to river routing schemes (Yamazaki et al. 2011; Li et al. 2013) and process representations and parameterization in LSMs (Lawrence et al. 2011). However, several critical surface processes such as evapotranspiration, snowmelt discharge and subsurface processes such as soil moisture, permafrost thawing, groundwater, and baseflow are still not well represented in the LSMs (Lawrence et al. 2012; Zaitchik et al. 2010; Li et al. 2011) as are elements of water management such as groundwater pumping, reservoir storage, and irrigation (Famiglietti et al. 2010). Also, atmospheric forcing inaccuracies affect simulated discharge (Li et al. 2015).

Gauged observations are sometimes blended with modeled discharge to obtain a spatiotemporally consistent dataset (Dai and Trenberth 2002; Dai et al. 2009; Fekete et al. 2002; Clark et al. 2015). The most comprehensive and long-term estimates of global discharge in the last few years are from Dai et al. (2009) and include gauged observations from the 925 largest exorheic (ocean draining) rivers. Unobserved discharge that occurs between gauging stations and the river mouth is estimated by regression using a station-to-mouth ratio of simulated discharge output from the Community Land Model, version 3 (CLM3) (Oleson et al. 2004). Temporal gaps in observations are filled through regression

analysis with nearby gauging stations or with simulated discharge, and the latter is also used to directly estimate discharge from unmonitored basins. These data are widely considered the “best available” estimates of discharge and used as discharge forcing for ocean models as a part of the Co-ordinated Ocean–Ice Reference Experiments, version 2 (COREv2), interannual forcing data (Large and Yeager 2009). COREv2 provide common surface forcing data for ocean–sea ice models, enabling intercomparison studies complementing the Coupled Model Intercomparison Project (CMIP) (Danabasoglu et al. 2014; Griffies et al. 2014; Danabasoglu et al. 2016).

However, hybrid approaches such as Dai et al. (2009) inevitably inherit some of the demerits of observations and of simulated discharge discussed above. Clark et al. (2015) used a similar approach to Dai et al. (2009) but achieved a global mean discharge about 25% higher than Dai et al. (2009) primarily because they used a different land surface model [Variable Infiltration Capacity (VIC) model]. Rodell et al. (2015) presented a comprehensive study of global water fluxes, optimizing multiple datasets for water and energy budget closure, and provided a discharge estimate greater than Dai et al. (2009) but less than Clark et al. (2015). With assumed continued decreases in the availability of gauging station data in the future, hybrid methods would be forced to rely more on simulated discharge and as a result be even more susceptible to these large model biases. Furthermore, as the hybrid methods rely on the carefully established relationship between simulated discharge and observations at each station, automating such analysis is not desirable, and as a result providing regular updates to such approaches is tedious. Dai et al. (2009) data are not available since 2006; hence, owing to a lack of current alternatives, COREv2 forcing data (Large and Yeager 2009) use the discharge climatology. Thus, the COREv2 discharge forcing for the past decade does not represent the ongoing changes in discharge such as the severe droughts in Amazon (Lewis et al. 2011; Jiménez-Muñoz et al. 2016).

Total continental discharge into the oceans can be estimated by solving the ocean mass balance:

$$R = \frac{d(M_{\text{OCN}})}{dt} - P_{\text{OCN}} + E_{\text{OCN}}, \quad (1)$$

where M , P , and E are mass of water, precipitation, and evaporation, respectively, and the subscript OCN implies ocean. Similarly, discharge R estimates at basin as well as at continental scale can be obtained by solving the landmass balance:

$$R = P_{\text{LND}} - E_{\text{LND}} - \frac{d(M_{\text{LND}})}{dt}, \quad (2)$$

where the subscript LND implies land and M_{LND} refers to the total mass of freshwater.

Syed et al. (2010) demonstrated that Eq. (1) can be solved for discharge using remote sensing datasets alone. Ocean mass is an important term in Eq. (1) and can be estimated from sea surface height from satellite altimetry after correcting for steric height changes and since 2002 can be observed directly with NASA's Gravity Recovery and Climate Experiment (GRACE) mission (Chambers et al. 2004). Remote sensing-based global precipitation data such as the Global Precipitation Climatology Project (GPCP) (Huffman et al. 1997) and Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) (Xie and Arkin 1997) and ocean evaporation data such as objectively analyzed ocean-atmosphere fluxes (OAFlux) (Yu et al. 2008) and SeaFlux (Curry et al. 2004) are available, as are several new reanalysis products. This enables solving the ocean mass balance [Eq. (1)] entirely using off-site (i.e., not in situ) data. Off-site discharge estimates based on remote sensing and reanalysis datasets have several advantages relative to ground-based measurements: they negate density and management inconsistencies and are free from data-sharing limitations of in situ observations; they include the entire basin discharge, including subsurface flows [baseflow as well as submarine groundwater discharge (Syed et al. 2005)]; they are temporally coherent; intermission biases can be removed during mission overlap period (e.g., as with satellite altimeters); and they can be updated in real or near-real time. They also include discharge from ice sheets, which is traditionally difficult to measure.

The process of land evapotranspiration (ET) is often more complex than ocean evaporation owing to heterogeneity in surface properties and hence is typically poorly observed and simulated (Wang and Dickinson 2012). Few remote sensing-based ET data are available, and reanalysis-based estimates of P and E suffer spurious trends due to changes in observations (Trenberth et al. 2011) and measurement biases, though newer reanalysis products perform somewhat better (Trenberth and Fasullo 2013a; Rodell et al. 2015). However, the term $P - E$ (i.e., net precipitation) can also be obtained by applying the atmospheric moisture budget as follows:

$$\frac{dW}{dt} + \nabla \cdot \mathbf{Q} = -(P - E), \quad (3)$$

where W is total column-integrated water vapor and $\nabla \cdot \mathbf{Q}$ is the horizontal convergence of moisture flux. Syed et al. (2005, 2009) and Munier et al. (2012) demonstrated that convergence-based $P - E$ can be used for estimating basin-scale to continental-scale discharge.

Trenberth et al. (2011) and Trenberth and Fasullo (2013a,b) provide comprehensive evidence that reanalysis $P - E$ computed from the moisture budget are much more reliable than $P - E$ computed from the difference between P and E estimates, especially in the newer generation of reanalysis data.

In this study, in addition to updating the analyses of Syed et al. (2009, 2010), we take advantage of several datasets to provide a comprehensive comparison of ocean and landmass balance discharge estimates from remote sensing and reanalysis. Novel aspects of this work include the first use of a multimission altimetry data with global coverage in such studies as well as mass change estimates from GRACE, and we use five state-of-the-art reanalysis data products to get robust estimates of the moisture convergence fields. More generally, we quantify and discuss the mean, trend, and uncertainty in each of the mass balance components, as well as the resultant discharge estimates. Given the observations-based methodology and global coverage of Dai et al. (2009) estimates, we evaluate our estimates relative to them at seasonal and interannual time scales. We also extend the analysis to include COREv2 freshwater fluxes. Last, we compare our land-based estimates with other studies for continent-wise discharges.

2. Data and methods

We solve Eqs. (1) and (2) for R using various combinations of dM/dt and $P - E$. We use the newly released GRACE mass concentration (mascon) solution from NASA JPL (JPL-RL05M) (Watkins et al. 2015) to compute dM/dt over land and ocean. The JPL-RL05M solution links an analytically expressed mascon function with measurements of range rate between the two GRACE satellites to directly estimate mass variations over 4451 equal-area mascons across the earth's surface. A key advantage of the mascon solution over a traditional spherical harmonics solution is that JPL-RL05M uses a priori information from geophysical models and observations as a constraint, and hence neither suffers from north-south striping or loses data as a result of the counter destriping (Watkins et al. 2015). The data are corrected for signal leakage at the ocean-land boundary using a coastline resolution improvement (CRI) filter (Wiese et al. 2016) and for glacial isostatic adjustment over Greenland based on A et al. (2013). In this study, by masking out the ocean from the JPL-RL05M mass anomalies, computing the monthly mass time series, and then taking the monthly derivative, we compute dM/dt over the land. To compute dM/dt over the ocean, the land is masked out. To ensure consistency between dM/dt over ocean and land (i.e., net mass lost from one

equals net mass gained by the other), we include Greenland and Antarctica in our land mask.

Ocean dM/dt are also computed by solving the global mean sea level (GMSL) budget for ocean mass anomalies and computing a monthly derivative. GMSL budget can be expressed as follows:

$$\text{GMSL} = \text{GMSL}_{\text{mass}} + \text{GMSL}_{\text{steric}}. \quad (4)$$

GMSL estimates are obtained from Archiving, Validation, and Interpretation of Satellite Oceanographic Data (AVISO), processed with SSALTO multimission ground segment/Data Unification and Altimeter Combination System (DUACS). The SSALTO/DUACS system merges data from several satellite missions, *European Remote-Sensing Satellites 1 and 2 (ERS-1 and ERS-2)*, *Environmental Satellite (Envisat)*, *Jason-1*, *Jason-2*, *TOPEX/Poseidon*, *Cryosat-2*, *Haiyang 2A (HY-2A)*, and *Satellite with ARGOS and Ka-band Altimeter (SARAL/AltiKa)*. Detailed processing steps for each dataset, as well as cross calibration and merging, are described in [AVISO \(2010\)](#).

An important advantage of the SSALTO/DUACS data product is its global coverage. Not being limited to 66°N–66°S (as in [Syed et al. 2010](#)) enables a much more robust comparison with GRACE as it eliminates the errors due to mass exchanges at the data boundary latitudes ([Morison et al. 2007](#)). The steric component ($\text{GMSL}_{\text{steric}}$) comes from the expansion of the GMSL due to the changes in ocean temperature and salinity. We use version 4 of the Met Office Hadley Centre's EN series (EN4) ([Good et al. 2013](#)). "EN" is named after the ENACT/ENSEMBLES systems ([Ingleby and Huddleston 2007](#)) of objectively analyzed subsurface temperature and salinity fields, which are corrected for instrument bias following [Levitus et al. \(2009\)](#), to compute the $\text{GMSL}_{\text{steric}}$ from the top 2000 m of global ocean. Input data for EN4 include the World Ocean Database 2009, as well as Argo floats ([Davis et al. 2001](#)) in recent years. The quantity $\text{GMSL}_{\text{steric}}$ is computed by integrating computed specific density across each depth level from temperature, salinity, and depth-derived pressure fields following [McDougall et al. \(2010\)](#).

Over the ocean, we use two satellite-based products for ocean precipitation and evaporation. We use GPCP, version 2.2 (GPCPv2.2), ([Huffman et al. 1997](#)) and CMAP ([Xie and Arkin 1997](#)) merged precipitation data from multiple satellites and in situ observations. Ocean evaporation data are from the OAFlux ([Yu et al. 2008](#)) and SeaFlux ([Curry et al. 2004](#)) datasets. OAFlux data are derived from merging satellite estimates, in situ measurements of observable variables from voluntary observing ships (VOS), and reanalysis products.

SeaFlux data are purely satellite based and are generally considered as the most accurate satellite-based observations of ocean evaporation.

As [Dai et al.'s \(2009\)](#) data is used in the COREv2 analysis in closing energy and water budgets, for comparison we also include COREv2 P and E in our analysis. COREv2's P is a latitude-based combination of GPCP and CMAP, while E is based on NCEP reanalysis. Detailed information on generation of CORE fluxes can be found in [Large and Yeager \(2009\)](#).

Vertically integrated zonal and meridional moisture fluxes and precipitable water (total column water vapor) fields are used to compute total column horizontal moisture flux divergence and precipitable water tendency to solve Eq. (3) for $E - P$. The fields are obtained from five state-of-the-art reanalysis products, namely, the ECMWF interim reanalysis (ERA-Interim, hereinafter ERA-I) ([Dee et al. 2011](#)), the Japanese 55-year Reanalysis (JRA-55) ([Kobayashi et al. 2015](#)), the NASA Global Modeling and Assimilation Office (GMAO) Modern-Era Retrospective Analysis for Research and Applications (MERRA) ([Rienecker et al. 2011](#)) and MERRA-2 ([Bosilovich et al. 2016](#)), and the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) ([Saha et al. 2010](#)). ERA-I and JRA-55 include four-dimensional (4D) variational data assimilation, a significant improvement from their predecessors, while MERRA and MERRA-2 involve an incremental analysis update (IAU) procedure that adjusts modeled states based on observed states. CFSR includes several key updates to all components in the NCEP Climate Forecast System (CFS) model.

Once the dM/dt and $P - E$ time series are computed, a low-pass filter of 5 months is applied to highlight lower than semiannual frequencies. Discharge is then computed for each combination of E , P , $P - E$, and dM/dt . Thus, in all, 28 estimates of global discharge are obtained. From this, estimates are grouped into five ensembles based on their component source and type (ocean, land, remote sensing, reanalysis, and dM/dt method), and ensemble averages are generated for each discharge group.

This study includes analysis of several commonly used datasets. There are uncertainties associated with instrument errors and processing errors for each of the datasets. While errors associated with some datasets such as GRACE and altimetry are well documented, error estimates are not provided for several other data such as the reanalysis datasets. Also, as the datasets in this study are widely used, detailed analyses of the errors associated with individual datasets already exist, and such analysis is beyond the scope of the current work. The goal of this work is to understand how off-site discharge estimates compare with traditional on-site

TABLE 1. The mean, standard deviation, and the trend for individual mass balance component time series. The 95% confidence intervals are provided for the mean and the trend. Trends are computed after removing the seasonal cycle.

Variable	Data	Time period analyzed	Mean ($\text{km}^3 \text{yr}^{-1}$)	σ ($\text{km}^3 \text{yr}^{-1}$)	Trend ($\text{km}^3 \text{yr}^{-2}$); p value (if ≥ 0.001)
MASS _{OCN}	GRACE	May 2002–Apr 2015	0	40 100	7800 ± 280
GMSL – GMSL _{steric}	Altimetry – EN4.1.1	Feb 1993–Jul 2015	0	61 600	7900 ± 170
dM/dt	COREv2	Feb 1993–Dec 2006	-2500 ± 2000	13 300	-120 ± 270 ; 0.385
dM/dt	GRACE	May 2002–Apr 2015	620 ± 2100	13 400	50 ± 40 ; 0.004
dM/dt	Altimetry – EN4.1.1	Feb 1993–Jul 2015	860 ± 1900	16 100	9 ± 30 ; 0.537
P	GPCP2	Feb 1993–Jul 2015	$385\,600 \pm 1000$	8700	-230 ± 90
P	CMAP	Feb 1993–Jul 2015	$374\,300 \pm 1000$	8400	-620 ± 90
E	OAFflux	Feb 1993–Jul 2015	$412\,800 \pm 1200$	9700	-330 ± 80
E	SeaFlux	Jan 1998–Dec 2007	$404\,400 \pm 2200$	12 200	3600 ± 180
$E - P$	SeaFlux–GPCP	Jan 1998–Dec 2007	$16\,300 \pm 2000$	11 100	2400 ± 210
$E - P$	SeaFlux–CMAP	Jan 1998–Dec 2007	$28\,200 \pm 2200$	12 200	3300 ± 300
$E - P$	OAFflux–GPCP	Feb 1993–Jul 2015	$27\,300 \pm 1100$	9600	-100 ± 100 ; 0.055
$E - P$	OAFflux –CMAP	Feb 1993–Jul 2015	$38\,600 \pm 1400$	11 500	290 ± 130
$(E - P)_{\text{RS}}$	Ensemble mean	Feb 1993–Jul 2015	$30\,300 \pm 1100$	9400	390 ± 100
$E - P$	ERA-I	Feb 1993–Jul 2015	$33\,800 \pm 850$	7100	160 ± 40
$E - P$	JRA-55	Feb 1993–Dec 2013	$33\,000 \pm 930$	7500	-20 ± 35 ; 0.277
$E - P$	MERRA	Feb 1993–Jul 2015	$35\,900 \pm 1100$	9000	170 ± 50
$E - P$	MERRA-2	Feb 1993–Jul 2015	$45\,100 \pm 1200$	9800	-310 ± 40
$E - P$	CFSR	Feb 1993–Dec 2009	$42\,800 \pm 1300$	9300	510 ± 50
$(E - P)_{\text{RE}}$	Ensemble mean	Feb 1993–Jul 2015	$37\,800 \pm 980$	8200	-10 ± 40 ; 0.519

estimates and to explore the potential of the off-site discharge estimation to serve as a viable technique for global discharge computation on a regular basis in the wake of rapidly reducing on-site observations. Hence, we provide ensembles of all discharge estimates possible by combining multiple datasets of water mass balance components and let the ensemble spread serve as an estimate of uncertainty of discharge. In figures featuring time series of the other water mass balance components, the errors provided represent the pointwise 95% (about 2σ) prediction bands of an ordinary least squares (OLS) fit to the time series after removing the climatology. Thus, the errors account for interannual variability and the long-term trend in the time series.

3. Results and discussion

a. Mass change over ocean and land

Table 1 provides general statistics of the mass balance components time series used in this study. As means to compare different datasets of dM/dt and $E - P$, correlation coefficient and RMS values for the monthly time series, deseasonalized time series, and deseasonalized as well as detrended time series are shown in Tables S1 and S2 of the supplemental material. Figure 1 (top) shows time series of the GMSL anomalies and the steric component. Both time series show increasing linear trends (from an ordinary least squares fit) of 2.92 and 0.98 mm yr^{-1} , respectively. The trend estimates are in agreement with recent studies on the global mean sea

level budget closure (e.g., Dieng et al. 2015; Leuliette 2015; Chambers et al. 2017; Rietbroek et al. 2016) that show increased contribution from the steric component to the GMSL trend compared to previous studies (e.g., Church et al. 2011). Figure 1 (bottom) shows ocean mass anomalies obtained after subtracting the steric component from the GMSL, as well as those from GRACE. GRACE-era mean is subtracted from both the time series to enable better visual comparison. Both the time series compare very well with $R = 0.97$.

Figure 2 shows dM/dt derived from the mass anomalies shown in bottom of Fig. 1. Also shown is dM/dt (red curve) obtained from solving Eq. (1) from COREv2 P , E , and R [COREv2 R is based on Dai et al. (2009) data] and dM/dt from GRACE over land (yellow dotted curve, inverted). As the estimates of global continental discharge into the ocean derived in this study are likely to be of interest to the oceanography research community, the water balance components in Fig. 2 and subsequent figures are also displayed in Sverdrups (Sv ; $1 \text{ Sv} \equiv 10^6 \text{ m}^3 \text{ s}^{-1}$), a commonly used unit in oceanographic studies. As the global mass is conserved while processing GRACE mascon data, mass anomalies over land, when inverted, are identical to those from over ocean. The dM/dt time series computed from altimetry matches very well with those from GRACE land and ocean, with $R = 0.89$ and RMS error of $6810 \text{ km}^3 \text{ yr}^{-1}$ over the overlapping period, whereas dM/dt from COREv2 shows relatively poor comparison with both dM/dt from altimetry ($R = 0.62$; $\text{RMS} = 13\,700 \text{ km}^3 \text{ yr}^{-1}$) and from

FIG. 1. (top) Monthly time series of GMSL (red) anomalies from AVISO SSALTO/DUACS merged multimission altimetry data and the steric component (GMSL_{steric}; magenta) from Hadley Centre EN4 subsurface temperature and salinity fields. (bottom) Time series of ocean mass anomalies derived from GMSL and the steric component (blue) and from GRACE (green). The shaded areas represent the pointwise 95% prediction bands of an OLS fit to the time series after removing the climatology.

GRACE ($R = 0.77$; $\text{RMS} = 8630 \text{ km}^3 \text{ yr}^{-1}$) for the corresponding overlapping periods. The poor comparison between dM/dt from altimetry and COREv2 is much more noticeable after deseasonalizing the time series (Fig. 2, bottom). While the correlation coefficients and RMS values among the time series comparisons show a general reduction after deseasonalizing and detrending the time series (Table S1), the results are still consistent with the monthly time series. Assuming the agreement between GRACE- and altimetry-derived mass anomalies as an evidence of their ability to approach the “true” dM/dt , the relatively poor agreement of the COREv2 dM/dt is likely to come from inaccuracies from COREv2’s other mass balance components (viz. P , E , or R).

b. Net precipitation over ocean and land

Figure 3 shows time series of global ocean evaporation from OAFlux and SeaFlux (top) and precipitation from GPCP and CMAP (bottom). Deseasonalized curves of these time series are shown in Fig. S1 of the supplemental material. It is apparent from the figures that the satellite-based estimates of both ocean P and E

show large discrepancies not just around the long-term mean but also with respect to interannual variability and long-term trends. The differences are more pronounced among the two ocean E datasets, even though the short period of overlap (of 10 years) makes the comparison more difficult. The differences are dominated by a sharp increasing trend (of about $3600 \text{ km}^3 \text{ yr}^{-2}$) for the 1998–2007 period shown by SeaFlux, which is not observed in the OAFlux time series. If the trend differences were absent, the two time series would actually compare quite well, as after detrending, the correlation between the time series improves dramatically from $R = 0.26$ to $R = 0.75$. The two P datasets show average correlation with $R = 0.53$ (which does not improve much after deseasonalizing and detrending). CMAP shows a lower long-term mean compared to GPCP, as can be seen in Table 1. The differences between ocean P from GPCP and CMAP are well documented by Yin et al. (2004) and Behrangi et al. (2014), who also highlight zonal differences between the two with CMAP showing higher precipitation at the tropics and lower precipitation at higher latitudes, compared to GPCP.

FIG. 2. (top) Global ocean mass change dM/dt estimates from altimetry (black), GRACE over ocean (blue), GRACE over land, inverted (yellow, dotted), and COREv2 (red). The shaded areas represent the pointwise 95% prediction bands of an OLS fit to the time series after removing the climatology. (bottom) As in (top), but deseasonalized.

Monthly time series of satellite- and reanalysis-based $E - P$ are shown in Fig. 4 and are also shown in Fig. S2 of the supplemental material after deseasonalizing. The differences among the ocean E and P datasets from Fig. 3 propagate into the satellite-based $E - P$ estimates shown in Fig. 4 (top). The estimates show a wide spread, with RMS among the individual time series ranging from 14 000 to 27 400 $\text{km}^3 \text{yr}^{-1}$ and R ranging from -0.06 to 0.78 . This poor intercomparison is largely due to the trend differences in ocean evaporation datasets. Figure 4 (bottom) shows moisture convergence estimates from reanalysis over the ocean (moisture convergences over land, when inverted, are nearly identical to those over ocean and hence not shown separately). These estimates of $E - P$ also show a spread across the mean (though relatively small; RMS ranging between 3200 and 13 000 $\text{km}^3 \text{yr}^{-1}$) but show remarkably good correlation (R ranging between 0.85 and 0.94). The closest agreement in the mean is seen between ERA-I and JRA-55, likely due to the similarity in their data assimilation technique, while MERRA-2 consistently shows higher estimates of $E - P$ compared to other reanalysis datasets. After deseasonalizing and detrending (Table S2), the correlation

improves among satellite-based $E - P$ time series; however, the RMS errors are still more than twice greater than those in reanalysis-based $E - P$ time series. This agreement among the reanalysis moisture convergences is not that surprising considering there is likely to be a considerable overlap in the model physics and in the observations that are assimilated. It should be noted that as these are spatially averaged estimates, local differences, if any, are likely to get masked out from these global ocean estimates.

c. Global continental discharge ensembles

The characteristics of dM/dt and $E - P$ accrue in the mass balance discharge estimates, as seen in Fig. 5, which shows four ensemble averages of ocean mass balance estimates of global discharge: $A + (E - P)_{\text{RS}}$; $G + (E - P)_{\text{RS}}$; $A + (E - P)_{\text{RE}}$; and $G + (E - P)_{\text{RE}}$. The quantities A , G , RS , and RE represent altimetry-based dM/dt , GRACE-based dM/dt , remote sensing-based $E - P$, and reanalysis-based $E - P$, respectively. The fifth ensemble average, computed from land-based mass balance estimates from GRACE and reanalysis moisture convergences, is not shown as its curve is

FIG. 3. The time series of remote sensing–based estimates of (top) global ocean evaporation and (bottom) precipitation. The shaded areas represent the pointwise 95% prediction bands of an OLS fit to the time series after removing the climatology.

almost identical to that of $G + (E - P)_{\text{RE}}$ (yellow). The shaded areas represent maximum spread of the ensemble members around the ensemble means. The observation–model hybrid estimate from Dai et al. (2009) (red) and discharge estimates computed with COREv2 $E - P$ with GRACE (magenta) and altimetry (green) dM/dt are also shown for comparison. Along with the monthly time series of the above mentioned time series (Fig. 5, top), their deseasonalized (Fig. 5, bottom) and climatological (Fig. 5, bottom, inset) curves are also shown. Individual time series of ensemble members are shown in Fig. S3 of the supplemental material.

It can be seen from Fig. 5, as well as from Table 2, all the mass balance estimates of discharge show reasonable agreement for mean annual discharge that compares well with that from observation-based hybrid discharge from Dai et al. (2009) (with the added time-invariant discharge of $2300 \text{ km}^3 \text{ yr}^{-1}$ from Antarctica, as a part of COREv2 flux). As expected, $(E - P)_{\text{RS}}$ -based discharge estimates show wider ensemble spread, including several instances of negative to near-zero discharge (which, though impossible in nature, is possible as the mass balance method enforces conservation of mass via budget closure). The $(E - P)_{\text{RE}}$ -based estimates show a much stronger agreement among the

ensemble members, as well as with Dai et al. (2009) estimates.

The $(E - P)_{\text{RS}}$ -based discharges also show distinctly higher seasonal amplitude and interannual variability compared to $(E - P)_{\text{RE}}$ -based estimates, resulting in higher RMS values against Dai et al. (2009) data (Table S3 in the supplemental material). Considering 10%–20% error in gauged values (Fekete et al. 2002), and Dai et al.'s (2009) reliance on a model output to account for about 30% of total global discharge, and that subsurface discharge into the ocean is not included in the gauged observations but is implicitly included in the mass balance estimates presented here, it is possible that the amplitude of seasonal and interannual variability are not fully represented in Dai et al. (2009) data. The same can be said for reanalysis-based $E - P$ as models are an intrinsic part of the reanalysis process. Hence, in order to understand whether it is practically possible to have the seasonal amplitudes as seen in remote sensing-based discharge estimates, an experiment was conducted wherein we optimized the Dai et al. (2009) data to have maximum seasonal amplitude at each coastal grid point without resulting in negative discharge. The experiment described an extreme (and less likely) scenario where each coastal grid point, including all major river mouths,

FIG. 4. The $E - P$ estimates over global oceans (top) from combinations of various remote sensing P and E datasets and (bottom) from moisture convergences from five reanalysis datasets over global ocean. The shaded areas represent the pointwise 95% prediction bands of an OLS fit to the time series after removing the climatology.

would have a zero discharge minima. Even under this scenario, the overall amplitude increase in discharge was modest and incapable of explaining the higher amplitude seen in $(E - P)_{RS}$ -based estimates. Thus, based on observation–model hybrid discharge estimates from Dai et al. (2009) as a reference for evaluation, we conclude that $(E - P)_{RE}$ -based discharge estimates are more reliable compared to $(E - P)_{RS}$ -based estimates.

Trends associated with our discharge time series are provided in Table 2. As dM/dt estimates from both altimetry and GRACE do not show significant trends, the trends in discharge estimates come from $E - P$ estimates. The $(E - P)_{RS}$ -based discharges show significant increasing trends ($400 \pm 100 \text{ km}^3 \text{ yr}^{-2}$ for 1993–2015 from altimetry-based mass balance and $280 \pm 210 \text{ km}^3 \text{ yr}^{-2}$ for 2002–15 from GRACE-based mass balance) that are comparable to the increasing trends reported in remote sensing-based ocean mass balance study by Syed et al. (2010). The minor differences in our trends and those found by Syed et al. (2010) arise from not including some datasets such as HOAPS, comparing different time lengths, and using updated versions of all datasets. The $(E - P)_{RE}$ -based discharge estimates show no significant trends (at 95% confidence interval) for the 1993–2015 period, which is in agreement with other global discharge

studies (Dai et al. 2009; Milliman et al. 2008; Munier et al. 2012; Alkama et al. 2011). All the time series show a general downward trend since 2008/09, and trend estimates from GRACE-based discharge are more influenced by these years owing to the shorter record of GRACE compared to altimetry. This recent decrease in the $(E - P)_{RS}$ -based discharge trends indicates that the observed trends are driven by internal variability and that detecting and isolating a hydrologic intensification signal in global discharge would require longer time series and further investigation.

We further compare the interannual variability in our discharge ensembles with respect to ENSO events in Fig. 6. Niño-3.4 (red, dotted) is a commonly used index to represent different ENSO phases (obtained from <https://www.ncdc.noaa.gov/>). The index time series is smoothed to remove seasonality. Also, as there is an inverse relationship between discharge and ENSO, the index time series is inverted in the figure for better visual comparison. The Dai et al. (2009) discharge time series (red, solid) is also shown. All time series are normalized by their standard deviation so that the relative differences in amplitudes are nullified, making the comparison more robust. Except for altimetry- and $(E - P)_{RS}$ -based ensemble discharge, all discharge time

FIG. 5. (top) Monthly, (bottom) deseasonalized, and monthly climatology (bottom inset; $\text{Km}^3 \text{yr}^{-1}$) ensemble time series of global continental discharge from ocean mass balance based on type of $E - P$ [remote sensing (RS); reanalysis (RE); and COREv2] and type of dM/dt [altimetry (A) and GRACE (G)]. Shading represents maximum spread of the ensemble members around the ensemble mean. The modified Dai et al. (2009) estimate from COREv2, and discharge estimates computed with $E - P$ from COREv2 and dM/dt from altimetry and GRACE are also shown (red, green, and magenta). For better visibility, the $G + (E - P)_{\text{RE}}$ curve is shown in yellow in (top) and in orange in (bottom).

series show interannual variability correlating with ENSO, with $R > 0.44$ for all of them, which is consistent with other studies featuring discharge–ENSO relationship (Dai et al. 2009; Munier et al. 2012; Syed et al. 2010). While none of the discharge time series show minima corresponding with the mega–El Niño of 1997/98, the time series seem to correspond well with the La Niña events, with peaks in variability coinciding with the 1998–2000, 2007/08, and the 2010/11 events. This interannual variability is likely to drive short-term trends and should be taken into account in trend analysis studies.

Owing to overall agreement between various $(E - P)_{\text{RE}}$ estimates, we combine (by computing arithmetic mean) all land water and ocean mass balance estimates of discharge estimates based on $E - P$ from reanalysis and dM/dt from altimetry and GRACE. The mean global continental discharge thus obtained is $38550 \pm 4800 \text{ km}^3 \text{yr}^{-1}$. The uncertainty estimate (which is about 13% of the long-term mean) is the standard deviation over the long-term mean estimates of 15 individual

discharge time series [five $(E - P)_{\text{RE}}$ estimates with GRACE-based dM/dt over land and ocean and with altimetry-based dM/dt over ocean] that were combined.

As mentioned earlier, COREv2 surface forcing data for ocean models use Dai et al. (2009) discharge data along with remote sensing– and older-generation reanalysis-based $E - P$. Based on Fig. 1, the COREv2 dM/dt , computed from solving the ocean mass balance using COREv2 discharge and $E - P$, shows poor agreement with observations-based dM/dt . Hence, we substituted COREv2 dM/dt by GRACE- and altimetry-based dM/dt to compute discharge. As can be seen in Fig. 5, these discharge estimates show poor agreement with Dai et al. (2009) estimates and are unable to provide water budget closure. This suggests questionable reliability of the remote sensing and older-generation reanalysis-based $E - P$ fields in the COREv2 forcing. As COREv2 is a widely used surface forcing for ocean-ice models, this result is likely to have considerable implications on ocean modeling studies.

TABLE 2. The mean, standard deviation, and the trend for global discharge estimates from the current work and other studies. The 95% confidence intervals are provided for the mean and the trend. Trends are computed after removing the seasonal cycle. The A, G, RS, and RE represent altimetry-based dM/dt , GRACE-based dM/dt , remote sensing-based $E - P$, and reanalysis-based $E - P$, respectively.

Data	Time period analyzed	Mean ($\text{km}^3 \text{ yr}^{-1}$)	σ ($\text{km}^3 \text{ yr}^{-1}$)	Trend ($\text{km}^3 \text{ yr}^{-2}$); p value (if ≥ 0.001)
Discharge ensembles				
$A + (E - P)_{\text{RS}}$	Feb 1993–Jul 2015	$32\,000 \pm 1800$	14 800	400 ± 100
$A + (E - P)_{\text{RE}}$	Feb 1993–Jul 2015	$38\,700 \pm 1100$	9300	-3 ± 40 ; 0.872
$G + (E - P)_{\text{RS}}$	May 2002–Apr 2015	$33\,300 \pm 1800$	11 300	280 ± 210 ; 0.008
$G + (E - P)_{\text{RE}}$	May 2002–Apr 2015	$38\,500 \pm 1100$	7100	-175 ± 70
$G + (E - P)_{\text{RE}}$ over land	May 2002–Apr 2015	$38\,500 \pm 1100$	6600	-180 ± 70
Discharge estimates used for comparison:				
$A + (E - P)_{\text{COREv2}}$	Feb 1993–Dec 2006	$42\,200 \pm 2600$	17 100	90 ± 290
$G + (E - P)_{\text{COREv2}}$	May 2002–Dec 2006	$39\,400 \pm 3600$	13 400	-1400 ± 840
Dai et al. (2009)	Feb 1993–Dec 2006	$39\,800 \pm 1200$	8100	-20 ± 30
Other studies (post 2009) ^a				
Syed et al. (2010)	Jan 1994–Dec 2006	36 100	16 200	540
Clark et al. (2015)	Jan 1948–Dec 2008	$44\,200 \pm 2700$	—	—
Rodell et al. (2015)	Jan 2000–Dec 2010	$45\,900 \pm 4400$	—	—

^a Please refer to Syed et al. (2009) and Clark et al. (2015) for studies before 2009.

d. Continent-scale discharge estimates

Mass balance estimates with GRACE and $(E - P)_{\text{RE}}$ over land also enable computation of continent- and basin-scale estimates. In Table 3, we list continent-wise average estimates of land-based discharge and compare them to those from Dai et al. (2009), Syed et al. (2009), Clark et al. (2015), and Rodell et al. (2015). Overall, our estimates agree the most with Dai et al.'s (2009) estimates, though some regional differences exist. Our estimates are much higher than Syed et al.'s (2009) estimates; however, that is likely from the exclusion of the Greenland and Antarctica ice sheets and Oceania (islands in the tropical Pacific Ocean) by Syed et al. (2009), which together account to about $8000 \text{ km}^3 \text{ yr}^{-1}$ in this study. Clark et al.'s (2015) estimates are the

highest of the compared studies, considering that they also exclude the two ice sheets. As Clark et al. (2015) offer a similar observation–model hybrid methodology as Dai et al. (2009), a major source of difference between the two estimates likely comes from use of different land surface models. As mentioned earlier, Rodell et al. (2015) use Clark et al. (2015) estimates as discharge input prior to optimizing all the water cycle components for budget closure and hence are closer to Clark et al.'s (2015) estimates than other studies in this comparison. The discharge estimates for the two ice sheets compare well with those from Rignot et al. (2011).

Taking the above factors into consideration, the continent-scale estimates are reasonably comparable. Our discharge values over Africa and Eurasia are lower compared to other studies, while the values of

FIG. 6. Same time series as in Fig. 5, but normalized by σ and compared with Niño-3.4 index, inverted (red, dotted).

TABLE 3. Continent-wise mean annual discharge ($\text{km}^3 \text{yr}^{-1}$). The uncertainties on our estimates are 95% confidence intervals over the mean. Uncertainty values are not provided for Dai et al. (2009).

	$G + (E - P)_{\text{RE}}$ over land 2002–15	Syed et al. (2009) 2003–05	Dai et al. (2009) ^a 1949–2004	Clark et al. (2015) ^b 1950–2008	Rodell et al. (2015) ^c 2000–10
South America	$11\,500 \pm 440$	$10\,200 \pm 420$	11 800	$13\,240 \pm 2430$	$12\,300 \pm 1000$
North America	5800 ± 350	6500 ± 260	6300	7140 ± 280	7900 ± 790
Africa	2600 ± 350	3600 ± 340	3800	3820 ± 720	3800 ± 330
Eurasia	$9950 \pm 1\,100$	8900 ± 450	12 900	$16\,640 \pm 750$	$16\,000 \pm 1600$
Australia–Oceania	5300 ± 390	480 ± 120	1200	3400 ± 120	3600 ± 410
Antarctica	2400 ± 100	—	2300	—	2300 ± 240
Greenland	950 ± 110	—	60	—	—
Global	$38\,500 \pm 1100$	$30\,400 \pm 1200$	38 400	$44\,240 \pm 2660$	$45\,900 \pm 4400$

^a Values as mentioned in Clark et al. (2015) except for Antarctica where values from COREv2 version of discharge are provided.

^b Excludes discharge from Greenland and Antarctica.

^c Greenland discharge is implicitly included in North America estimate.

Australia–Oceania (driven by Indonesia) are higher. These are some of the least gauged regions and are likely to be influenced by the land surface model capabilities in the observation–model hybrid estimates (Dai et al. 2009; Clark et al. 2015). The errors in water balance closure over Australia–Oceania and Eurasia are some of the highest found by Rodell et al. (2015). Compared to observations, Trenberth et al. (2011) and Trenberth and Fasullo (2013a) found differences among ERA-I and MERRA precipitation fields over central Africa. Overall, the spread among the estimates is indicative of complex hydrology in these regions, and more in situ observations are needed to provide further constraints. Other possible sources of errors are different time periods of these studies and differences in the regional masks. We recommend caution while applying the mass balance method to further smaller scale as GRACE's reliability decreases over regions less than $200\,000 \text{ km}^2$ and heterogeneity over land surface is likely to affect the atmospheric moisture fluxes from the reanalysis.

4. Conclusions

This work provides a summary of the current state of our ability to measure global continental discharge into the oceans using the water mass balance method. It explores the mass balance approaches over land and ocean, which provide a simple yet compelling method for estimating global continental discharge. We demonstrate that two independent remote sensing methods (satellite altimetry and gravimetry) provide remarkably similar estimates of ocean mass change, a critical component of mass balance, thus giving us confidence in both the methods and our estimates of ocean mass change. The biggest uncertainty in the mass balance method comes from $E - P$ estimates. Discharge estimates computed using satellite-based $E - P$ show a larger spread and

higher variability at seasonal and interannual scales compared to moisture convergences-based $E - P$ from reanalysis. Reanalysis-based discharge also offers a closer agreement to observation–model hybrid discharge estimates from Dai et al. (2009), which despite inheriting limitations from in situ observations and land surface models, offer a spatiotemporally consistent reference for evaluation. Based on this, we provide the estimate of mean annual global continental discharge as $38\,550 \pm 4800 \text{ km}^3 \text{yr}^{-1}$. We also demonstrate that the ocean water mass budget cannot be closed from a widely used ocean surface forcing data, COREv2, if observations-based dM/dt is used, suggesting questionable reliability of the COREv2 E and P fields.

There has been a rapid decrease in the publicly accessible ground observations of discharge. Since 2006, there are no observation-based datasets of global continental discharge available. The mass balance method of discharge estimation complements existing remote sensing methods of estimating discharge (e.g., Alsdorf et al. 2007; Getirana and Peters-Lidard 2013; Papa et al. 2010). The discharge computed from land water mass balance using reanalysis and GRACE (and GRACE Follow-On mission, which is scheduled to be launched in late 2017) has the ability to provide discharge estimates based on spatial domains (i.e., basins/continents/oceans), which is useful for studying regional hydrologic cycle variability and as a source of observations in data-poor basins. In basins where accurate measurements of gauged discharge are available, this method can be used to further constrain the uncertainties in $E - P$, and to estimate difficult-to-observe components of water cycle, such as submarine groundwater discharge (SGD).

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