Rivers and floodplains as key components of global terrestrial water storage variability

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Key points

1. SWS contributes to TWS primarily in the tropics, and in major rivers flowing over arid regions or at high latitudes.
2. SWS has low impact in Western U.S., Northern Africa, Middle-East and central Asia and most of Australia.
3. Rivers and floodplains store 2400km³ with an annual variability of 2700km³, contributing to 7% of TWS change globally.

Abstract

This study aims to quantify the contribution of rivers and floodplains on the global terrestrial water storage (TWS) variability. We use state-of-the-art models to simulate
land surface processes and river dynamics in order to separate TWS into its main components. Based on a proposed impact index, we show that surface water storage (SWS) contributes to 7% of TWS globally, but that contribution highly varies spatially. The primary contribution of SWS to TWS is in the tropics, and in major rivers flowing over arid regions or at high latitudes. About 20-23% of both Amazon and Nile basins’ TWS changes are due to SWS. SWS has low impact in Western U.S., Northern Africa, Middle-East and central Asia. Based on comparisons against GRACE-based estimates, we conclude that using SWS significantly improves TWS simulations in most South America, Africa and Northern India, confirming the need for SWS as a key component of TWS change.

1. Introduction

Since the launch of the Gravity Recovery and Climate Experiment (GRACE) mission (Tapley et al., 2004) in 2002, the scientific community has gained significant insight into terrestrial water storage (TWS) variations around the world. Still, understanding of the relationship between TWS variations and changes in its individual components (groundwater, soil moisture, surface waters, snow, and vegetation water storage) has not advanced beyond small-scale studies based on in situ data (e.g., Rodell and Famiglietti, 2001). Although a few studies have demonstrated the impact that surface water storage (SWS) has on TWS in tropical basins (e.g. Papa et al., 2013; Pokhrel et al., 2013; Salameh et al., 2017), the vast majority of investigations on TWS decomposition systematically neglect SWS by assuming that its contribution to TWS is trivial (Houborg et al., 2012). Such studies have combined either model outputs or observations with GRACE data in order to estimate groundwater variability and change over the U.S.
(Famiglietti et al., 2011), India (Rodell et al., 2009; Tiwari et al., 2009; Chen et al., 2014; Joodaki et al., 2014; Girotto et al., 2017) and the Middle East (Voss et al., 2013). The contribution of reservoir operation to global TWS change has also been evaluated in Zhou et al. (2016), but neglecting the contribution of rivers and floodplains. Among the GRACE data assimilation (DA) initiatives, very few studies have considered SWS, mostly using relatively simple water balance models and approaches (Eicker, et al., 2014; Van Dijk et al., 2014; Tian et al., 2017). However, the majority assumes TWS as the sum of land surface model (LSM) water storage (LWS) components, e.g. groundwater storage (GWS), soil moisture (SM), snow water equivalent (SWE) and total canopy interception water storage (CAN) (e.g. Zaitchik et al., 2008; Kumar et al., 2016; Girotto et al., 2016, 2017). Notably these studies ignore the SWS contribution from rivers, floodplains, wetlands, lakes and reservoirs. Even though that assumption might be a close representation of the truth in specific locations, as evidenced in Rodell & Famiglietti (2001) over Illinois, in the U.S., the actual impact of SWS on the global TWS change and its spatial variability is unknown.

Based on the aforementioned limitations in the TWS representation and a current lack of knowledge on the actual weight of SWS on global TWS and its spatial variability, the objective of this study is to determine the actual impact of SWS on TWS change within a modeling framework. Two state-of-the-art models, the Noah LSM with multiparameterization options (Noah-MP: Niu et al., 2011) and the Hydrological Modeling and Analysis Platform (HyMAP) river routing scheme (Getirana et al., 2012), are combined in order to represent the physical processes controlling the global water balance and dynamics. An impact index is proposed and applied globally, allowing the
identification of how different water storage components contribute to TWS variability. We further investigate the spatially distributed gain in accuracy obtained by summing SWS and LWS, as compared with GRACE-based TWS estimates. An inherent assumption of the study is that Noah-MP and HyMAP provide realistic and compatible estimates of variations in the TWS components. We believe this is reasonable based recently published evaluations (e.g. Xia et al., 2017; Getirana et al., 2017), however, it will lead to uncertainty in our results. Further, the fact that these models do not account for human impacts on the water cycle, including irrigated agriculture and reservoir operations, is a limitation. Evaluation of uncertainties related to inaccurate model parameterization, limited representation of physical and anthropogenic processes, and forcing errors is beyond the scope of this work.

2. Modeling framework and evaluation

The model run was performed within the NASA Land Information System (LIS: Kumar et al., 2006), where Noah-MP and HyMAP are one-way coupled. This means that, at each time step, gridded surface runoff and baseflow simulated by Noah-MP are transferred to HyMAP and used to simulate spatially continuous surface water dynamics. No information is returned from HyMAP to Noah-MP.

The Noah-MP land surface model

The Noah-MP LSM, which is jointly developed and maintained by the National Center for Atmospheric Research (NCAR) and the National Centers for Environmental Prediction (NCEP), is a multi-physics version of the community Noah LSM. Similar to traditional LSMS, Noah-MP maintains surface energy and water balances while
simulating direct evaporation from soil, transpiration from vegetation, evaporation of interception and snow sublimation, and estimating key surface energy and moisture prognostics such as land surface temperature, snowpack, soil moisture and soil temperature. In addition, Noah-MP incorporates extensive physics upgrades over the original Noah including the representation of dynamic vegetation phenology, a carbon budget and carbon-based photosynthesis, an explicit vegetation canopy layer, a three-layer snow physics component, and a groundwater module with a prognostic water table (Niu et al., 2011).

**HyMAP river routing scheme**

HyMAP is a global scale river routing scheme capable of simulating flow dynamics in both rivers and floodplains. In this study, HyMAP was utilized with the local inertia formulation (Bates et al., 2010; Getirana et al., 2017), accounting for a more stable and computationally efficient representation of backwater effects. SWS [mm] is obtained by dividing the water stored in rivers and floodplains by the grid cell surface area.

Evaporation from open waters is considered in HyMAP, resulting in an improved representation of the water budget over wet surfaces, not represented in Noah-MP. That is possible because the physical relationship between the water surface and atmosphere has been simplified, such as considering the air and surface water temperatures approximately the same. The Penman–Monteith formula is used in this context. Ocean tides have been neglected in this study. Thus, the downstream boundary water elevation near river outlets is set to zero meters constant over time. More details on the HyMAP parameterization can be found in Getirana et al. (2012, 2013).
Although lakes and reservoirs have an important role in the water storage and dynamics at the regional and global scales (e.g. Haddeland et al., 2006; Doll et al., 2009), they are currently not featured in HyMAP. As a consequence, they have been neglected in this study. In this sense, SWS is exclusively represented by water stored in rivers and floodplains. This means that the amplitude and timing of simulated water storage components in regions highly impacted by human activities, such as the U.S., parts of Western Europe, and Southern and Eastern Asia, might considerably differ from reality.

**Modeling configuration**

The Princeton meteorological dataset is used as forcing for Noah-MP. The dataset is available on a 3-hourly time step and at a 1-degree spatial resolution (Sheffield et al. 2006) for the 1948–2014 period. LIS/Noah-MP/HyMAP was run for 35 years (1980-2014) at 1-hour time step and 1-degree spatial resolution. The Courant–Freidrichs–Levy (CFL) condition is used in order to determine HyMAP’s optimal time steps for numerical stability (Bates et al., 2010; Getirana et al., 2017). A 32-year spinup was performed allowing the models’ water storage components to reach stability.

**Evaluation procedure**

Two evaluation procedures have been performed in order to determine the impact SWS on TWS: first, an impact index $I$ has been defined here as a function of each water storage component contribution $C$ to TWS. And $C$ is defined as the sum of absolute monthly climatological anomaly values:

$$C_i = \sum_{t=1}^{12} |S_{i,t} - S_t|$$

(1)
where \( i \) and \( t \) are indexes related to water storage components and time step, respectively, and \( nc=5 \), corresponding to the water stored \((S)\) in the components considered in this study: SWS, GWS, SM, SWE and CAN. The sum of impact indexes of all water storage components equals 1.

Such an index is preferred over the ratio of amplitudes, as suggested in previous studies (e.g. Pokhrel et al., 2013) due to the fact that occasional lags between the different water storage components may result in impact values superior to the unit. Using the proposed index guarantees that the sum of all \( I_i \) equals to one. The impact evaluation has been performed for the full simulation period, i.e. from 1980 to 2014.

Impacts are evaluated globally and at the basin scale. In that sense, we selected the 15 largest river basins, plus Ganges-Brahmaputra, Mekong and Tigris-Euphrates River basins. Table 1 summarizes the selected river basins and lists 17 gauge stations used to evaluate streamflow simulations through long-term averages. Streamflow observations are available through the Global Runoff Data Centre (GRDC) at the daily time step (except for the monthly observations at El Ekhsase, in the Nile River). Stations draining the largest surface have been chosen for all selected basins, except for the Indus and Tigris-Euphrates Rivers, where no data is available for the study period.

The second evaluation quantifies the gain in considering SWS as part of TWS by comparing simulated LWS and TWS (i.e. SWS+LWS) against GRACE-based TWS using the Kling-Gupta (KG) efficiency coefficient (Gupta et al., 2009). KG measures the Euclidean distance from an ideal point of the Pareto line and is a function of the
correlation \( (r) \), bias \( (\beta) \) and standard deviation ratio \( (\gamma) \), also called variability, between simulations \( (s) \) and observations \( (o) \):

\[
\text{KG} = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2}
\]  

\[
\beta = \frac{\mu_s}{\mu_o}
\]  

\[
\gamma = \frac{\sigma_s}{\sigma_o}
\]

where \( \mu \) and \( \sigma \) stand for the mean and standard deviation of TWS time series. The optimal value for \( r, \beta, \gamma \) and \( \text{KG} \) is 1. Since the KG is computed for anomaly time series, the bias term is neglected. This means that KG is a function of phasing and amplitude ratio between \( s \) and \( o \). The spatial distribution of improvements and deterioration with the inclusion of SWS is obtained with the differential KG (i.e. \( \Delta \text{KG} = \text{KG}_{\text{TWS}} - \text{KG}_{\text{LWS}} \)).

The version RL05 spherical harmonics fields (Landerer and Swenson, 2012) of GRACE monthly mass grids produced by the University of Texas Center for Space Research (CSR) are used in this study. These data are the truncated and smoothed using a Gaussian filter and are provided on a 1-degree global grid at a monthly time step. The TWS comparison has been performed for the 2003-2014 period, when both meteorological forcings and GRACE data overlap.

Monthly SWS and LWS simulations were also smoothed using a 300 km half-width Gaussian filter, then re-gridded onto the GRACE grid. These operations were needed in order to obtain simulations that were spatially and temporally consistent with the GRACE-based TWS fields. Details on the smoothening process can be found in Wahr et
al. (1998). It is important to note that this procedure was only performed for the comparison against GRACE data.

3. Results and Discussion

Impacts on the terrestrial water storage change

Results indicate that all land surface on Earth (~112×10^6 km^2, Greenland excluded) stores about 2400 km^3 of water in rivers and floodplains. This number is in the same order of magnitude as previous estimates found in the literature, varying from 2000 km^3 (Oki and Kanae, 2006) to 2120 km^3 (Shiklomanov, 1993). 30% of that water (or ~720 km^3) is concentrated in the Amazon basin (see Table 1 for mean SWS values at the selected 18 river basins). Globally, $I_{SWS}$ is 7%, compared to 15%, 55% and 23% from $I_{GWS}$, $I_{SM}$ and $I_{SWE}$. However, these impacts have a high spatial variability. Fig. 1 shows the impact index spatial distribution of the four water storage components (SWS, GWS, SM and SWE - canopy interception CAN was neglected in the analysis due its minimal impact). $I_{SWS}$ can be seen in tropical areas in South America, Africa and Asia, and along most major global rivers. $I_{SWS}$ is particularly high along rivers crossing arid regions, such as the Tigris-Euphrates (T-E) Rivers, in Iraq, the Nile and Niger Rivers over the Sahara, the Sao Francisco River, in Northeastern Brazil, among others. $I_{SWS}$ values are also prominent over large rivers in the high latitudes, such as Ob, Yenisei, Lena, Amur, Volga and Mackenzie Rivers. Little impact has been detected over arid regions, such as the Atacama Desert, most of Northern and Eastern Africa, the Middle East, central Asia, and most of Australia. $I_{SWS}$ values are also low over the dry Western and Mid-Western U.S. On the other hand, the SWS presents a high impact on TWS over the more humid Eastern U.S., in particular near the lower Mississippi River. Over Northern India, including the
Indus and Ganges-Brahmaputra (G-B) River basins, $I_{SW}$ values are as high as 60%. $I_{SM}$ is particularly dominant in drier regions, and also where $I_{SW}$ and $I_{SWE}$ are low, counterbalancing $I_{GWS}$, with higher values over humid areas. $I_{SWE}$ prevails in the high latitudes (mostly in the Northern Hemisphere) and the Himalayas.

SWS and GWS changes are in phase and have similar magnitudes in most major basins, as shown in Fig. 2. This may be attributed to the fact that surface water and groundwater are tightly coupled, with surface waters occurring largely where the water table intersects the land surface, such that groundwater and surface water are sometimes considered to be a single resource (e.g., Winter, 1998; Rodell et al., 2007). SM dominates the monthly TWS change in all basins located in low latitudes, with impacts varying from 50% in the Amazon to 82% in the T-E River basin. For the high latitude basins, SWE controls more than 50% of TWS change, as observed in the Ob, Yenisei, Lena Volga and Mackenzie River basins. In those basins, a 3-month lag is noticed between SWE and SWS, and, in some cases, the amplitude of annual SWE variability is higher than TWS annual variability.

The Amazon basin has the highest mean $I_{SW}$ value (27%), with a mean annual amplitude of $\sim$116 mm, corresponding to 37% of the TWS’ amplitude (312 mm). This amplitude ratio is about the mean of two estimates (27% and 50%) previously suggested in Pokhrel et al. (2013) and Papa et al. (2013) using modeling and satellite data, respectively. $I_{SW}$ is also high in the Nile basin (20%), which is due to the low GWS and SM variability in the arid part of the basin. These two basins are the only ones where $I_{SW}$ is higher than $I_{GWS}$.

Other basins, such as Congo, Parana, Niger, Yangtze, Volga, Zambezi Indus, G-B and Mekong have major SWS impacts on TWS. In particular, $I_{SW}$ is 13% over G-B an
SWS/TWS amplitude ratio of 24%, which is about half of the estimated value (50%) suggested in a previous study combining multi-satellite data (Salameh et al., 2017).

**Comparison against GRACE data**

The impact of incorporating SWS in TWS is quantified using the changes in the KG metric ($\Delta$KG). The global averaged improvement of adding SWS and LWS towards a better representation of TWS, compared to simply using LWS, is nominal (i.e. $\Delta$KG=0 for all land surface). However, the impact of $I_{SWS}$ in certain regions, as described in the previous section, is noticeable in the $\Delta$KG spatial distribution. The top panel of Fig. 3 shows the $\Delta$KG map, highlighting 12 regions selected for further discussion, and differential values of its two components, as defined in Eq. (3): differential correlation $\Delta r$ and differential standard deviation ratio $\Delta \gamma$. 57% of land surfaces presented improved correlations with the addition of SWS, while 87% showed improved standard deviation ratios. However, these improvements were small in most places, counterbalancing with the high local deteriorations, and resulting in no changes in the global $\Delta r$ and $\Delta \gamma$ averages.

The bottom panel of Fig. 3 shows the respective annual variability of GRACE observations and simulated TWS, LWS and SWS. The impact of SWS is substantial over South America and Africa, in particular in (1) the central Amazon, (2) the central and lower Nile, (3) the Zambezi and Southern Congo River basins, and most of the Sahel. SWS variability is also conspicuous in (4) Northern India and G-B River basin, (5) the lower T-E River basin, and some regions in high latitudes.
SWS and LWS are in phase over region 1, but the large SWS annual variability increases
the amplitude of simulated TWS towards a better match with GRACE-based
observations, and significantly improves KG values. Region 2 is within the desert, where
LWS change is negligible; hence TWS change is governed by SWS. This can be clearly
observed in the annual variability shown in Fig. 3. Streamflow simulations in the Nile
River are overestimated in about three times (as shown in Table 1) and may be resulting
in higher TWS amplitudes when compared to GRACE-based observations. The Nile
River is also highly impacted by intense irrigation along the river and reservoir operation
at the Aswan dam, which can also explain differences between simulated and observed
TWS amplitudes. TWS change over region 3 is dominated by soil moisture and,
secondarily, by GWS but it experiences a non-negligible amplitude increase and a slight
shift in the lag with the inclusion of SWS.

Fig. 3 also highlights seven regions where adding SWS to LWS deteriorated the
comparison between TWS and GRACE. Most of those regions have in common a high
SWS annual variability, which significantly increases the TWS amplitude, resulting in
negative $\Delta \gamma$ and $\Delta KG$. This is the case in the lower Mississippi and Yangtze River basins
(regions 6 and 7, respectively), as well as the Parana River basin (8), Niger’s inner delta
(9), the lower Congo and Amur River basins (regions 10 and 11, respectively). The
exception is the high latitude region (12), where the considerably lagged SWS
counterbalances LWS, decreasing the amplitude and shifting the peaks.

Adding SWS to LWS improves the phase agreement between simulated TWS and
GRACE-based observations in regions 6, 7 and 12. Region 8 is highly impacted by
human activities, in particular reservoir operation (Getirana, 2016), with major dams
modifying the hydrological regime of the main river and tributaries. The Pantanal wetland, identified in the map as the upper red spot within the region, is a complex hydrological system commonly misrepresented in global-scale models. The absence of a proper representation of these natural and anthropogenic processes highly impacts the lower Parana River dynamics, resulting in an early and amplified SWS peak, negatively altering TWS simulations.

Most major river’s outlets reveal a high SWS amplitude, such as observed in regions 6-11, and elsewhere in the map in Fig. 3, resulting in substantially low $\Delta\gamma$ and $\Delta KG$ values. This could be explained by HyMAP limitations in representing the surface water dynamics at the interface between rivers and oceans and major lakes.

4. Summary

The main goal of this study is to quantify the contribution of surface water storage to the global terrestrial water storage. It has been motivated by the fact that most hydrological studies employ the LSM-based water storage as TWS, neglecting SWS. Here, we use the state-of-the-art Noah-MP LSM and HyMAP river routing scheme in order to simulate the global water balance. We also propose an index to determine the impact of the major water storage components, i.e. SWS, groundwater storage, soil moisture and snow water equivalent, on TWS change. These impacts are evaluated both distributed spatially and averaged for 18 major river basins. A second analysis focuses on how adding SWS to LWS contributes to accurately estimating TWS, using GRACE-based TWS estimates as reference. The Kling-Gupta efficiency coefficient is used to determine where improvements and deteriorations happened.
Results show high SWS impact in the tropics, and major rivers flowing over arid regions and high latitudes. We also demonstrate considerable SWS impacts in the Tigris-Euphrates River basin and Northern India (including the G-B and Indus River basins), where that storage component has been neglected in previous hydrological studies. In addition, we show that neglecting SWS in a TWS data assimilation framework over the U.S. could be an acceptable simplification for part of the country (in particular, the Western and Mid-Western regions), but surface water has a significant impact in the Eastern part of the country.

Recent developments on land surface and river dynamic modeling have resulted in major improvements in the representation of large-scale hydrological processes. However, we acknowledge that computational models, including those used in this study, still present limitations in global parameterizations. Besides, although human activities, such as reservoir operation and irrigation, have been neglected in this study, we recognize that they may have non-negligible impacts on TWS change. Results may largely vary as a function of different modeling configurations, so we caution that the findings presented in this study are representative for adopted particular modeling system, its parameterization and forcings. Further investigation considering different modeling and observational techniques is highly encouraged. The coarse spatial resolution of GRACE also plays an important role in the evaluation, since signals over rivers can be smoothed out and may not be realistic.

Simplifications aside, these results will be valuable for future studies to determine the importance of (i) integrating river routing schemes into LSMS, (ii) considering SWS when composing or decomposing TWS, and (iii) assimilating TWS and new variables
within a multivariate DA framework in hydrology (e.g. Tian et al., 2017), based on the impact of each water storage component. In that sense, simultaneously assimilating TWS and surface water level from existing (e.g. Jason-3, SARAL/AltiKa, and Sentinel-3) and future (Surface Water and Ocean Topography - SWOT) sensors within integrated global-scale modeling systems will greatly improve our understanding the spatial and temporal variability of terrestrial water storage and its components.

Acknowledgements

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References


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Table 1. Summary of the 15 world’s largest river basins, plus Ganges-Brahmaputra, Mekong and Tigris-Euphrates. All land surface is also listed.

<table>
<thead>
<tr>
<th>Basin #</th>
<th>River basin</th>
<th>Surface area</th>
<th>Mean SWS</th>
<th>Mean SWS annual variability</th>
<th>Station</th>
<th>Drainage area at station</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Observed years</th>
<th>Q_{obs}</th>
<th>Q_{sim}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Amazon</td>
<td>5901</td>
<td>719.3</td>
<td>700.3</td>
<td>Óbidos</td>
<td>4680</td>
<td>-55.5</td>
<td>-2.0</td>
<td>1980-1997</td>
<td>165,687</td>
<td>145,777</td>
</tr>
<tr>
<td>2</td>
<td>Congo</td>
<td>3713</td>
<td>148.5</td>
<td>175.8</td>
<td>Kinshasa</td>
<td>3475</td>
<td>15.3</td>
<td>-4.3</td>
<td>1980-2010</td>
<td>38,617</td>
<td>55,250</td>
</tr>
<tr>
<td>3</td>
<td>Mississippi</td>
<td>3184</td>
<td>61.4</td>
<td>40.6</td>
<td>Vicksburg</td>
<td>2964.3</td>
<td>-90.9</td>
<td>32.3</td>
<td>1980-2014</td>
<td>18,838</td>
<td>18,627</td>
</tr>
<tr>
<td>4</td>
<td>Nile</td>
<td>3048</td>
<td>67.2</td>
<td>97.0</td>
<td>El Ekhsase</td>
<td>2900</td>
<td>31.3</td>
<td>29.7</td>
<td>1980-1984</td>
<td>1277</td>
<td>4875</td>
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<tr>
<td>5</td>
<td>Ob</td>
<td>2629</td>
<td>58.2</td>
<td>34.1</td>
<td>Salekhard</td>
<td>2950</td>
<td>66.6</td>
<td>66.6</td>
<td>1980-2010</td>
<td>12,884</td>
<td>9377</td>
</tr>
<tr>
<td>6</td>
<td>Parana</td>
<td>2621</td>
<td>116.1</td>
<td>144.3</td>
<td>Timbues</td>
<td>2346</td>
<td>-60.7</td>
<td>-32.7</td>
<td>1980-2014</td>
<td>18,161</td>
<td>29,532</td>
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<tr>
<td>7</td>
<td>Yenisei</td>
<td>2515</td>
<td>62.5</td>
<td>38.1</td>
<td>Igarka</td>
<td>2440</td>
<td>86.5</td>
<td>67.5</td>
<td>1980-2011</td>
<td>19,457</td>
<td>11,231</td>
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<td>8</td>
<td>Lena</td>
<td>2455</td>
<td>54.4</td>
<td>24.2</td>
<td>Stolb</td>
<td>2460</td>
<td>126.8</td>
<td>72.4</td>
<td>1980-2002</td>
<td>15,737</td>
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<td>9</td>
<td>Niger</td>
<td>2149</td>
<td>44.7</td>
<td>97.6</td>
<td>Malanville</td>
<td>1000</td>
<td>3.4</td>
<td>11.9</td>
<td>1980-1995</td>
<td>763</td>
<td>1980</td>
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<td>10</td>
<td>Amur</td>
<td>1969</td>
<td>29.6</td>
<td>24.7</td>
<td>Bogorodskoye</td>
<td>17900</td>
<td>140.5</td>
<td>52.5</td>
<td>1980-1987</td>
<td>11,467</td>
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<td>11</td>
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<td>17.3</td>
<td>Artic Red River</td>
<td>16600</td>
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<td>1980-2014</td>
<td>9192</td>
<td>4945</td>
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<td>12</td>
<td>Yangtze</td>
<td>1735</td>
<td>78.1</td>
<td>73.3</td>
<td>Datong</td>
<td>1705</td>
<td>117.6</td>
<td>30.8</td>
<td>2004-2004</td>
<td>25,012</td>
<td>19,224</td>
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<td>13</td>
<td>Volga</td>
<td>1404</td>
<td>67.6</td>
<td>59.2</td>
<td>Volgograd Power Plant</td>
<td>1360</td>
<td>44.6</td>
<td>48.8</td>
<td>1980-2010</td>
<td>8127</td>
<td>8446</td>
</tr>
<tr>
<td>14</td>
<td>Zambezi</td>
<td>1386</td>
<td>28.0</td>
<td>59.1</td>
<td>Matundo-Cais</td>
<td>940</td>
<td>33.6</td>
<td>-16.2</td>
<td>1980-2004</td>
<td>2155</td>
<td>8458</td>
</tr>
<tr>
<td>15</td>
<td>Indus</td>
<td>1068</td>
<td>5.3</td>
<td>5.2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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</tr>
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<td>16</td>
<td>Ganges-Brahmaputra</td>
<td>1472</td>
<td>35.6</td>
<td>78.8</td>
<td>Hardinge Bridge</td>
<td>846</td>
<td>89.0</td>
<td>24.1</td>
<td>1985-1991</td>
<td>11,146</td>
<td>10,763</td>
</tr>
<tr>
<td>17</td>
<td>Mekong</td>
<td>786</td>
<td>42.9</td>
<td>90.7</td>
<td>Stung Treng</td>
<td>635</td>
<td>106.0</td>
<td>13.5</td>
<td>1991-1994</td>
<td>14,456</td>
<td>10,410</td>
</tr>
<tr>
<td>18</td>
<td>Tigris-Euphrates</td>
<td>911</td>
<td>3.6</td>
<td>5.1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>All land surface</td>
<td>112,134</td>
<td>2388.3</td>
<td>2706.2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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</tr>
</tbody>
</table>

1 Based on HyMAP parameters. 2 Based on GRDC data. 3 Greenland excluded.
Figure 1. Spatially distributed impact of surface water storage (SWS), groundwater storage (GWS), soil moisture (SM) and snow water equivalent (SWE) for the 1980-2014 period.

Figure 2. Annual variability in mm equivalent height of water of simulated TWS, SWS, GWS, SM and SWE at 18 major river basins for the 1980-2014 period. Their impacts are also provided (ordered by importance – see colors in the legend).

Figure 3. On top, the spatial distribution of efficiency coefficients between LWS and TWS using GRACE as the reference: differential Kling-Gupta ($\Delta$KG), differential correlation ($\Delta r$) and differential standard deviation ratio ($\Delta \gamma$). In the bottom, the annual variability in mm equivalent height of water of GRACE observations and simulated TWS, LWS and SWS at 12 selected regions for the 2003-2014 period.