

# 1 Rivers and floodplains as key components of global terrestrial 2 water storage variability

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## 11 Key points

12 1. SWS contributes to TWS primarily in the tropics, and in major rivers flowing over arid  
13 regions or at high latitudes.

14 2. SWS has low impact in Western U.S., Northern Africa, Middle-East and central Asia  
15 and most of Australia.

16 3. Rivers and floodplains store  $2400\text{km}^3$  with an annual variability of  $2700\text{km}^3$ ,  
17 contributing to 7% of TWS change globally.

## 18 Abstract

19 This study aims to quantify the contribution of rivers and floodplains on the global  
20 terrestrial water storage (TWS) variability. We use state-of-the-art models to simulate

21 land surface processes and river dynamics in order to separate TWS into its main  
22 components. Based on a proposed impact index, we show that surface water storage  
23 (SWS) contributes to 7% of TWS globally, but that contribution highly varies spatially.  
24 The primary contribution of SWS to TWS is in the tropics, and in major rivers flowing  
25 over arid regions or at high latitudes. About 20-23% of both Amazon and Nile basins'  
26 TWS changes are due to SWS. SWS has low impact in Western U.S., Northern Africa,  
27 Middle-East and central Asia. Based on comparisons against GRACE-based estimates,  
28 we conclude that using SWS significantly improves TWS simulations in most South  
29 America, Africa and Northern India, confirming the need for SWS as a key component of  
30 TWS change.

## 31 **1. Introduction**

32 Since the launch of the Gravity Recovery and Climate Experiment (GRACE) mission  
33 (Tapley et al., 2004) in 2002, the scientific community has gained significant insight into  
34 terrestrial water storage (TWS) variations around the world. Still, understanding of the  
35 relationship between TWS variations and changes in its individual components  
36 (groundwater, soil moisture, surface waters, snow, and vegetation water storage) has not  
37 advanced beyond small-scale studies based on in situ data (e.g., Rodell and Famiglietti,  
38 2001). Although a few studies have demonstrated the impact that surface water storage  
39 (SWS) has on TWS in tropical basins (e.g. Papa et al., 2013; Pokhrel et al., 2013;  
40 Salameh et al., 2017), the vast majority of investigations on TWS decomposition  
41 systematically neglect SWS by assuming that its contribution to TWS is trivial (Houborg  
42 et al., 2012). Such studies have combined either model outputs or observations with  
43 GRACE data in order to estimate groundwater variability and change over the U.S.

44 (Famiglietti et al., 2011), India (Rodell et al., 2009; Tiwari et al., 2009; Chen et al., 2014;  
45 Joodaki et al., 2014; Giroto et al., 2017) and the Middle East (Voss et al., 2013). The  
46 contribution of reservoir operation to global TWS change has also been evaluated in  
47 Zhou et al. (2016), but neglecting the contribution of rivers and floodplains. Among the  
48 GRACE data assimilation (DA) initiatives, very few studies have considered SWS,  
49 mostly using relatively simple water balance models and approaches (Eicker, et al.,  
50 2014; Van Dijk et al., 2014; Tian et al., 2017). However, the majority assumes TWS as  
51 the sum of land surface model (LSM) water storage (LWS) components, e.g.  
52 groundwater storage (GWS), soil moisture (SM), snow water equivalent (SWE) and total  
53 canopy interception water storage (CAN) (e.g. Zaitchik et al., 2008; Kumar et al., 2016;  
54 Giroto et al., 2016, 2017). Notably these studies ignore the SWS contribution from  
55 rivers, floodplains, wetlands, lakes and reservoirs. Even though that assumption might be  
56 a close representation of the truth in specific locations, as evidenced in Rodell &  
57 Famiglietti (2001) over Illinois, in the U.S., the actual impact of SWS on the global TWS  
58 change and its spatial variability is unknown.

59 Based on the aforementioned limitations in the TWS representation and a current lack of  
60 knowledge on the actual weight of SWS on global TWS and its spatial variability, the  
61 objective of this study is to determine the actual impact of SWS on TWS change within a  
62 modeling framework. Two state-of-the-art models, the Noah LSM with  
63 multiparameterization options (Noah-MP: Niu et al., 2011) and the Hydrological  
64 Modeling and Analysis Platform (HyMAP) river routing scheme (Getirana et al., 2012),  
65 are combined in order to represent the physical processes controlling the global water  
66 balance and dynamics. An impact index is proposed and applied globally, allowing the

67 identification of how different water storage components contribute to TWS variability.  
68 We further investigate the spatially distributed gain in accuracy obtained by summing  
69 SWS and LWS, as compared with GRACE-based TWS estimates. An inherent  
70 assumption of the study is that Noah-MP and HyMAP provide realistic and compatible  
71 estimates of variations in the TWS components. We believe this is reasonable based  
72 recently published evaluations (e.g. Xia et al., 2017; Getirana et al., 2017), however, it  
73 will lead to uncertainty in our results. Further, the fact that these models do not account  
74 for human impacts on the water cycle, including irrigated agriculture and reservoir  
75 operations, is a limitation. Evaluation of uncertainties related to inaccurate model  
76 parameterization, limited representation of physical and anthropogenic processes, and  
77 forcing errors is beyond the scope of this work.

## 78 **2. Modeling framework and evaluation**

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

### 84 **The Noah-MP land surface model**

85 The Noah-MP LSM, which is jointly developed and maintained by the National Center  
86 for Atmospheric Research (NCAR) and the National Centers for Environmental  
87 Prediction (NCEP), is a multi-physics version of the community Noah LSM. Similar to  
88 traditional LSMs, Noah-MP maintains surface energy and water balances while

89 simulating direct evaporation from soil, transpiration from vegetation, evaporation of  
90 interception and snow sublimation, and estimating key surface energy and moisture  
91 prognostics such as land surface temperature, snowpack, soil moisture and soil  
92 temperature. In addition, Noah-MP incorporates extensive physics upgrades over the  
93 original Noah including the representation of dynamic vegetation phenology, a carbon  
94 budget and carbon-based photosynthesis, an explicit vegetation canopy layer, a three-  
95 layer snow physics component, and a groundwater module with a prognostic water table  
96 (Niu et al., 2011).

### 97 **HyMAP river routing scheme**

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

103 Evaporation from open waters is considered in HyMAP, resulting in an improved  
104 representation of the water budget over wet surfaces, not represented in Noah-MP. That  
105 is possible because the physical relationship between the water surface and atmosphere  
106 has been simplified, such as considering the air and surface water temperatures  
107 approximately the same. The Penman–Monteith formula is used in this context. Ocean  
108 tides have been neglected in this study. Thus, the downstream boundary water elevation  
109 near river outlets is set to zero meters constant over time. More details on the HyMAP  
110 parameterization can be found in Getirana et al. (2012, 2013).

111 Although lakes and reservoirs have an important role in the water storage and dynamics  
112 at the regional and global scales (e.g. Haddeland et al., 2006; Doll et al., 2009), they are  
113 currently not featured in HyMAP. As a consequence, they have been neglected in this  
114 study. In this sense, SWS is exclusively represented by water stored in rivers and  
115 floodplains. This means that the amplitude and timing of simulated water storage  
116 components in regions highly impacted by human activities, such as the U.S., parts of  
117 Western Europe, and Southern and Eastern Asia, might considerably differ from reality.

### 118 **Modeling configuration**

119 The Princeton meteorological dataset is used as forcing for Noah-MP. The dataset is  
120 available on a 3-hourly time step and at a 1-degree spatial resolution (Sheffield et al.  
121 2006) for the 1948–2014 period. LIS/Noah-MP/HyMAP was run for 35 years (1980-  
122 2014) at 1-hour time step and 1-degree spatial resolution. The Courant–Freidrichs–Levy  
123 (CFL) condition is used in order to determine HyMAP’s optimal time steps for numerical  
124 stability (Bates et al., 2010; Getirana et al., 2017). A 32-year spinup was performed  
125 allowing the models’ water storage components to reach stability.

### 126 **Evaluation procedure**

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

$$131 \quad C_i = \sum_{t=1}^{12} |S_{i,t} - \bar{S}_i| \quad (1)$$

132 
$$I_i = \frac{c_i}{\sum_{i=1}^{nc} c_i} \quad (2)$$

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

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

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

150 The second evaluation quantifies the gain in considering SWS as part of TWS by  
151 comparing simulated LWS and TWS (i.e. SWS+LWS) against GRACE-based TWS  
152 using the Kling-Gupta (KG) efficiency coefficient (Gupta et al., 2009). KG measures the  
153 Euclidean distance from an ideal point of the Pareto line and is a function of the

154 correlation ( $r$ ), bias ( $\beta$ ) and standard deviation ratio ( $\gamma$ ), also called variability, between  
155 simulations ( $s$ ) and observations ( $o$ ):

$$156 \quad KG = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad (3)$$

$$157 \quad \beta = \frac{\mu_s}{\mu_o} \quad (4)$$

$$158 \quad \gamma = \frac{\sigma_s}{\sigma_o} \quad (5)$$

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

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

170 Monthly SWS and LWS simulations were also smoothed using a 300 km half-width  
171 Gaussian filter, then re-gridded onto the GRACE grid. These operations were needed in  
172 order to obtain simulations that were spatially and temporally consistent with the  
173 GRACE-based TWS fields. Details on the smoothing process can be found in Wahr et



174 al. (1998). It is important to note that this procedure was only performed for the  
175 comparison against GRACE data.

### 176 **3. Results and Discussion**

#### 177 **Impacts on the terrestrial water storage change**

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

197 Indus and Ganges-Brahmaputra (G-B) River basins,  $I_{SWS}$  values are as high as 60%.  $I_{SM}$  is  
198 particularly dominant in drier regions, and also where  $I_{SWS}$  and  $I_{SWE}$  are low,  
199 counterbalancing  $I_{GWS}$ , with higher values over humid areas.  $I_{SWE}$  prevails in the high  
200 latitudes (mostly in the Northern Hemisphere) and the Himalayas.

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

212 The Amazon basin has the highest mean  $I_{SWS}$  value (27%), with a mean annual amplitude  
213 of ~116mm, corresponding to 37% of the TWS' amplitude (312mm). This amplitude  
214 ratio is about the mean of two estimates (27% and 50%) previously suggested in Pokhrel  
215 et al. (2013) and Papa et al. (2013) using modeling and satellite data, respectively.  $I_{SWS}$  is  
216 also high in the Nile basin (20%), which is due to the low GWS and SM variability in the  
217 arid part of the basin. These two basins are the only ones where  $I_{SWS}$  is higher than  $I_{GWS}$ .  
218 Other basins, such as Congo, Parana, Niger, Yangtze, Volga, Zambezi Indus, G-B and  
219 Mekong have major SWS impacts on TWS. In particular,  $I_{SWS}$  is 13% over G-B an

220 SWS/TWS amplitude ratio of 24%, which is about half of the estimated value (50%)  
221 suggested in a previous study combining multi-satellite data (Salameh et al., 2017).

## 222 **Comparison against GRACE data**

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

235 The bottom panel of Fig. 3 shows the respective annual variability of GRACE  
236 observations and simulated TWS, LWS and SWS. The impact of SWS is substantial over  
237 South America and Africa, in particular in (1) the central Amazon, (2) the central and  
238 lower Nile, (3) the Zambezi and Southern Congo River basins, and most of the Sahel.  
239 SWS variability is also conspicuous in (4) Northern India and G-B River basin, (5) the  
240 lower T-E River basin, and some regions in high latitudes.

241 SWS and LWS are in phase over region 1, but the large SWS annual variability increases  
242 the amplitude of simulated TWS towards a better match with GRACE-based  
243 observations, and significantly improves KG values. Region 2 is within the desert, where  
244 LWS change is negligible; hence TWS change is governed by SWS. This can be clearly  
245 observed in the annual variability shown in Fig. 3. Streamflow simulations in the Nile  
246 River are overestimated in about three times (as shown in Table 1) and may be resulting  
247 in higher TWS amplitudes when compared to GRACE-based observations. The Nile  
248 River is also highly impacted by intense irrigation along the river and reservoir operation  
249 at the Aswan dam, which can also explain differences between simulated and observed  
250 TWS amplitudes. TWS change over region 3 is dominated by soil moisture and,  
251 secondarily, by GWS but it experiences a non-negligible amplitude increase and a slight  
252 shift in the lag with the inclusion of SWS.

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

261 Adding SWS to LWS improves the phase agreement between simulated TWS and  
262 GRACE-based observations in regions 6, 7 and 12. Region 8 is highly impacted by  
263 human activities, in particular reservoir operation (Getirana, 2016), with major dams

264 modifying the hydrological regime of the main river and tributaries. The Pantanal  
265 wetland, identified in the map as the upper red spot within the region, is a complex  
266 hydrological system commonly misrepresented in global-scale models. The absence of a  
267 proper representation of these natural and anthropogenic processes highly impacts the  
268 lower Parana River dynamics, resulting in an early and amplified SWS peak, negatively  
269 altering TWS simulations.

270 Most major river's outlets reveal a high SWS amplitude, such as observed in regions 6-  
271 11, and elsewhere in the map in Fig. 3, resulting in substantially low  $\Delta\gamma$  and  $\Delta KG$  values.  
272 This could be explained by HyMAP limitations in representing the surface water  
273 dynamics at the interface between rivers and oceans and major lakes.

#### 274 **4. Summary**

275 The main goal of this study is to quantify the contribution of surface water storage to the  
276 global terrestrial water storage. It has been motivated by the fact that most hydrological  
277 studies employ the LSM-based water storage as TWS, neglecting SWS. Here, we use the  
278 state-of-the-art Noah-MP LSM and HyMAP river routing scheme in order to simulate the  
279 global water balance. We also propose an index to determine the impact of the major  
280 water storage components, i.e. SWS, groundwater storage, soil moisture and snow water  
281 equivalent, on TWS change. These impacts are evaluated both distributed spatially and  
282 averaged for 18 major river basins. A second analysis focuses on how adding SWS to  
283 LWS contributes to accurately estimating TWS, using GRACE-based TWS estimates as  
284 reference. The Kling-Gupta efficiency coefficient is used to determine where  
285 improvements and deteriorations happened.

286 Results show high SWS impact in the tropics, and major rivers flowing over arid regions  
287 and high latitudes. We also demonstrate considerable SWS impacts in the Tigris-  
288 Euphrates River basin and Northern India (including the G-B and Indus River basins),  
289 where that storage component has been neglected in previous hydrological studies. In  
290 addition, we show that neglecting SWS in a TWS data assimilation framework over the  
291 U.S. could be an acceptable simplification for part of the country (in particular, the  
292 Western and Mid-Western regions), but surface water has a significant impact in the  
293 Eastern part of the country.

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

306 Simplifications aside, these results will be valuable for future studies to determine the  
307 importance of (i) integrating river routing schemes into LSMs, (ii) considering SWS  
308 when composing or decomposing TWS, and (iii) assimilating TWS and new variables

309 within a multivariate DA framework in hydrology (e.g. Tian et al., 2017), based on the  
310 impact of each water storage component. In that sense, simultaneously assimilating TWS  
311 and surface water level from existing (e.g. Jason-3, SARAL/AltiKa, and Sentinel-3) and  
312 future (Surface Water and Ocean Topography - SWOT) sensors within integrated global-  
313 scale modeling systems will greatly improve our understanding the spatial and temporal  
314 variability of terrestrial water storage and its components.

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321 Hydrology Group (<http://hydrology.princeton.edu/data.pgf.php>).

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

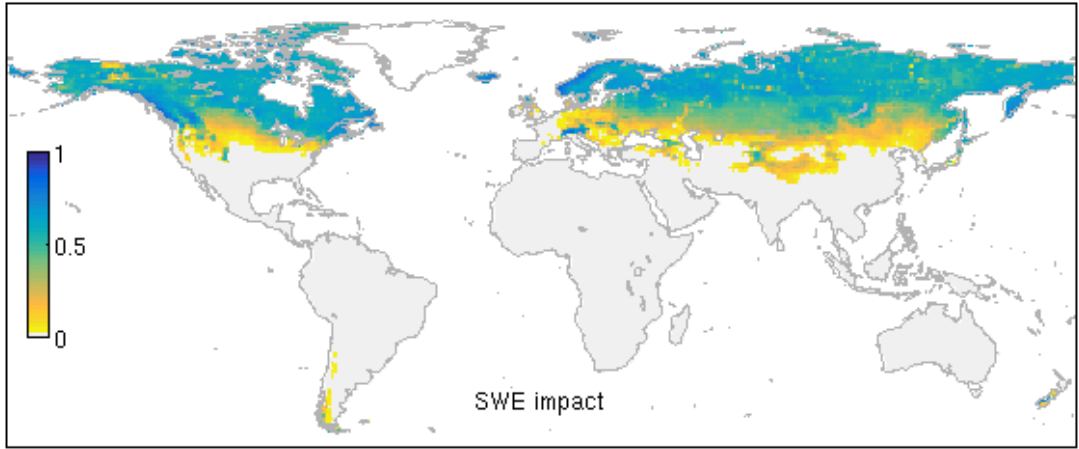
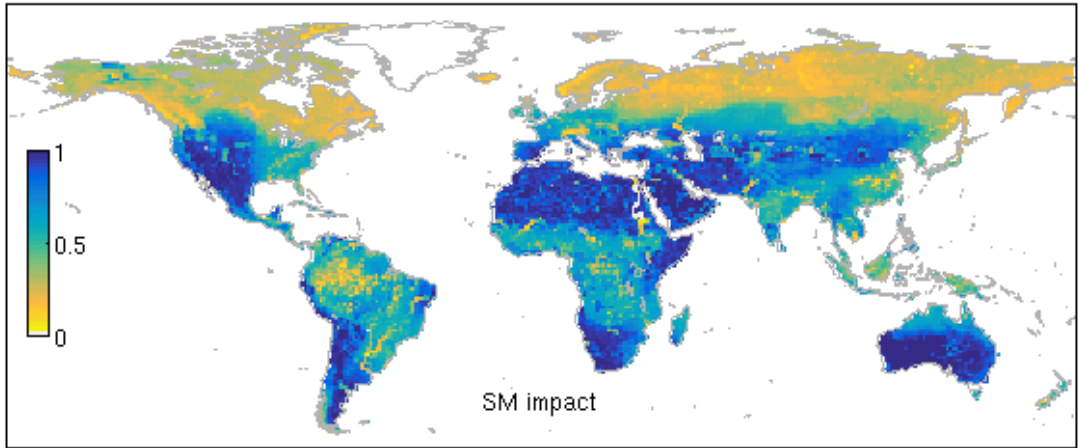
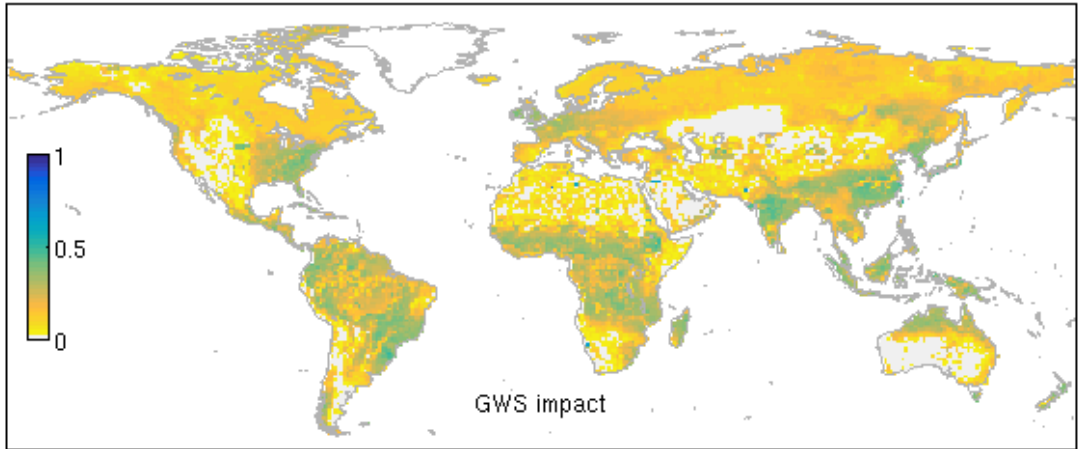
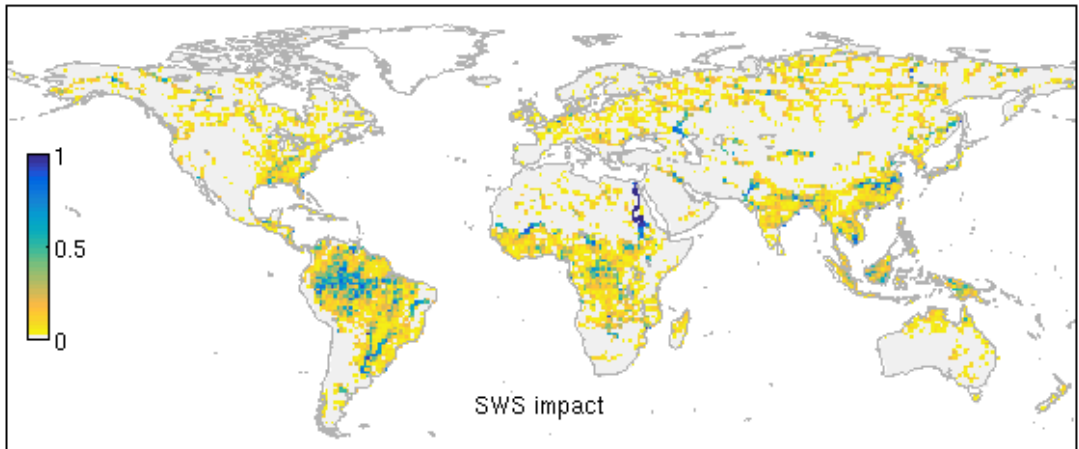
Basin #	River basin	Surface area <sup>1</sup> [10 <sup>3</sup> km <sup>2</sup> ]	Mean SWS [km <sup>3</sup> ]	Mean SWS annual variability [km <sup>3</sup> ]	Station	Drainage area at station <sup>2</sup> [10 <sup>3</sup> km <sup>2</sup> ]	Longitude	Latitude	Observed years	Q <sub>obs</sub> [m <sup>3</sup> .s <sup>-1</sup> ]	Q <sub>sim</sub> [m <sup>3</sup> .s <sup>-1</sup> ]
1	Amazon	5901	719.3	700.3	Óbidos	4680	-55.5	-2.0	1980-1997	165,687	145,777
2	Congo	3713	148.5	175.8	Kinshasa	3475	15.3	-4.3	1980-2010	38,617	55,250
3	Mississippi	3184	61.4	40.6	Vicksburg	2964.3	-90.9	32.3	1980-2014	18,838	18,627
4	Nile	3048	67.2	97.0	El Ekhsase	2900	31.3	29.7	1980-1984	1277	4875
5	Ob	2629	58.2	34.1	Salekhard	2950	66.5	66.6	1980-2010	12,884	9377
6	Parana	2621	116.1	144.3	Timbues	2346	-60.7	-32.7	1980-2014	18,161	29,532
7	Yenisei	2515	62.5	38.1	Igarka	2440	86.5	67.5	1980-2011	19,457	11,231
8	Lena	2455	54.4	24.2	Stolb	2460	126.8	72.4	1980-2002	15,737	8242
9	Niger	2149	44.7	97.6	Malanville	1000	3.4	11.9	1980-1995	763	1980
10	Amur	1969	29.6	24.7	Bogorodskoye	17900	140.5	52.5	1980-1987	11,467	9028
11	Mackenzie	1770	32.2	17.3	Artic Red River	16600	-133.8	67.5	1980-2014	9192	4945
12	Yangtze	1735	78.1	73.3	Datong	1705	117.6	30.8	2004-2004	25,012	19,224
13	Volga	1404	67.6	59.2	Volgograd Power Plant	1360	44.6	48.8	1980-2010	8127	8446
14	Zambezi	1386	28.0	59.1	Matundo-Cais	940	33.6	-16.2	1980-2004	2155	8458
15	Indus	1068	5.3	5.2	-	-	-	-	-	-	-
16	Ganges-Brahmaputra	1472			Hardinge Bridge	846	89.0	24.1	1985-1991	11,146	10,763
			35.6	78.8	Bahadurabad	636	89.7	25.2	1985-1991	23,165	13,624
17	Mekong	786	42.9	90.7	Stung Treng	635	106.0	13.5	1991-1994	14,456	10,410
18	Tigris-Euphrates	911	3.6	5.1	-	-	-	-	-	-	-
All land surface <sup>3</sup>		112,134	2388.3	2706.2	-	-	-	-	-	-	-

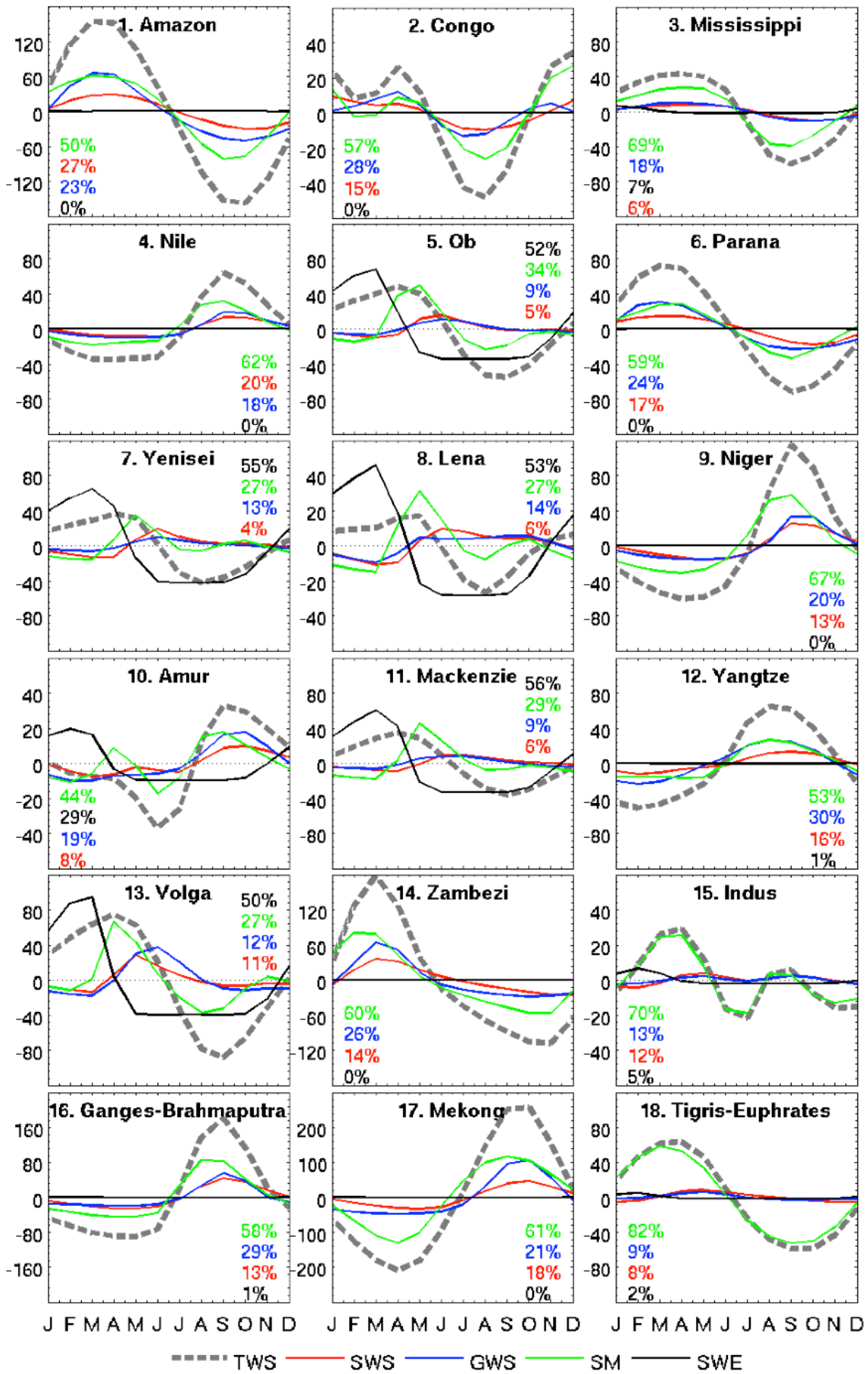
450 <sup>1</sup>Based on HyMAP parameters. <sup>2</sup>Based on GRDC data. <sup>3</sup>Greenland excluded.

451 **Figure 1. Spatially distributed impact of surface water storage (SWS), groundwater**  
452 **storage (GWS), soil moisture (SM) and snow water equivalent (SWE) for the 1980-**  
453 **2014 period.**

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

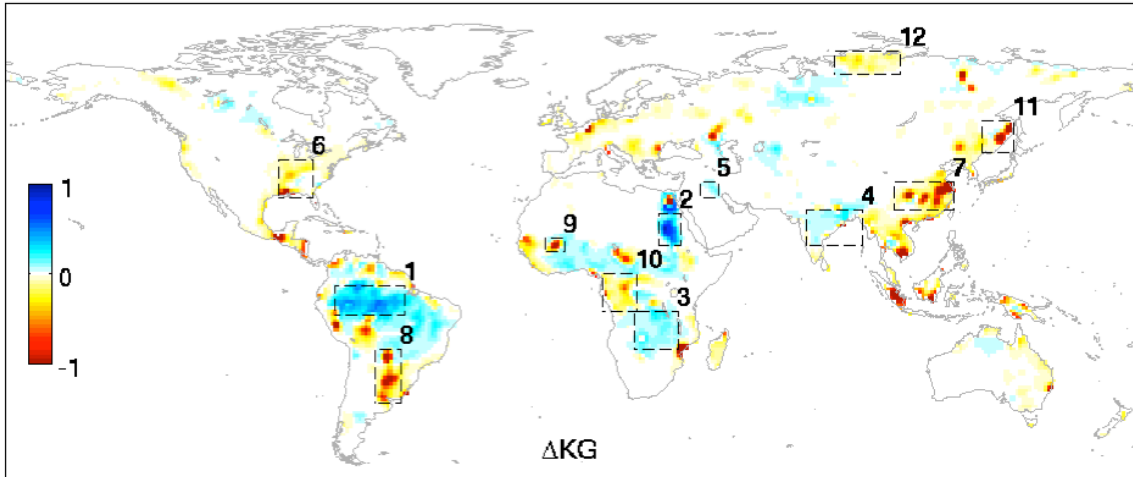
457 **Figure 3. On top, the spatial distribution of efficiency coefficients between LWS and**  
458 **TWS using GRACE as the reference: differential Kling-Gupta ( $\Delta KG$ ), differential**  
459 **correlation ( $\Delta r$ ) and differential standard deviation ratio ( $\Delta \gamma$ ). In the bottom,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



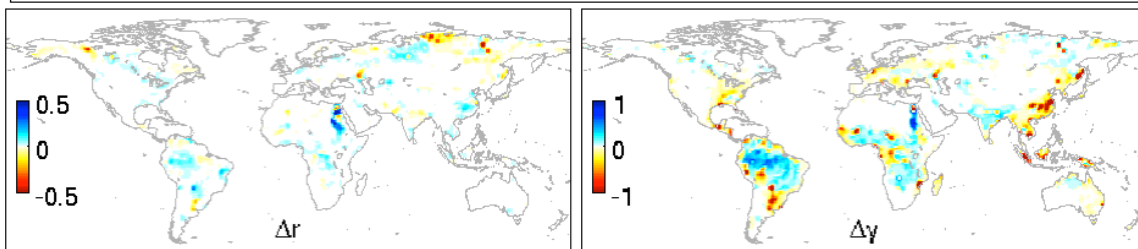




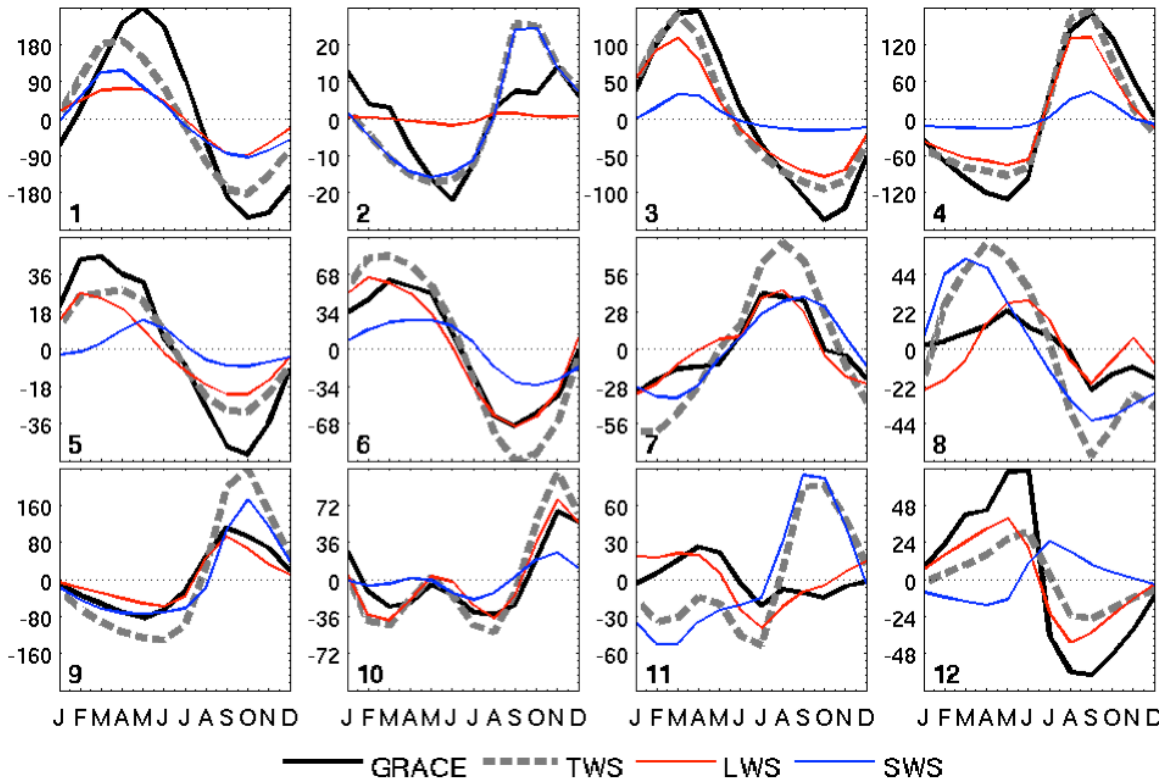
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