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Satellite Gravimetry Improves Seasonal Streamflow Forecast Initialization in Africa

Augusto Getirana[1,2], Hahn Chul Jung[1,3], Kristi Arsenault[1,4], Shraddhanand Shukla[5], Sujay Kumar[1], Christa Peters-Lidard[1], Issoufou Maigari[6], and Bako Mamane[6]

[1]Hydrological Sciences Laboratory, NASA Goddard Space Flight Center, Greenbelt, MD, USA, [2]Earth System Science Interdisciplinary Center, University of Maryland, MD, USA, [3]Science Systems and Applications, Inc., Lanham, MD, USA, [4]Science Applications International Corporation, Reston, VA, USA, [5]Climate Hazards Center, University of California, Santa Barbara, CA, USA, [6]Centre Regional AGRHYMET, Niamey, Niger

Key Points:
- Initial hydrological conditions informed by satellite-based terrestrial water storage (TWS) estimates improve seasonal streamflow forecasts
- Streamflow forecasts are notably improved at locations draining from large basin areas, in particular, over the Niger River basin
- The long memory of groundwater and deep soil moisture is reflected in prolonged improvements in streamflow forecasts

Supporting Information:
- Supporting Information S1

Correspondence to:
A. Getirana,
augusto.getirana@nasa.gov

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Abstract West Africa is one of the poorest regions in the world and highly vulnerable to extreme hydrological events due to the lack of reliable monitoring and forecast systems. For the first time, we demonstrate that initial hydrological conditions informed by satellite-based terrestrial water storage (TWS) estimates improve seasonal streamflow forecasts. TWS variability detected by the Gravity Recovery and Climate Experiment (GRACE) satellites is assimilated into a land surface model during 2003–2016 and used to initialize 6-month hindcasts (i.e., forecasts of past events) during West Africa's wet seasons. We find that GRACE data assimilation (DA) generally increases groundwater and soil moisture storage in the region, resulting in increased evapotranspiration and reduced total runoff. Total runoff is particularly lower at the headwaters of the Niger River, positively impacting streamflow simulations and hindcast initializations. Compared to simulations without GRACE-DA, hindcasts are notably improved at locations draining from large basin areas, in particular, over the Niger River basin, which is consistent with GRACE's coarse spatial resolution. The long memory of groundwater and deep soil moisture, two main TWS components updated by GRACE-DA, is reflected in prolonged improvements in the streamflow hindcasts. Model accuracy at Niamey, Niger, the most populated city where streamflow observations are available, improved up to 33% during the flood season. These new findings directly contribute to ongoing developments in food security, flood potential forecast, and water-related disaster warning systems for Africa.

1. Introduction

Extreme hydrological events have socioeconomic and political impacts in several countries in West Africa. In particular, floods can damage infrastructure and farmland, affecting livelihood in the region. Numerous studies have observed trends of extreme hydrological events in the region, leading to increasing flood peaks (e.g., Amogu et al., 2016; Descroix et al., 2012; Panthou et al., 2014). The impact of floods is more intense on populations missing urban infrastructure and risk zone management, such as informal settlements (Aich et al., 2016). The lack of accurate and efficient forecast systems increases the vulnerability of populations to disasters driven by climate change in dense urban and rural areas. In this context, understanding and predicting streamflow in West Africa is fundamental to evaluate socioeconomic impacts of flood potential and its role in the water cycle. In order to address these limitations, international initiatives, such as the African Monsoon Multidisciplinary Analysis (AMMA; Redelsperger et al., 2006) Land Model Intercomparison Analysis (ALMIP; Boone, de Rosnay, et al., 2009), and its second phase, ALMIP-2 (Boone, Getirana, et al., 2009; Getirana, Boone, & Peugeot , 2014), focused on better understanding how hydrological models represent the water and energy cycles in West Africa at different spatial and temporal scales (e.g., Grippa et al., 2011; Grippa et al., 2017). The overall conclusion from these projects was that uncertainties related to land surface model (LSM) parameterizations and meteorological forcing data sets are limiting factors in accurately simulating streamflow in West Africa (e.g., Pedinotti et al., 2012; Getirana, Boone, et al., 2017). The Princeton African Flood and Drought Monitor system (Sheffield et al., 2014) is another initiative that provides historical and short-range (7 days) agricultural and hydrological forecasts over the African continent. Similarly, the Famine Early Warning Systems Network Land Data Assimilation System (FLDAS; McNally et al., 2017) provides drought and water availability indices derived from different LSMs for Africa with a focus on food insecurity.

The need for more reliable early warning systems used to minimize damages caused by extreme events has led to recent progress in hydrologic forecast techniques and understanding (e.g., Wanders et al., 2019). Two factors are commonly identified as key constraints for obtaining skillful seasonal hydrologic forecasts (e.g., Li et al., 2009; Wood & Lettenmaier, 2008): (i) uncertainties in initial hydrological conditions (IHCs) and (ii) climate forecast skill over the forecast period. Their impact on the hydrologic forecast skill generally depends on the location, forecast lead time, and season (Shukla & Lettenmaier, 2011; Yossef et al., 2013). Uncertainties in IHCs are mostly explained by inaccuracy in both model parameterization and meteorological forcing data sets. Based on a multimodel seasonal hydrological forecast system, Wanders et al. (2019) showed that IHCs, in particular groundwater, can explain at least half of the variance in hydrological forecasts in Europe at lead times of up to three months. IHCs can be generally improved through model calibration (e.g., Shi et al., 2008) and data assimilation (DA) (e.g., DeChant & Moradkhani, 2012; Paiva et al., 2013). The increasing satellite data availability has motivated the development and implementation of remote sensing DA with LSMs, showing improvements in simulations of different water storage components (Kumar et al., 2015; Kumar et al., 2016; Tian et al., 2017; Zaitchik et al., 2008).

The twin-based Gravity Recovery and Climate Experiment (GRACE) mission (Tapley et al., 2004) and the GRACE follow-on (GRACE-FO) satellite missions offer unique measurements of changes in the gravity field that can be translated into mass changes. Although such changes are mostly attributed to terrestrial water storage (TWS) variability, they may also represent surface deformation, earthquakes, and other solid Earth phenomena. GRACE-based TWS is a result of the vertical water storage change, which includes five major components: surface water storage (SWS), water intercepted by the canopy, soil moisture, snow, and groundwater. Since its launch in 2002, numerous studies have demonstrated the usefulness of GRACE-based TWS in detecting and characterizing recent global water storage trends (Rodell et al., 2018) and extreme hydrological events (e.g., Getirana, 2016; Thomas et al., 2014). In particular, recent research shows that assimilating GRACE data into LSMs improves the representation of TWS variability, as demonstrated in North America (Forman et al., 2012; Houborg et al., 2012; Kumar et al., 2016; Nie et al., 2017; Getirana et al., 2019), South America (Khaki & Awange 2019), Europe (Li et al., 2012), Asia (Girotto et al., 2017) and globally (Li et al., 2019). Jung, Getirana, Arsenault, Kumar, & Maigary (2019), using in situ observations acquired from AMMA and multisensor satellite data, found that GRACE-DA positively impacts surface soil moisture in West Africa. Such studies, however, mainly focus on GRACE-DA impacts on soil moisture and groundwater storage variability, and a limited number of them evaluate the impacts of GRACE-DA on water fluxes, mostly reporting overall little improvement or degradation in streamflow (Kumar et al., 2016; Li et al., 2012; Tangdamrongsub et al., 2015; Tian et al., 2017).

Building upon the previously mentioned water monitoring systems, state-of-the-art DA and modeling tools, and urgent need for an extreme event forecast system in West Africa, we explore, for the first time, the potential of assimilating GRACE-based TWS into an LSM to improve IHCs that could contribute to seasonal forecasts of extreme hydrological events. Our hypothesis is that assimilating TWS into an LSM could improve its water storage states, in particular, groundwater and deep soil moisture, which could further impact water fluxes (e.g., total runoff, TR), leading to more accurate streamflow simulations. Groundwater and deep soil moisture have long-term storage memory and changes in their states through DA could result in a prolonged impact on seasonal forecasts. These improvements should be expected in poorly equipped regions such as West Africa, where inaccurate meteorological data sets and land surface parameters contribute to increased uncertainty in hydrological model states. Uncertainties could be particularly high during rainy periods, maximizing the potential of DA to improve streamflow peak simulations. Though the temporal resolution of GRACE-based TWS is coarse, it is sufficient for the detection of slow processes, as observed in deeper soil water storage. In terms of water fluxes, although previous studies have shown that GRACE-DA has little or no improvement on streamflow, as described above, we believe that that could be a result of performing DA in well-equipped regions, where meteorological forcing data are generally more accurate, in particular, compared to the West African domain, and model parameterizations have been intensively optimized (e.g., USA, Europe, and Australia), meaning that impacts from DA should be significantly reduced. Other reasons for such studies to report poor impacts of GRACE-DA on streamflow could be (i) the spatial scales, which are, in some cases, substantially finer than the satellite spatial resolution, and (ii) depending on how the model's physical processes are formulated, DA can improve storage variability but lead to a possible degradation in water fluxes, such as ET (e.g., Girotto et al., 2017). West Africa, as many other regions in the continent, is poorly monitored, lacking reliable meteorological data sets and knowledge of geomorphological conditions. Remotely sensed DA for hydrological monitoring and forecast becomes crucial in such conditions.

2. Modeling Framework and Evaluation

A land data assimilation system (LDAS) was developed for the West African domain (defined here by the coordinates 4–25°N latitude and 18°W to 25°E longitude) using the National Aeronautics and Space Administration (NASA) Land Information System (LIS; Kumar et al., 2006), which is a software framework supporting a range of LSMs, DA methods, and a variety of data sets. This West Africa LDAS is composed of two state-of-the-art models: the Catchment LSM (CLSM; Koster et al., 2000) and the Hydrological Modeling and Analysis Platform (HyMAP; Getirana et al., 2012). CLSM and HyMAP are global land and surface water parameterizations used routinely in numerous water monitoring systems, such as FLDAS, the Global LDAS (GLDAS; Rodell, 2004) Version 2, and the National Climate Assessment LDAS (NCA-LDAS; Kumar et al., 2018). CLSM simulates the vertical water and energy transfers between the atmosphere, vegetation and soil, and HyMAP the surface water dynamics, including rivers and floodplains. CLSM has been widely used in the GRACE-DA context (e.g., Girotto et al., 2016; Girotto et al., 2017; Kumar et al., 2016; Li et al., 2012; Zaitchik et al., 2008), and HyMAP has been successfully used to simulate surface water dynamics in numerous applications worldwide (e.g., Getirana & Peters-Lidard, 2013; Getirana, Kumar et al., 2017; McNally et al., 2019) and to quantify the impacts of land surface parameterization and DA on streamflow (e.g., Getirana, Dutra, et al., 2014; Jung et al., 2017; Kumar et al., 2015; Toure et al., 2018). In this study, HyMAP and CLSM are one-way coupled. This means that surface runoff and baseflow derived from CLSM are collected at each grid cell and routed via HyMAP to simulate the surface water dynamics, but no surface water states are returned to CLSM. Previous hydrological modeling attempts in the region have proposed robust ways to represent interactions between surface and ground water in the region (e.g., Getirana, Boone, & Peugeot, 2014; Pedinotti et al., 2012). In this study, since our models are currently one-way coupled, such interactions are neglected at this time. Models were run at a 15-min time step and 0.25° spatial resolution.

A 3-D based Ensemble Kalman Smoother (EnKS; e.g., Evensen & Van Leeuwen, 2000) approach, as described in Zaitchik et al. (2008) and Kumar et al. (2016), was used to assimilate GRACE-based TWS estimates into CLSM. The 0.5° GRACE Mascon solution Version RL05, processed and made available by Center for Space Research (Save et al., 2016), was used in the DA scheme. Mascon-based products have been shown to provide slightly higher signal and reduced errors than products based on spherical harmonics (e.g., Rowlands et al., 2010; Save et al., 2012). GRACE data accuracy has been estimated to be less than 1 cm in equivalent water height, when averaged over areas larger than about 4×10^5 km^2, and errors increase as the area under observation decreases (Swenson et al., 2003). The Center for Space Research does not account for earthquakes in the GRACE data processing. This means that such signals are not corrected for and may be present in the TWS products (Save et al., 2016). This study does not focus on the mitigation of such limitations, but rather on the use of GRACE data to improve seasonal hydrological forecast initialization through DA, taking into account its error estimates.

The current version of GRACE-DA in LIS only updates CLSM water storage components. CLSM only simulates land surface water storage (LWS) components, that is, groundwater, soil moisture, snow, and canopy interception, neglecting SWS. SWS, in turn, is simulated by HyMAP. As a consequence, for consistency, GRACE-based TWS was corrected by removing SWS before the assimilation. First, SWS is simulated in the baseline model run, referred to here as the open loop (OL). Then, SWS is subtracted from GRACE-based TWS, resulting in LWS, which is assimilated into CLSM. As a result, only LWS signals are assimilated into CLSM. Such a solution has been previously adopted in Khaki & Awange (2019) using HyMAP-based SWS derived from a model ensemble average described in Getirana, Kumar, et al. (2017). While this solution is not ideal, the proper integration of SWS in the GRACE-DA scheme as another prognostic variable to be perturbed is outside the scope of this study. We employed a bilinear interpolation approach to convert GRACE TWS to the model space based on the gridded GRACE-DA scheme, established in Kumar et al. (2016). All model parameters, initial conditions, and DA inputs were preprocessed using the Land surface Data Toolkit (Arsenault et al., 2018). Figure 1 shows a schematic of GRACE data

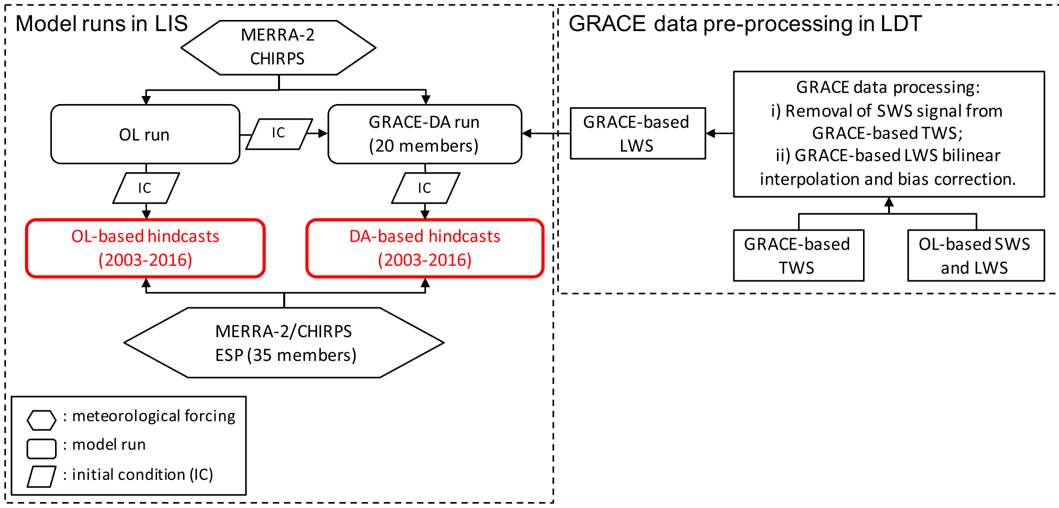

Figure 1. Schematic of model runs and GRACE data pre-processing. For practical reasons, the 55-year spin up run was omitted.

preprocessing and model runs. More details on CLSM, HyMAP and the DA approach can be found in Appendix A.

Models are driven with NASA's Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2; Reichle et al., 2017) meteorological data set, and precipitation from the Climate Hazards Group InfraRed Precipitation with Station data, version 2.0 (CHIRPSv2; Funk et al., 2015), which utilizes satellite-based estimates and station-based precipitation. Although previous studies have found high uncertainties in satellite-based precipitation estimates over Africa (e.g., Awange et al., 2016), CHIRPSv2's station-based component contributes to a superior spatial and temporal precipitation distribution in the continent, as demonstrated by several studies (e.g., Bichet & Diedhiou, 2018; Dembélé & Zwart, 2016; Dinku et al., 2018; Poméon et al., 2017). This is reflected in a better representation of hydrological processes in Africa (e.g., Jung et al., 2017). The model was spun up for 55 years, first using MERRA-2 and CHIRPS data sets from 1982 to 2016, then restarted from 1982 to 2001, and OL and GRACE-DA were run for 2002–2016. Monthly hydrological hindcasts up to 6 months were performed using historical forecasts generated through the Ensemble Streamflow Prediction (ESP; Day, 1985) method. ESP is a statistical technique based on historical meteorological data and is intended to provide a "null" atmospheric forecast, in which the ensemble of meteorological fields represents a probability-weighted sampling from the historic record. We used MERRA-2 meteorological data and CHIRPS precipitation from 1982 to 2016 to generate the 35-member ensemble. Since GRACE-DA and ESP ensembles have different sizes, hindcast initial conditions were generated by first averaging the GRACE-DA-based IHC ensemble, then that average was used to initialize each ESP member. This means that, for each hindcast run, all 35 members were initialized with the same IHC. IHCs are composed of water storage components (in the surface and in the different soil layers) and soil temperature. Hindcasts were initialized on the first of each month of the year for 2003–2016, using states from the OL and GRACE-DA simulations as the initial conditions to the ESP hindcasts. No DA was performed during the hindcasts and model outputs were evaluated by deterministic means, that is, using the hindcast ensemble means.

In situ streamflow data was acquired at 40 gauging stations distributed within the region. Stations are mostly located within the Niger (15 stations), Volta (11 stations), and Chad (6 stations) River basins, with drainage areas varying from 7,000 km^2 (at Patalao, in the Chad basin) to ~2.2×10^6 km^2 (at Lokoja, near Niger River's outlet). Table 1 lists the gauging stations used in this study and their key information. Geographical locations of the stations are shown in Figure 2.

2.1. Evaluation Procedure

The impact of GRACE-DA on IHC was evaluated during the main flood seasons at 40 gauging stations. Flood seasons were defined as the three consecutive months with the highest mean climatological

Table 1
List of Gauging Stations in West Africa

Gauging station	River	Basin	Country	Longitude	Latitude	Drain. area (km^2)	Avg. streamflow (m^3/s)	PIP	Wet season
Patalao	—	Chad	Chad	15.3	9.9	6,958	43	314,730	August–October
Samandéni	Black Volta	Volta	Burkina Faso	−4.5	11.5	7,261	18	227,375	August–October
Yendere	Leraba	Komoé	Burkina Faso	−5.1	10.2	7,474	28	337,387	August–October
Folonzo	Komoé	Komoé	Burkina Faso	−4.6	9.9	9,257	31	304,097	August–October
Wiasi	Sisili	Volta	Ghana	−1.4	10.3	9,375	28	204,123	August–October
Beterou	Ouemé	Ouemé	Benin	2.3	9.2	10,140	43	226,768	August–October
Yagaba	Kulpawn	Volta	Ghana	−1.3	10.3	10,470	43	0	August–October
Kedougou	Gambie	Gambie	Senegal	−12.2	12.6	10,687	90	332,780	August–October
Couberi	Sota	Niger	Benin	3.3	11.8	13,006	35	220,284	August–October
Nwokuy	Black Volta	Volta	Burkina Faso	−3.6	12.5	15,892	45	174,850	September–November
Zuénoula	Marahoue	Bandama	Côte d'Ivoire	−6.1	7.4	19,157	66	367,557	August–October
Dimbokoro	Nzi	Bandama	Côte d'Ivoire	−4.7	6.6	24,100	46	240,618	September–November
Save	Ouemé	Ouemé	Benin	2.4	8	25,373	155	359,813	August–October
Porga	Oti	Volta	Benin	1	11	31,140	53	131,224	August–October
Diolia	Bagoe	Niger	Mali	−6.8	12.5	32,368	124	268,521	August–October
Pankourou	Bagoe	Niger	Mali	−6.6	11.4	35,079	131	109,959	August–October
Moundou	Logone	Chad	Chad	16.1	8.5	35,150	389	436,124	August–October
Garbey-Kourou	Sirba	Niger	Niger	1.6	13.7	38,000	49	0	July–September
Saboba	Oti	Volta	Ghana	−0.3	9.6	49,741	390	77,054	August–October
Sarh	Chari	Chad	Chad	18.4	9.2	63,226	157	0	September–November
Banankoro	Niger	Niger	Mali	−8.7	11.7	71,905	603	193,379	August–October
Lawra	Black Volta	Volta	Ghana	−2.9	10.6	92,877	98	248,862	August–October
Logone-Gana	Logone	Chad	Chad	15.2	11.6	93,946	409	87,779	August–October
Daboya	White Volta	Volta	Ghana	−1.4	9.5	95,130	265	232,643	August–October
Dapola	Black Volta	Volta	Ghana	−2.9	10.6	106,175	127	232,643	August–October
Koulikoro	Niger	Niger	Mali	−7.6	12.9	120,000	1,086	676,298	August–October
Bui	Black Volta	Volta	Ghana	−2.2	8.3	123,648	225	72,273	August–October
Macina	Niger	Niger	Mali	−5.4	14	137,146	896	163,415	August–October
Bamboi	Black Volta	Volta	Ghana	−2	8.2	143,604	620	0	August–October
Hellibonga	Chari	Chad	Chad	18.3	9.3	225,990	222	427,800	September–November
Manda	Ouham	Chad	Chad	18.2	9.2	225,990	809	427,800	September–November
Mopti	Niger	Niger	Mali	−4.2	14.5	271,446	891	75,305	September–November
Diré	Niger	Niger	Mali	−3.9	16.3	362,279	845	163,360	October–December
Ansongo	Niger	Niger	Mali	0.5	15.7	539,645	773	83,139	November–January
Kandadji	Niger	Niger	Niger	1	14.6	613,613	834	0	November–January
Ndjamena	Chari	Chad	Chad	15	12.1	621,908	618	1,406,240	September–November
Niamey	Niger	Niger	Niger	2.1	13.5	684,475	930	1,977,826	November–January
Malanville	Niger	Niger	Benin	3.4	11.9	1,348,874	784	0	September–November
Jidere-Bode	Niger	Niger	Nigeria	4.1	11.2	1,588,000	1,178	347,022	August–October
Lokoja	Niger	Niger	Nigeria	6.8	7.8	2,117,015	6,083	339,882	August–October

Note. Drainage areas are derived from HyMAP parameters. Values provided by agencies, when available, are also listed. Data availability and average streamflow are provided for the study period (2003–2016).

streamflow observations. The West African monsoon and flood wave travel time are the main factors defining streamflow peaks. As a result, seasons vary according to the location of gauging stations. Four 6-month hindcasts fully overlap with each 3-month season. For example, 6-month hindcasts initialized in May through August fully overlap with the wet season occurring in August–October, where hindcasts initialized in May and August correspond to lead Months 3 and 0, respectively. Streamflow forecasts were evaluated at the monthly time step, resulting in three streamflow values per year. As shown in Figure 2, five different peak seasons were identified in the region, with first months varying from August to November.

Following Kumar et al. (2014), we used evaluation metrics in the form of normalized information contribution (NIC) applied to the Nash-Sutcliffe (NS) coefficient, correlation (r), and the root-mean-square error (RMSE) between simulations (s) and observations (o). NS and RMSE are defined as follows:

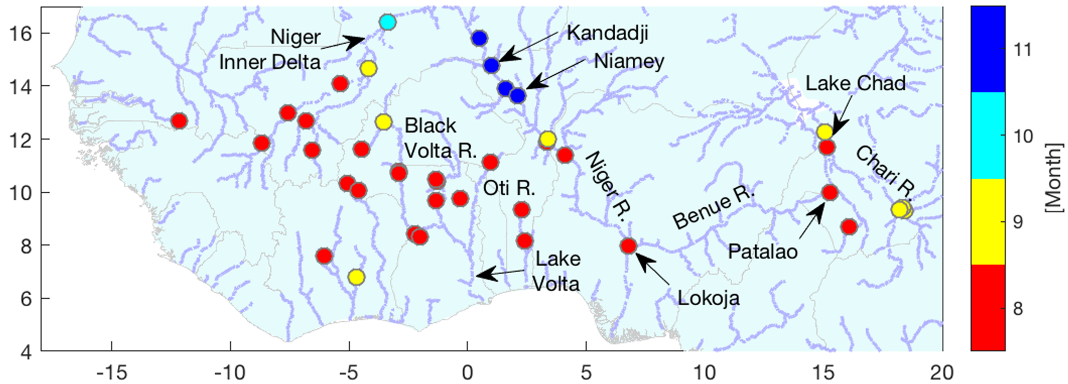

Figure 2. Geographical location of gauging stations in West Africa. Colors represent first months of climatological peak seasons. Blue lines represent major rivers.

$$NS = 1 - \frac{\sum_{t=1}^{nt}(o_t - s_t)^2}{\sum_{t=1}^{nt}(o_t - \bar{o})^2} \tag{1}$$

$$\mathrm{RMSE} = \left[\frac{\sum_{t=1}^{nt}(s_t - o_t)^2}{nt}\right]^{1/2} \tag{2}$$

where t is the time step in months, nt is the period length, and $\bar{o}$ is the mean value of the observations.

NIC applied to these metrics is useful to determine the overall improvements resulting from GRACE-DA compared to the OL run. Their respective NIC values are defined below:

$$NS_{NIC} = \frac{(NS_{DA} - NS_{OL})}{(1 - NS_{OL})} \tag{3}$$

$$RMSE_{NIC} = \frac{(RMSE_{OL} - RMSE_{DA})}{RMSE_{OL}} \tag{4}$$

$$r_{NIC} = \frac{(r_{DA} - r_{OL})}{(1 - r_{OL})} \tag{5}$$

All three metrics range from $-\infty$ to 1, where values above 0 indicate improvement, below 0 indicates degradation, and 0 means no added skill.

Improvements in peak streamflow hindcasts were also evaluated in terms of areas where human lives could be most impacted, referred to here as the potentially impacted population (PIP). A similar approach has been previously adopted by Aich et al. (2016), where the authors used three factors (observed annual maximum streamflow, population density, and human development indexes) to determine flood potential within the Niger River basin. The approach proposed here indicates whether improved hindcasts are obtained where impacts might be the greatest, that is, where extreme events may cause major socioeconomic losses. PIP was determined for locations where observations are available using estimates for 2015 derived from the Gridded Population of the World, Version 4 (GPWv4; CIESIN, 2018) product. We considered that improvements at a particular gauging station affects riverine cities within a 100-km river reach (50-km upstream and downstream of the station). River reaches were derived from the 1-km Global Drainage Basin Database (Masutomi et al., 2009) digital elevation map and a 5-km buffer was used to locate riverine cities and villages.

The focus of this study is on seasonal scale streamflow and hydrologic forecasts (i.e., 3–6 months in advance), which have been the focus of several other past studies as well operational systems (Crochemore et al., 2016; Emerton et al., 2016; Foster & Uvo, 2010; Najafi & Moradkhani, 2016; Shukla & Lettenmaier, 2013; Yuan, 2016; Yuan & Wood, 2012). Seasonal scale streamflow forecasts can trigger a “watch” for closely monitoring flood conditions and short-term flood potential forecasting, several months ahead of a flood season. Therefore, although not precise enough for saving lives they can still substantially contribute to mitigation of damages as they can provide plenty of notice before the season and, hence, time to prepare and respond. Given the goal of this work, and as suggested in previous studies, an evaluation at the monthly scale is therefore adequate.

3. Results

3.1. GRACE-DA Impacts on Water Storage and Fluxes

In order to understand how GRACE-DA impacts IHCs for streamflow forecasts, we first looked at its effects on water storages and fluxes. The humid and subhumid climate regions of West Africa (below ~13°N) have experienced a recent increase of TWS anomaly in the past several years, as reported in the literature (Ndehedehe et al., 2016) and explained by increasing precipitation rates in the region (Rodell et al., 2018). That positive trend is quantified by GRACE as 5.5 mm/year, corresponding to a regional average water gain of ~80 mm during 2003–2016. The underestimated trend obtained with the OL run (2.5 mm/year) is improved with GRACE-DA (4.1 mm/year), resulting in better agreement with observations (see top of Figure 2). DA improved the spatial agreement between simulated and observed TWS throughout the region (not shown), with a spatially averaged correlation increase of 0.12 and RMSE decrease of 25 mm. Groundwater and 1-m depth root zone soil layer soil moisture derived from GRACE-DA also increased by 10.1 and 1.3 mm, respectively, for the region when compared to the OL run. Spatially averaged differences at the monthly timescale can be as high as 35 and 4 mm, with even higher differences in regional subsets, as shown in the time series in Figure 3. The additional water availability in the soil increased the average evapotranspiration (ET) rate over the domain by 0.2 mm/day. The increased ET resulted in a TR (i.e., sum of simulated surface runoff and baseflow) decrease. TR was mostly impacted during wet seasons of humid and subhumid climate regions. Although the average TR decrease over the domain is small ($\Delta TR = -0.01$ mm/day), high differences are observed in the western coast and in the surroundings of the Niger River delta. These regions are characterized by high precipitation rates and leaf index areas (not shown), resulting in overall higher evapotranspiration (Jung, Getirana, Arsenault, Holmes, & McNally , 2019). The average precipitation in the region is 2.57 mm/day, partitioned into ET = 2.14 mm/day and TR = 0.43 mm/day in the OL run. GRACE-DA changed these fluxes to 2.25 and 0.41 mm/day, respectively, resulting in a water budget imbalance of 0.09 mm/day. Water balance violation is expected within a GRACE-DA framework, although recent efforts have been made to minimize that error (e.g., Khaki et al., 2019). Observed TR over the upper Oueme River basin has been estimated as 0.37 mm/day, or 12% of precipitation (Getirana, Boone, & Peugeot, 2014). Here, over the same basin, TR was estimated as 0.28 mm/day from both OL and GRACE-DA, or 9% of precipitation. Such a negligible impact can be related to the low amplitude of TWS variability in that area, as discussed in Jung, Getirana, Arsenault, Kumar, & Maigary (2019). The overall low TR-precipitation ratio shows that ET is mainly driven by water availability, mostly occurring during the monsoons, and that a small change in precipitation during that rainy season could have a significant impact on TR. A model intercomparison presented in Getirana, Boone, et al. (2017) shows how widely simulated water fluxes over the upper Oueme River basin range, as a function of LSMs and precipitation forcing data, with TR varying from 0.1 to 2 mm/day. It is important to note that that comparison is for a small subset of West Africa and does not explain TR estimates over the whole region.

Changes in TR rates resulted in an overall improvement in streamflow simulations during 2003–2016. As shown in Figure 4 (top row), NS and RMSE improved at 31 stations, and correlation improved at all 40 stations, with average normalized improvements varying from 0.04 to 0.07. A clear positive impact of GRACE-DA is observed at stations draining larger areas, in particular at stations located over the Niger River, with improvements as high as $NS_{NIC} = 0.35$, at Kandadji. On the other hand, improvements are not directly correlated to metrics resulting from the OL run (see Figure S1 in the supporting information for NS, *r*, and normalized RMSE derived from OL). Such an improvement is due to the significant decrease of TR observed in the Niger River headwater, in the southwestern part of the region, which is propagated throughout the river. However, degraded results are observed at Lokoja, the gauging station draining the largest area, located near the Niger River's outlet. That degradation is explained by additional TR underestimation in the eastern part of the region, drained by the Benue River, a major tributary of the Niger River. Observed streamflow uncertainty could be another plausible explanation for metric

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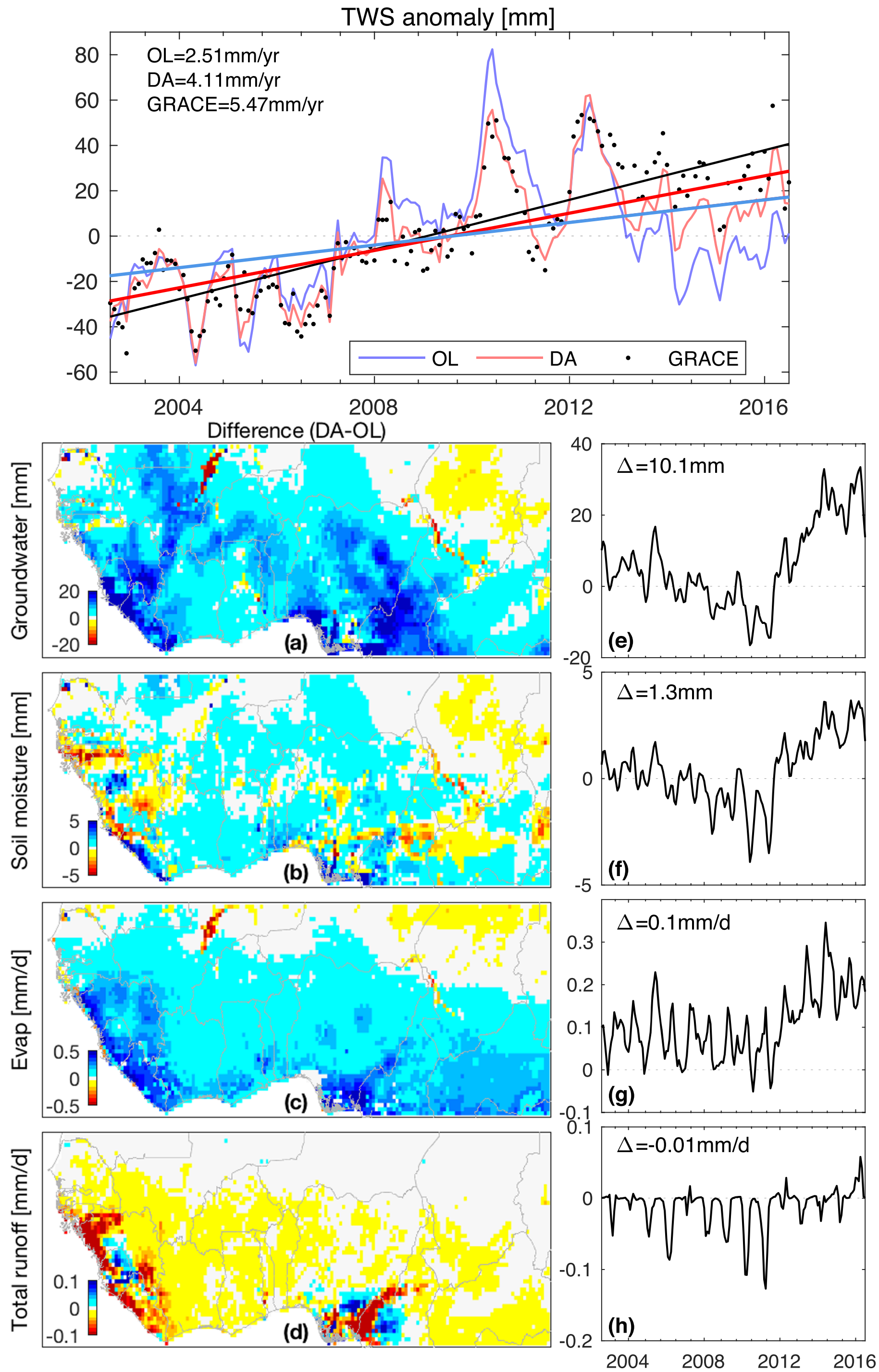

Figure 3. In the top figure panel, terrestrial water storage (TWS) anomaly (i.e., monthly annual cycle removed) and trends derived from GRACE (after conversion to the model space), open loop (OL), and GRACE-DA runs. In the bottom panels, the impact of GRACE-DA on vertical water storage and fluxes is shown over West Africa during 2003–2016. In (a)–(d), spatially distributed differences are shown between GRACE-DA and OL ($\Delta = \text{DA} - \text{OL}$). In (e)–(h), time series of spatially averaged differences are plotted. Soil moisture corresponds to the 1-m depth root zone soil layer.

degradation. Although there was a significant effort to correct or remove inaccurate data from the time series acquired at gauging stations, we acknowledge that uncertainty related to instrumentation, data record, among others, may still exist.

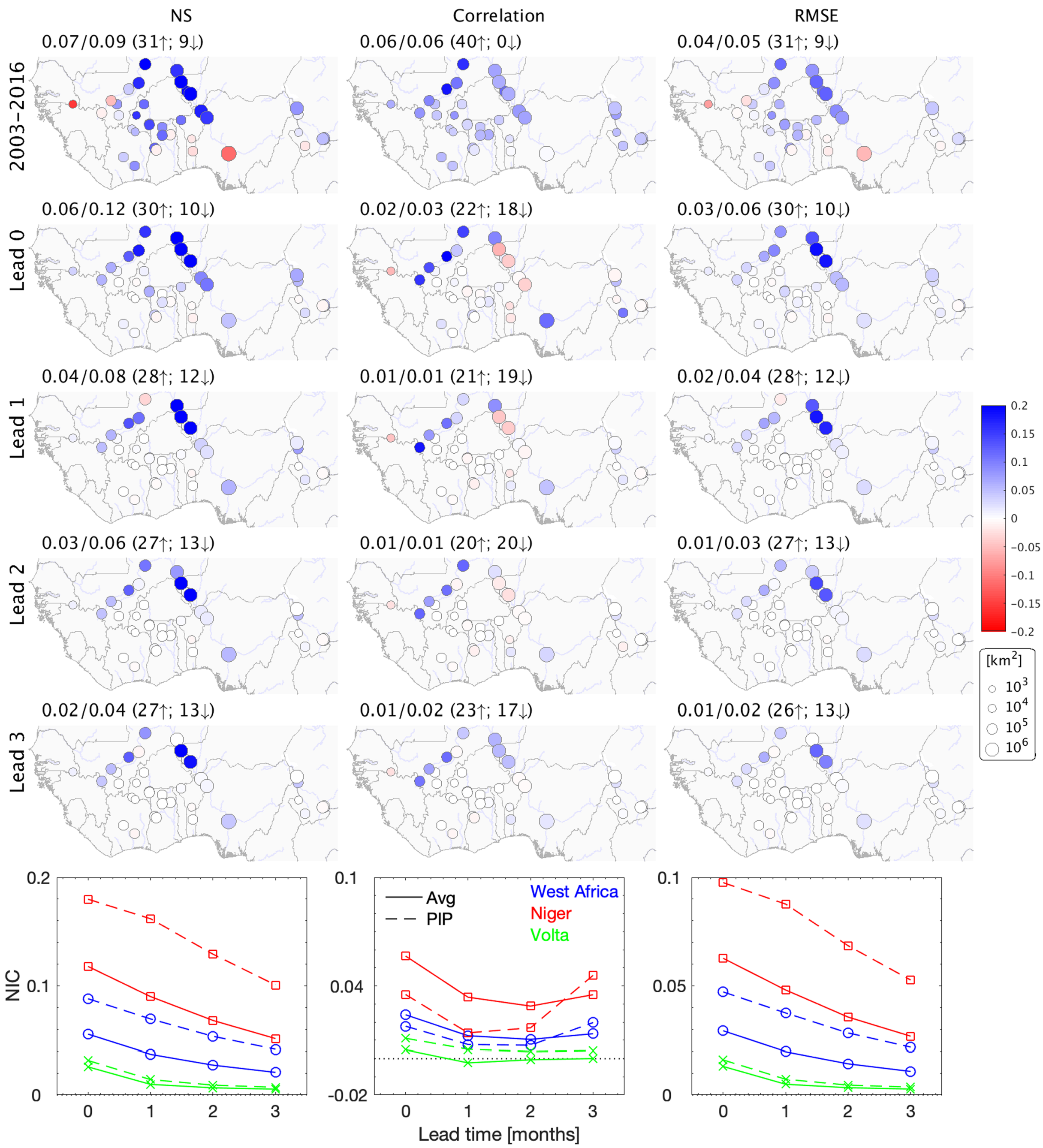

Figure 4. Nash-Sutcliffe (NS), correlation and root-mean-square error (RMSE) normalized improvement coefficients (NIC) between GRACE-DA and open loop (OL) runs. Maps show NIC values at 40 gauging stations in West Africa for the 2003–2016 retrospective run (top) and hindcasts from lead time 0 to 3 overlapping with 3-month peak seasons (Rows 2–5). In the upper left of each map, both mean and drainage-area-weighted mean NIC values, and number of gauging stations with improved (↑) and degraded (↓) metrics are provided. The bottom row panels show average NIC values for NS, correlation, and RMSE for lead times (0 to 3) for selected regions (West Africa, Niger River, and Volta River basin). The potentially impacted population (PIP)-weighted NIC averages are also provided.

3.2. GRACE-DA Impact on Forecast of Extreme Hydrological Events

Updated IHC resulting from GRACE-DA improved the overall hindcast skill of streamflow simulations throughout West Africa and showed patterns similar to those observed in the 2003–2016 retrospective runs. Based on normalized improvements of NS, *r*, and RMSE, hindcasts initialized at the beginning of peak seasons (lead time 0) present the best overall added skill. Figure 4 also shows the improvement for each lead

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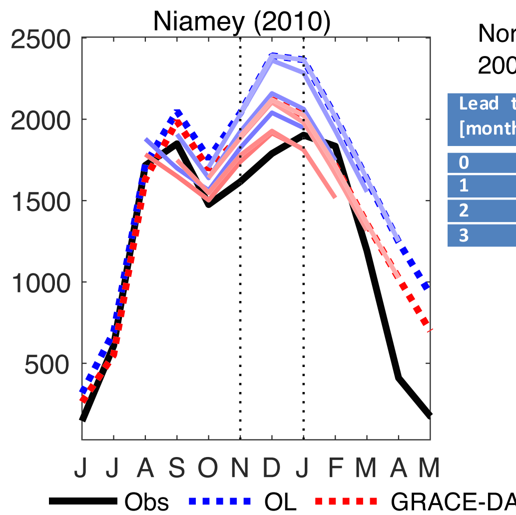

Normalized improvement 2003-2016 peaks

Lead time [month]	NS_{NIC}	r_{NIC}	$RMSE_{NIC}$
0	0.33	-0.04	0.18
1	0.31	-0.04	0.17
2	0.24	-0.02	0.13
3	0.10	0.05	0.10

Figure 5. Streamflow (m^3/s) from observations (Obs), open loop (OL), and GRACE-DA simulations for the 2010 hydrological year (June through May) at Niamey, in the Niger River. Six-month hindcasts initialized with OL and GRACE-DA (solid blue and red lines, respectively) and overlapping with the 3-month peak season (November–January, as delimited by vertical black ticked lines) are also shown. On the right, NS, *r*, and RMSE normalized improvement coefficients (NIC) [-] for peak hindcasts over the 2003–2016 period. NIC values are shown for each lead month. The 2010 peak is the highest that occurred in Niamey from the study period.

time averaged for the stations located over the Niger River (in red), the Volta River basin (in green), and all of West Africa (in blue). Improvements at stations related to smaller draining areas within the Volta River basin are low, reducing the average for the whole region. On the other hand, stations over the Niger River with drainage areas averaging ~714,000km^2 show the highest improvement in forecast skill, with NS_{NIC}, r_{NIC}, and $RMSE_{NIC}$ values as high as 0.12, 0.06, and 0.06, respectively, for the 0-lead months. Such an improvement, as explained earlier, is due to the GRACE-DA impact on water fluxes at the Niger River headwaters. Lower changed in the rest of the region results in smaller improvements in other river basins, such as Volta. Improvements drop at longer time leads but are positive, demonstrating the long-term memory of groundwater and soil moisture on improving seasonal streamflow forecasts.

3.3. Potentially Impacted Population

Potentially impacted populations are listed in Table 1. Niamey has the largest PIP (~2 million people), corresponding to 17% of the total PIP of the whole West Africa study domain. Our results show that GRACE-based IHC significantly improved NS and RMSE for streamflow peak hindcasts at that station, with NS_{NIC} and $RMSE_{NIC}$ values as high as 0.33 and 0.18, respectively. This improvement is attributed to a decreased TR generation during the second seasonal peak in December, as depicted in Figure 5 for streamflow simulations in 2010. The second streamflow peak originates at the Niger River headwaters, in the southwestern part of the region, where GRACE-DA causes a significant decrease of TR. The TR decrease also causes a slight change of peak timing, resulting in a slight degradation of correlation in lead times 0 to 2. PIP along the Niger River totals to about 4 million people (35% of all potentially impacted population), where improvements in streamflow hindcasts were the highest. The PIP-weighted improvements for Niger River stations were $NS_{NIC} = 0.18$, $r_{NIC} = 0.04$, and $RMSE_{NIC} = 0.10$ for lead time 0 (see bottom of Figure 4), and 0.09, 0.02, and 0.05, respectively, over the whole region. A decrease is observed at longer lead times, which is in agreement with results described above. PIP-weighted improvements are higher than those obtained with the simple average, indicating that more significant improvements occur at locations with larger populations.

4. Summary and Final Discussion

We evaluated the potential of GRACE terrestrial water storage to improve the IHCs for seasonal hydrological forecasts in West Africa, focusing on streamflow. Our premise is that the long memory of groundwater and deep soil moisture, two major TWS components, when updated with satellite observations, can positively change water fluxes and states of hydrological variables, in particular, when averaged over large domains, resulting in improved long-range hydrological forecasts. GRACE-DA can be particularly effective in regions such as West Africa, where there is limited access to ground-based observations, such as precipitation or soil moisture, and can provide better simulated IHCs, particularly when models are run routinely. As it often occurs in real-time operations, ground-based data are reported with substantial lag, leading to potentially low-quality precipitation fields. Six-month hindcasts were initialized with hydrological conditions derived from two model runs, with and without GRACE-DA, during 2003–2016. The skill added by GRACE-DA is quantified in terms of normalized improvements in three metrics (Nash-Sutcliffe coefficient, correlation, and RMSE) during wet seasons at several locations within West Africa. Overall improvements are observed for all hindcasts fully overlapping with seasons, that is, up to four initializations within a year, in particular, during streamflow peaks. Gauging stations measuring large basin areas showed the highest improvements in forecast skill. These stations are mostly concentrated along the Niger River, whose headwater is located in a humid region and had water fluxes highly impacted by GRACE-DA. We also demonstrated that GRACE-DA positively impacts streamflow forecasts at densely populated regions, such as Niamey, in Niger. These results demonstrate that groundwater and deep soil moisture memories have a prolonged impact on water fluxes and confirming the potential of GRACE-DA for long-range hydrological forecasts. Little impact or degradation of streamflow simulations is also observed in a few locations, which could be explained by poor model parametrization (e.g., parameters related to soil and groundwater), uncertainties in meteorological data sets and in situ observations, limited representation of physical processes by models and assumptions in the DA scheme. In particular, it is possible that GRACE-DA is not properly attributing mass change to the different soil layers (i.e., surface soil moisture, root zone soil moisture, and groundwater), impacting ET and TR. That issue could be addressed with an improved parameterization and multisensor DA, including assimilation of soil moisture.

As aforementioned, previous GRACE-DA applications in other regions failed in improving (e.g., Kumar et al., 2016; Tangdamrongsub et al., 2015; Tian et al., 2017) or resulted in little improvement (e.g., Li et al., 2012) in streamflow simulations. Those studies were mostly applied to well-equipped domains and streamflow evaluated over small basins or performed with calibrated models. Such characteristics could hinder the potential of GRACE to positively have an impact on fluxes, considering that its uncertainty is minimized at coarser spatial resolutions (Swenson et al., 2003). In addition, it is expected that DA will generally show improvements in applications where meteorological data and/or parameterizations are poor, which is the case of many regions in Africa. In this sense, we acknowledge that improvements observed in streamflow forecasts through GRACE-DA could be specific for our domain and modeling framework. However, it is expected that regions with similar conditions can benefit from DA for seasonal streamflow and flood potential forecast.

Here, baseline seasonal forecasts were derived using ESP. This straightforward technique is based on historical events and sufficient for the objectives established in this study. However, we recommend that future work evaluate the accuracy of different dynamical models based forecast techniques and their synergy with GRACE-DA. As suggested in Getirana, Kumar, et al. (2017), SWS was considered as a TWS component. SWS variability was derived from OL, then removed from GRACE-based TWS before its assimilation into CLSM. We acknowledge that this procedure is not ideal because SWS is not updated by GRACE-DA. Evaluating uncertainties introduced by this approach is not in the scope of this study, and future work should focus on a proper integration of SWS into a GRACE-DA scheme, as an additional state subjected to updates. Multivariate DA (Kumar et al., 2018), combining GRACE data and radar altimetry, could further improve streamflow monitoring and forecast. Although hindcasts were improved in terms of both NS and RMSE, very little improvement was detected in correlation. This could be related to the timing of TR generation and propagation through the river network, and fixed with further customization of river routing parameters (e.g., Getirana et al., 2013).

To our knowledge, GRACE-DA has never been used to improve forecast IHCs, in particular, for streamflow forecasts. Our findings will significantly contribute to the development of an LDAS focused on extreme event forecasting for West Africa, which can be extended to the whole continent. Such efforts are currently led through NASA's Applied Sciences Program projects, focusing on the early warning system for water-related disasters and food insecurity in Africa.

Appendix A: Models and Data Assimilation CLSM

The CLSM (Koster et al., 2000) is driven on area-varying topographic catchments, which are each partitioned into "wilting," "transpiring," and "saturated" subregions that account for independent water budget terms. The surface energy budget and also evaporation terms are based on the original Mosaic LSM physics (Koster and Suarez, 1996) but are also partitioned for each subregion. CLSM has a lumped effective resistance term, which includes canopy and bare soil resistance terms, for example, adopting a Jarvis formulation approach. Soil water content is diagnosed in three layers (surface layer soil moisture, at 2-cm depth, and root zone soil moisture, at 1-m depth, and groundwater, from 1 m down to bedrock depth), including the saturated zone, and is also represented as the depth of water at which saturation is achieved in the catchment's soil profile. CLSM's catchment deficit prognostic variable is constrained by a bedrock depth parameter, which can impact how the soil moisture and storage change in time. Houborg et al. (2012) documented issues with the constraint of the bedrock depth, which imposes an artificial "dry limit" on the model's groundwater and its control on the response of the catchment deficit and saturation within the catchment. Thus, they uniformly expanded the bedrock depth term by 2 m, which reduced some of the constraint of this limit. This 2-m addition has been adopted in different studies (e.g., Kumar et al., 2016; Li et al., 2012) and was also included in this study.

HyMAP

HyMAP (Getirana et al., 2012; Getirana, Peters-Lidard, et al., 2017) is a state-of-the-art global scale river routing scheme capable of simulating flow dynamics in both rivers and floodplains—this includes both stage and discharge in-stream as well as floodplain inundation. HyMAP simulates surface water dynamics with the local inertia formulation (Bates et al., 2010), derived from the full hydrodynamic equations. The local inertia formulation accounts for a more stable and computationally efficient representation of river flow diffusiveness, essential for a physically based representation of wetlands, floodplains, and tidal effects. The Courant-Freidrichs-Levy condition is used in order to determine HyMAP's optimal sub–time steps for numerical stability. In this study, HyMAP parameters at 0.25° were derived from the 1-km Global Drainage Basin Database (Masutomi et al., 2009) digital elevation map (flow directions, river slope, and drainage area) using the Flexible Location of Waterways upscaling algorithm (Yamazaki et al., 2009). Other parameters, such as river geometry and roughness in rivers and floodplains, were derived from empirical equations. More details on the HyMAP parameterization can be found in Getirana et al. (2012, 2013) and Getirana, Peters-Lidard, et al. (2017).

DA Procedure

In order to deal with GRACE's coarse spatial and temporal resolutions, a 3-D-based EnKS (e.g., Evensen & Van Leeuwen, 2000) approach, as described in Zaitchik et al. (2008) and Kumar et al. (2016), was used to assimilate GRACE-based TWS into CLSM. The EnKS, as applied here, includes a 2° spatial correlation window and a monthly temporal window within which two passes are performed: (1) the first pass integrates a forecast step to generate the ensemble of CLSM-based TWS state terms (no assimilation) and (2) the second pass performs the assimilation update based on the relative weights of the model estimates and observations (i.e., in terms of their error covariance matrices), which are determined by the Kalman gain matrix. In the first pass, the CLSM TWS-based states are stored on the 5th, 15th, and 25th of each month (approximately related to the overpass frequency of GRACE). In the second pass, the ensemble is reinitialized, and the monthly analysis increments are applied evenly across the month. Two CLSM prognostic soil moisture variables are perturbed with normally distributed additive perturbations, and three snow water equivalent state layers are perturbed with a lognormal, mean 1, multiplicative perturbation. To account for uncertainty in the meteorological fields, perturbations were also applied to three of the fields: incoming longwave radiation (additive perturbations), incoming shortwave radiation, and precipitation (both multiplicative perturbations). For the TWS observational standard error covariance, we applied a spatially uniform scalar value of 10 mm (Zaitchik et al., 2008). GRACE-DA was performed with an ensemble of 20 members. It is important to note that our 3-D-based EnKS does not account for the inherently low spatial resolution of the GRACE products used in this study. Our DA simulations cannot, at this time, completely distill the spatially smooth

GRACE TWS' estimates to capture all local variability. More details on the GRACE-DA configuration and specific perturbation settings used in this study can be found in Kumar et al. (2016).

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