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Role of rivers in the seasonal variations of terrestrial water storage over global basins

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[1] The role of rivers in total terrestrial water storage (TWS) variations is evaluated in 29 basins. The contribution of individual storage components to total TWS is investigated by using ensemble hydrological simulations with river routing. The observed Gravity Recovery And Climate Experiment (GRACE) TWS data are used to validate model simulations. It is found TWS simulations are more accurate when river storage is taken into account except for dry basins. Rivers play different roles in various climatic regions as indicated by two new indices quantifying the significance of each TWS component and their interactions. River storage, which effectively includes downslope movement of shallow groundwater, explains up to 73% of TWS variations in Amazon. It also acts as "buffer" which smoothes TWS seasonal variations particularly in snow-dominated basins. Neglecting river storage may lead to mismatch in the amplitude and phase of TWS seasonal variations compared to the GRACE observations.
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1. Introduction

[2] Terrestrial water storage (TWS), i.e., the sum of soil moisture, groundwater, snow and ice, water in biomass, and surface water in lakes, reservoirs, wetlands and river channels, play a significant role in the climate system, primarily through the exchange of water and energy at the land surface. TWS controls the partitioning of precipitation into evaporation and runoff with significant implications for hydrologic extremes [*Yeh et al.*, 1998; *Eltahir and Yeh*, 1999; *Hirschi et al.*, 2006; *Yeh and Famiglietti*, 2008].

[3] Despite its importance, the role of TWS in the global hydrological cycle has received little attention relative to other hydrologic processes, and there are no extensive networks currently in existence for monitoring TWS changes. The recently launched Gravity Recovery And Climate Experiment (GRACE) mission [*Tapley et al.*, 2004] has provided a unique new opportunity to monitor TWS variations from space. This has allowed, for the first time, observations of the variations of total TWS in large river basins to continental scales [e.g., *Syed et al.*, 2008]. However, a critical evaluation of the potential to isolate GRACE signals into individual TWS components has yet to be conducted. Since GRACE is not able to measure vertical profile of TWS, hydrological modeling [*Rodell et al.*, 2004; *Güntner et al.*, 2007; *Syed et al.*, 2008] is a valuable tool for the partitioning of GRACE signals into individual storage component.

[4] Among terrestrial hydrological processes, river plays a significant role in large basins through the transport of freshwater to the ocean, which affects water balance of the oceans and forms a part of hydrological circulation on the Earth. Also, river discharge is the major part of available renewable freshwater resource [*Oki and Kanae*, 2006]. However, most of the previous studies of GRACE hydrology applications do not considered river processes are important contributors to TWS variations. Although a pilot modeling study by *Oki* [1999] and recent satellite observations [*Frappart et al.*, 2008; *Han et al.*, 2009] have both indicated the dominant role of river and surface water storage variations in the Amazon basin, it is still not clear how significant river storage would contribute to the seasonal variability of total TWS under various climate and hydrological conditions.

[5] In this study, we investigate the temporal variations of three major TWS components; snow water, soil moisture and river storage, by using the hydrologic modeling approach. The simulated TWS is validated against GRACE data from 2002 to 2007 in 29 world large river basins. The contributions of individual components to the total TWS variations are quantified, and their interactions are examined.

2. Methods

2.1. Ensemble Land Surface Simulations

[6] The modeling framework used in this study consists of a land surface model (LSM), the Minimal Advanced Treatment of Surface Interaction Runoff (MATSIRO) [*Takata et al.*, 2003], and a global runoff routing scheme, the Total Runoff Integrated Pathway (TRIP) [*Oki and Sud*, 1998]. MATSIRO has a single layer of canopy, three variable snow layers with the subgrid distribution of snow cover, and five soil layers of 4-m total thickness. TRIP is a global river routing scheme which routes LSM-simulated runoff through river networks based on topographic gradient. Based on mass conservation, i.e., $dS/dt = Flow_{in} - Flow_{out}$, river storage S is formulated as a single linear reservoir, and calculated at each grid point of TRIP, according to: $S(t_0 + \delta t) = \exp(-\frac{u_e}{d}\delta t)S(t_0) + (1 - \exp(-\frac{u_e}{d}\delta t))Flow_{in}\frac{d}{u_e}$, where u_e is the effective velocity, d is the distance between grid boxes, and δt is the calculation interval. The effective velocity u_e is an integrated mean velocity of rainwater traveling from land surface to river mouth through various paths, thus TRIP is able to effectively simulate unrepresented fast sub-surface processes as a part of its dynamics [*Oki et al.*, 1999]. In this study, river dynamics provide the driving force

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Table 1. Specifications of Five Observational Precipitation Data Used in This Study

Product	Type	Spat. Res.	Temp. Res.	Period
GPCC full [*Rudolf and Rubel*, 2005]	Gauge	1.0°	Monthly	1901–2007
PREC/L [*Chen et al.*, 2002]	Gauge	1.0°	Monthly	1948–
CPC unified [*Chen et al.*, 2008]	Gauge	0.5°	Daily	1979–
GPCP v2 [*Adler et al.*, 2003]	Satellite-Gauge	2.5°	Monthly	1979–
CMAP [*Xie and Arkin*, 1997]	Satellite-Gauge	2.5°	Monthly	1979–

to transport surface and sub-surface runoff. Therefore, the river storages calculated by TRIP are the water storages moving sub-horizontally toward the stream outlets including both surface flow and downslope movement of shallow groundwater. The MATSIRO-TRIP modeling framework has been applied to the studies of terrestrial water cycle estimation [*Hirabayashi et al.*, 2005] and the assessment of hydrological extremes in both regional [*Yoshimura et al.*, 2008] and global scales [*Hirabayashi et al.*, 2008].

[7] The model simulations in this study span over the period of GRACE mission (2002 to 2007) with a global $1^\circ \times 1^\circ$ resolution. Atmospheric forcing variables (precipitation, temperature, radiations, pressure, humidity, and wind speed) are based on the atmospheric reanalysis data provided by Japanese Meteorological Agency (JMA) Climate Data Assimilation System (JCDAS) [*Onogi et al.*, 2007], and an altitude correction has been applied to temperature, pressure and humidity [*Ngo-Duc et al.*, 2005]. Ensemble simulations are conducted by using five observed global precipitation datasets (Table 1) in order to reduce the uncertainty in forcing variables. All the reanalysis and observed precipitation datasets are bi-linearly interpolated or aggregated into the $1^\circ \times 1^\circ$ grids. Observed daily or monthly precipitation is disaggregated based on the temporal distribution of 6-hourly reanalysis precipitation field. Input land surface properties including land cover, soil texture, soil and vegetation parameters are specified as same as for the Global Soil Wetness Project 2 (GSWP2) [*Dirmeyer et al.*, 2006], and other MATSIRO-specific parameters follow the default values of *Takata et al.* [2003].

[8] In this study, total TWS consists of three main components: soil moisture, snow water and river storage. Soil moisture and snow water are calculated as the arithmetic mean of LSM ensemble simulations. In order to obtain optimal river storage simulations for the realization of temporal variations of effective velocity, the Bayesian Model Averaging (BMA) [*Duan et al.*, 2007] is applied to ten TRIP runs with perturbed effective velocities ranging from 0.1 to 1.0 m/s. The average of ensemble simulations is optimized to maximize the weight-averaged likelihood of ensemble members, and the observed Global Runoff Data Center (GRDC) discharge is taken as the training data. The procedure is performed for each basin respectively, since effective velocity is highly dependent on basin-specific topography and river morphology. The simulated total TWSA is spatially averaged over each basin for the comparison with GRACE data.

[9] The GRACE data of the version ‘dpc200711’ with a $1^\circ \times 1^\circ$ global resolution and a 0km smoothing are used in this study, which are provided for averaging pixels over larger areas, for example, a hydrologic basin. The arithmetic mean of GRACE TWS anomalies from the Center for Space Research (CSR), GeoForschungsZentrum (GFZ) and Jet Propulsion Laboratory (JPL) are used in the comparison. We have also compared and found the differences among three GRACE datasets are negligible (see http://hydro.iis.u-tokyo.ac.jp/~hjkim/tws@2009GRL).

2.2. Component Contribution Ratio and Component Exchange Intensity

[10] In order to compare how individual storage components contribute to total TWS variations and the interaction among them, the following two new indices are devised:

[11] 1. Component Contribution Ratio (CCR): defined as the ratio of mean absolute deviation (MAD) of a component ($\frac{1}{N}\sum_t^N |S_t - \overline{S}|$; here, N is number of months) to total variability (TV) which is the summation of MAD of each component ($\sum_S^{Storages} MAD_S$),

$$CCR_S = \frac{MAD_S}{TV} \tag{1}$$

where S is the indices of soil moisture (SM), snow water (SW), and river storage (RS) storage components. The CCR quantifies the average contribution of each storage component to TV.

[12] 2. Component Exchange Intensity (CEI): defined as one minus the ratio of MAD of total TWS to TV,

$$CEI = 1 - \frac{MAD_{TWS}}{TV} \tag{2}$$

which quantifies the intensity of component interactions (i.e., amplification or compensation) due to different amplitude and phase of each component. The CEI equals to one when components are entirely out of phase and completely compensates each other, while equals to zero when they are perfectly in phase.

3. Results

[13] From the total 178 global river basins, those with the size larger than 220,000 km^2 were initially chosen. Since the quality of river discharge simulations also reflects to some extent the quality of TWS simulations, basins in which the comparison between simulated and observed (GRDC) river discharge indicates a low correlate coefficient (CC) (<0.5), or a high Root-Mean-Squared-Error (RMSE) (>100 mm/month), or a worse CC and RMSE than the case without runoff routing, were excluded in this study. This results in the final 29 river basins to be used in the following analyses.

3.1. Role of River Storage Component in Terrestrial Water Storage Variations

[14] According to CCR_{RS} and mean ambient temperature (T_{Avg}), 29 basins were classified into five groups based on the following criteria: dry (CCR_{RS} < 0.15 Chari, Murray-

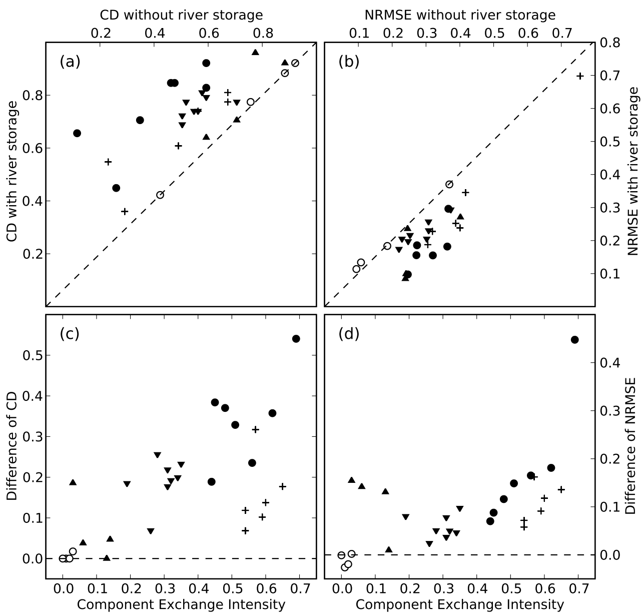

Figure 1. Comparison of the statistics of total TWS simulations between the cases with river storage and without river storage: (a) CD and (b) NRMSE. The relationship between CEI and the improvement of TWS simulation accuracy in (c) CD and (d) NRMSE when river storage is considered. Blank circles (○), lower triangles (▼), filled circles (●), upper triangles (▲), and crosses (+) denote the basins in dry, temperate, cold, wet, and polar regions, respectively.

Darling, Niger, and Zambezi), temperate ($0.15 < CCR_{RS} < 0.30$ Amu Darya, Colombia, Danube, Don, Mississippi, Northern Dvina, Pechora, and Ural), cold ($0.30 < CCR_{RS} < 0.55$ Amur, Mackenzie, Neva, Ob, St. Lawrence, Volga, and Yenisei), wet ($CCR_{RS} > 0.55$ Amazon, Brahmaputra, Chang Jiang, and Orinoco), and polar ($T_{Avg} < 270$ K Indigirka, Khatanga, Kolyma, Lena, Yana, and Yukon). In general, basins were properly classified except for Northern Dvina and Pechora that are expected to be classified into the cold region. For these two basins, the simulated TWSA were overestimated by exaggerated snow water variations (not shown) at the expense of underestimated CCR_{RS}.

[15] Figure 1 demonstrates the influence of river routing to TWS simulations in the temporal variations and the relationship between CEI and the improvement of TWS simulations based on the comparison between the simulations and GRACE data. Both the coefficient of determination (CD) and the normalized root-mean-squared-error (NRMSE) show substantial improvements in TWS simulations with river routing except for the basins where the role of river is negligible. Among total 29 basins, four dry basins (Niger, Zambezi, Chari and Murray-Darling) do not show significant improvement in TWS simulations considering river storage, since the influence of incorporating river storage on the phase shift of total TWS is negligible in these basins because of relatively small amount of runoff. This is possibly caused by overestimated quick runoff generation by MATSIRO since the depth of soil layers (4m) may not be enough to simulate low-frequency storage changes in deeper soils or groundwater in dry regions properly.

[16] It is also found (Figures 1c and 1d) that the role of river is more significant in the basins where storage components intensively interact with each other in the transition of seasons, or when river network contains a relatively large amount of water. The improvement of TWS simulations when river storage is considered appears to be proportional to CEI, and each basin group is clearly distinguished by climate characteristics. Increase of CD is higher in cold basins than in polar basins, indicating that the role of river in buffering direct runoff caused by rapid snow melting is weaker in polar basins because of lower temperature. NRMSE also shows similar relationship, but basins located in wet regions form another distinct group because their large river storage results in significant improvements due to additional amplitude of total TWS variations.

3.2. Temporal Variations of Terrestrial Water Storage Component in Major River Basins

[17] Eight out of total 29 river basins are selected for the further analyses by considering climatic and geographical balances. Figure 2 plots the temporal variations of river discharge, TWSA, and relative TWS for the 8 basins in comparison with corresponding observations. The identical plots for the rest 21 basins can be found at http://hydro.iis.u-tokyo.ac.jp/~hjkim/tws@2009GRL. To calculate relative TWS, absolute values of three storage components are summed up, and the minima of individual components are subtracted since their exact storage sizes are uncertain. The mean of this relative TWS is added to the GRACE TWSA anomaly for the comparison shown in Figure 2c. River discharge simulations for both cases (with and without TRIP routing) are compared to observed GRDC data, while TWS simulations compared to GRACE TWS. As shown, for all 8 basins, the seasonal changes in both discharge and TWS simulations are well reproduced, and the inter-annual variability of total TWS is also well captured. When river routing is conducted, all basins show amplitude attenuation and one- to two-months delay in the peak of simulated discharge. This also improves TWS simulations in a different manner for the basins in different climate regions.

[18] Amazon (Orinoco) is located in wet region without snow where the simulations indicates the dominant role of river. River storage including downslope movement of shallow groundwater explains 73% (64%) of total variability of TWS. It shows a similar phase to soil moisture in seasonal changes, which amplifies the amplitude of total variability of TWS. The weak net exchange among the components leads to low CEI value (0.03 (0.06)). For the basins in temperate regions such as Mississippi (Danube), soil moisture dominates TWS variations, which contributes 46% (46%) of total variability of TWS. However, river and snow are still of important components, and they contribute up to 28% (27%) and 26% (27%) respectively. The seasonal cycle of total TWS is smoothed compared to the case without considering river routing.

[19] The role of rivers is more significant in snow-dominated than soil moisture-dominated regions. Total variability of TWS in Yenisei (Amur) is partitioned into 59% (48%), 31% (36%), and 9% (16%) for snow water, river storage, and soil moisture, respectively. Although the basins in snow dominated regions have a slightly greater value of CCR_{RS} than the basins in temperate regions, in

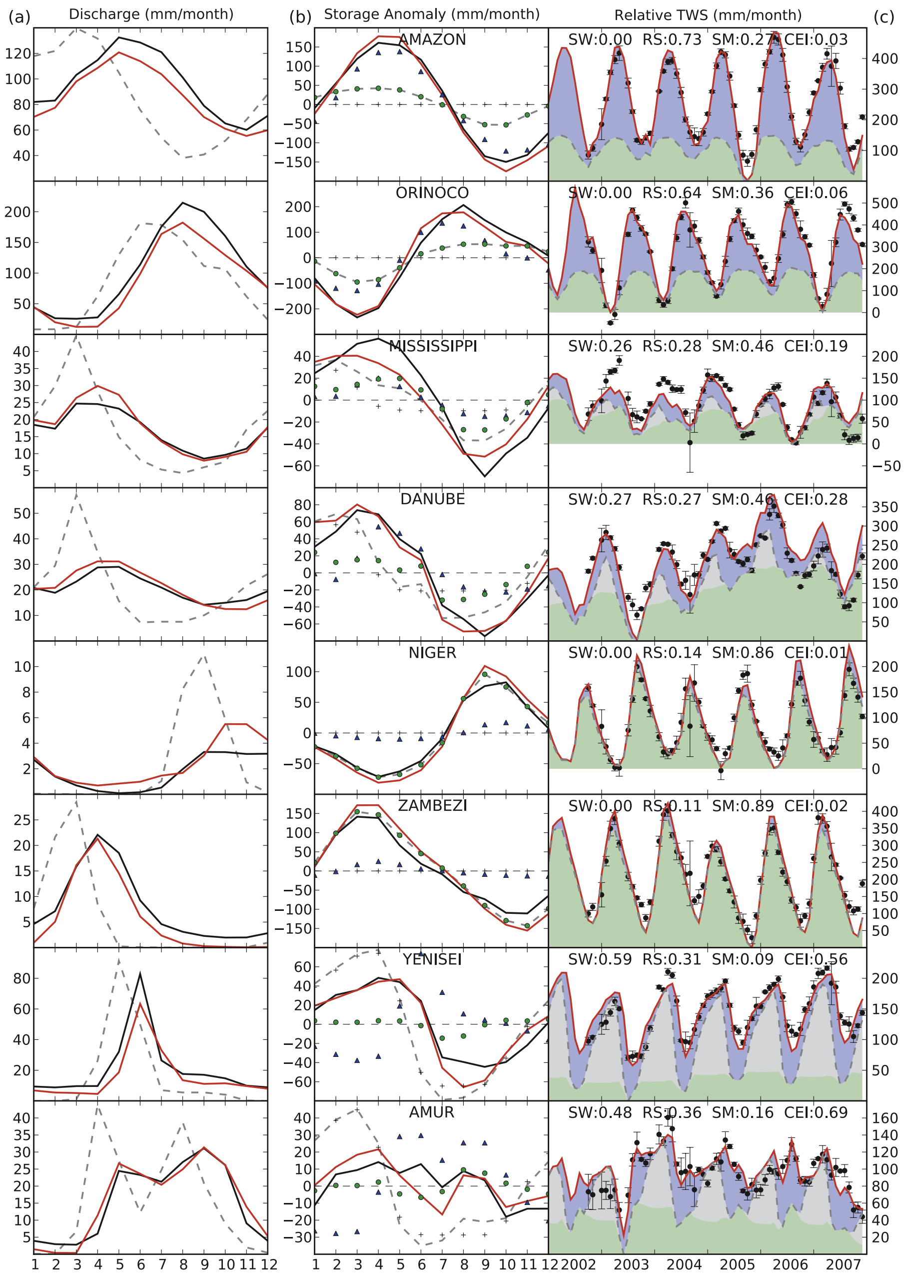

Figure 2. (a) Comparison of seasonal cycles of observed GRDC discharge (black solid line), discharge routed by TRIP (red solid line), and runoff without routing (gray dashed line). (b) Comparison of seasonal cycles of GRACE TWSA (black solid line), simulated TWSA with river storage (red solid line), simulated TWSA without river storage (gray dashed line), and the major water storage components in TWS. Gray crosses (+), green circles (●), and blue triangles (▲) represent snow water, soil moisture, and river storage, respectively. (c) Inter-annual variations of relative TWS: GRACE observation (black dot), and the TWS simulations with river storage (red solid line) and without river storage (gray dashed line). Each area shaded by blue, gray, and green indicates the portion of river storage, snow water, and soil moisture in the simulated relative TWS, respectively.

those basins rivers control the seasonal variations of total TWS. It is found that river effectively smoothes the total TWS in cold basins. Moreover, the Amur basin exhibits rather weak TWS seasonal variations, which are difficult to be simulated if only soil moisture and snow water are considered as major TWS components. The intensive interaction of water storage components is indicated by the higher CEI values (0.56 (0.69)) than other basins in different climatic regions. However, river effect is rarely significant in the dry basins (Niger and Zambezi) where CCR_{SM} explains most of TWS variations, and other components are negligible because of insufficient precipitation for runoff generation.

4. Conclusions

[20] In this study, we have quantified the contribution of individual water storage components and evaluated the importance of rivers in the seasonal variations of TWS by

using ensemble hydrological simulations with river routing in 29 river basins worldwide. The simulated river discharge and total TWS are validated against GRDC discharge and GRACE TWS data, respectively, with close agreement found in most basins. When river storage is taken into account, the model-simulated total TWS is substantially improved in terms of both amplitude and phase, which indicates significant contribution of river storage to the seasonal TWS variations. However, it should be noted river storage in this study lumps downslope movement of shallow groundwater unrepresented in our LSM, since TRIP routes both surface and sub-surface runoff to the river mouth. Rivers not only explain different portions of total TWS variations (from almost 0 in dry basins to 73% in Amazon), but also play different roles in different climatic regions. Fluvial transport is the dominant terrestrial hydrological process in wet basins (e.g., Amazon and Orinoco), and it acts as a "buffer" which smoothes the seasonal variations of total TWS particularly in snow-dominated basins (e.g., Amur and Yenisei). The indices developed in this study well describe the dependence of basin TWS variations on each water storage component, which in turn provide a criterion for geographical classifications and water resources applications based on TWS characteristics. It is concluded that river storage, which has not received much attention in previous hydrological simulations, is an important major water storage component in addition to soil moisture and snow water storages. Without an appropriate representation of river processes in TWS simulations, it may not be able to reproduce the amplitude and seasonal variations of observed GRACE TWS data.

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