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A new global method of satellite dataset merging and quality characterization constrained by the terrestrial water budget

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ABSTRACT

During the last decades, satellite observations have increasingly been used to study the global water cycle over land. Although their value is now appreciated by the hydrological community, they are still limited by their uncertainties and their inability to close the water budget. In a previous study, we optimally integrated several datasets for each component (precipitation, evapotranspiration, storage change and discharge) to close this budget at a basin scale. Furthermore, an independent and simple calibration of each satellite dataset was designed to reduce the budget residual. In this paper, we extend the calibration procedure to the global scale. Pixels are first classified into surface types characterized by their NDVI and net precipitation values. We show that the global calibration transforms the original datasets towards a consensus that is hydrologically more coherent, with a budget residual reduced by 26%. The calibrated datasets are compared to ground-based observations, showing an improvement for more than 65% of the sites tested. This opens new perspectives to generate long-term datasets at global scale based purely on all available satellites observations, which describe all the terrestrial water components useful for climate purposes. Beyond the simple calibration presented here, inconsistencies among the various satellite datasets can be used as a proxy for satellite observation uncertainties. The quality of our calibration procedure is constrained by the availability of discharge measurements, and could therefore be improved in the future, as discharge measurement networks become more extensive.

1. Introduction

Under a changing climate, the global hydrological cycle is expected to accelerate and intensify (e.g., Trenberth, 1999; Huntington, 2006; Coumou and Rahmstorf, 2012). Roderick et al. (2014) use a general modelling framework to understand the response of the water cycle to global warming, at the pixel scale and over both land and ocean. However, global satellite datasets able to fully describe the water cycle to help evaluate such climate models are still a limitation. Although changes have already been observed on precipitation (e.g., Dai et al., 2004) and actual evapotranspiration (Zhang et al., 2016b), quantifying the intensification is a difficult task and no consensus has been reached by the scientific community. One of the main reasons is the lack of consistency between datasets that describe the parameters involved in the hydrological cycle over land, namely the precipitation (P), the actual evapotranspiration (E), the water storage changes (sum of water stored in the vegetation, snow, lakes and rivers, soil moisture and groundwater, ΔS) and the runoff (or river discharge, R). For each parameter, several global scale datasets have been developed recently, either from *in situ* or remote sensing observations or a combination of both, from hydrological models or from reanalyses. Despite significant efforts, within the Global Energy and Water Exchanges project (GEWEX) for instance, large discrepancies between the datasets still exist due to biases and uncertainties as well as a lack of reference global datasets that make consensus among the scientific community. As a key consequence, determining which datasets best describe the hydrological cycle and simultaneously allow the closure of the water budget, which is achieved by nullifying the budget residual defined by Eq. (1), is still under investigation (e.g., Azarderakhsh et al., 2011; Tang et al., 2016).

$$G = P - E - R - \Delta S \tag{1}$$

Since no dataset can be considered as perfect, many authors preferred to combine different available datasets within budget closure experiments (Sheffield et al., 2009; Sahoo et al., 2011; Lorenz et al., 2014). For instance Pan et al. (2012) and Zhang et al. (2016a) used an assimilation strategy based on Kalman Filter algorithms to derive a coherent dataset of the four components (P, E, R and S) over different

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basins around the world, but the method is limited to the basin scale and cannot be directly extended at the pixel scale, unless Land Surface Models are used. Rodell et al. (2015) used variational methods to close the water budget at the global and annual scales.

In previous studies (e.g., Aires, 2014; Pan and Wood, 2006), several methodologies have been developed to integrate different hydrological datasets with a budget closure coherency, which consisted of partitioning the budget residual G among the components based on the uncertainties of the respective datasets. One of the methods described in Aires (2014) was applied by Munier et al. (2014) over the well-documented Mississippi basin using satellite datasets for P, E and ΔS and gauge observations for R. The optimal integration of the several Earth observation datasets relies on a Simple Weighting (SW) average and a closure Post-Filtering (PF). The authors showed that it improved the quality of water budget components when compared to *in situ* data. Besides, a Closure Correction Model (CCM) was developed based on the integrated product, able to correct each dataset independently and to greatly reduce the budget residual. This CCM calibration provides new optimized datasets at the pixel scale (not only the basin scale). It is important to notice that no model was used in this study, which makes the resulting datasets interesting for model calibration/validation. One main limitation of the CCM method relies on the datasets availability and their potentially large and unknown uncertainties. Namely, datasets based on satellite observations generally cover the last two decades, while discharge observations are not available over this time period for many large basins around the world. Hence, extending the method to the global scale, in particular on ungauged regions, is not straightforward.

In the present study, we investigate an original method to extend the CCM at a global scale with the objectives of 1) developing a coherent, pixel wise and global dataset of the four terrestrial water budget components (precipitation, evapotranspiration, storage change and discharge) and 2) estimating their biases and uncertainties. To calibrate the CCM, we considered 11 large basins for which discharge data are available over the last two decades. The method consists of considering all the basins as a single one to calibrate the CCM. In order to account for the various hydroclimatic conditions of the different basins, an index called Calibration Index for Closure (CIC) is derived from a combination of net precipitation ($P - E$) and the Normalized Difference Vegetation Index (NDVI). The basins are classified among four surface-type classes based on the CIC and a CCM is calibrated for each class. These new calibrated CCM can then be used globally, following the derived CIC classes. The CIC calibration method is evaluated at the basin scale in terms of budget closure performances, and over sites all around the world with independent ground-based observations. The paper is organized as follows: Section 2 presents the datasets and the considered basins, Section 3 presents the method, results are presented and discussed in Section 4.

2. Datasets and considered basins

2.1. Satellite-derived datasets

We aim at showing the potential of satellite based datasets to represent the hydrological cycle coherently with respect to budget closure. Consequently, we maximized the use of datasets based on satellite observations for P, E and ΔS. We considered four precipitation datasets: the Tropical Rainfall Measuring Mission (TRMM, 3B43 V7) Multi-Satellite Precipitation Analysis (TMPA), the NOAA CPC Morphing Technique (CMORPH, V1.0), the Naval Research Laboratory Blended Technique (NRL) and the Global Precipitation Climatology Project (GPCP, V2.2). It has to be noticed that the TMPA and GPCP products have been corrected using *in situ* gauge observations. For evapotranspiration, three products were chosen: Global Land Evaporation Amsterdam Model (GLEAM, V3.0), MODIS Global Evapotranspiration Project (MOD16) and NTSG Land Surface Evapotranspiration (NTSG).

Table 1
Data sources for the four components and main characteristics (from Munier et al., 2014).

Name	Source	Period	Spatial resolution	Reference
Precipitation (P)				
TMPA	Satellite	1998–present	0.25°	Huffman et al. (2007)
CMORPH	Satellite	1998–present	0.25°	Joyce et al. (2004)
NRL	Satellite	2003–2010	0.25°	Turk et al. (2010)
GPCP	Satellite	1979–present	2.5°	Adler et al. (2003)
Evapotranspiration (E)				
GLEAM	Satellite	1980–2011	0.25°	Miralles et al. (2011)
MOD16	Satellite	2000–2012	1 km	Mu et al. (2007)
NTSG	Satellite	1983–2006	8 km	Zhang et al. (2010)
Water storage change (ΔS)				
CSR	Satellite	2002–present	Basin	http://grace.jpl.nasa.gov/data/
GFZ	Satellite	2002–present	Basin	http://grace.jpl.nasa.gov/data/
JPL	Satellite	2002–present	Basin	http://grace.jpl.nasa.gov/data/
GRGS	Satellite	2002–present	Basin	http://grgs.obs-mip.fr/grace/
River discharge (R)				
GRDC	Gauges	1900–present	Basin	http://www.grdc.sr.unh.edu/

The continental water storage variations were estimated using four products, all of them based on the Gravity Recovery and Climate Experiment (GRACE, Tapley et al., 2004) but obtained with different pre- and post-processing: Jet Propulsion Laboratory (JPL), Center for Space Research (CSR), German Research Centre for Geosciences (GFZ) and Groupe de Recherche en Géodésie Spatiale (GRGS). Since the GRACE mission started in 2002, the period considered in this study covers the period 2002–2010. Details and references of the considered datasets are given in Table 1. More details can be found in Munier et al. (2014), including a discussion on their respective uncertainties. Biases and uncertainties are further discussed in Section 4.2.

All the gridded datasets used in the integration process have been resampled at a spatial resolution of 1° and averaged at the monthly time scale.

2.2. Ground-based FLUXNET data

Ground-based observations were used to validate the correction method over several sites around the world. Precipitation and evapotranspiration data were extracted from the FLUXNET2015 dataset (available at http://fluxnet.fluxdata.org/) that gathers eddy covariance data acquired and shared by the FLUXNET community. A total of 117 were selected, based on their availability over the period 2002–2010. These stations are located all around the world and cover a large panel of hydro-climatic conditions. Similar to the other datasets, data were resampled at the monthly time scale.

2.3. Considered basins

Since the discharge component is not observed from space, we used *in situ* observations extracted from the Global Runoff Data Centre (GRDC). The availability of discharge data over the last decade was the limiting point in the choice of the basins used to calibrate the CCM. The selection of basins is highly restricted by two factors: 1) availability of discharge data over the period 2002–2010, and 2) size of the basin compatible with GRACE spatial resolution (greater than 500.000 km^2). Also, basins at high latitudes have been excluded because some precipitation datasets are not available there. In the GRDC database, we found 10 basins fulfilling these criteria. Discharge data from the Murray-Darling Basin Authority (http://www.mdba.gov.au) were also used to increase the number of basins. Table 2 presents the 11 basins considered in this study and their main characteristics. For the Amazon,