Understanding the influence of climate variability on surface water hydrology in the Congo basin

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Abstract

Understanding the impacts of climate on surface water hydrology is required to predict consequences and implications on freshwater habitats, ecological assets, and wetland functions. Although the Congo basin is considerably a freshwater-rich region, largely characterised by numerous water resources after the similitude of the Amazon basin, recent accounts of droughts in the basin are indications that even the most humid regions of the world can be affected by droughts and its impacts. Given the scarcity and limited availability of hydrological data in the region, GRACE (Gravity Recovery and Climate Experiment) observations are combined with model and SPEI (standardized precipitation evapotranspiration index) data to investigate the likelihood of such impacts on the Congo basin's surface water hydrology. By integrating multivariate analysis with support vector machine regression (SVMR), this study provides some highlights on the characteristics (intensity and variability) of drought events and GRACE-derived terrestrial water storage (TWS) and the influence of global climate on the Congo river discharge. The southern section of the basin shows considerable variability in the spatial and temporal patterns of SPEI and extreme droughts over the Congo basin appear to have persisted with more than 40% coverage in 1994. However, there has been a considerable fall in drought intensities since 2007 and coincides with periods of strong positive anomalies in discharge (i.e., 2007-010). GRACE-derived TWS over the Congo basin is driven by annual fluctuations in rainfall ($r = 0.81$ at three months phase lag) and strong inter-annual variations of river discharge ($r = 0.88$, $\alpha = 0.05$). Generally, results show that changes in the surface water variations (from gauge and model output) of the Congo basin is a key component of the GRACE water column. The outputs of the SVMR scheme indicate that global climate through sea surface temperature anomalies of the Atlantic ($r = 0.79$, $\alpha = 0.05$), Pacific ($r = 0.79$, $\alpha = 0.05$), and Indian ($r = 0.74$, $\alpha = 0.05$) oceans are associated with fluctuations in the Congo river discharge, and confirm the importance of climatic influence on surface water hydrology in the Congo basin.

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Abstract

Understanding the impacts of climate on surface water hydrology is required to predict consequences and implications on freshwater habitats, ecological assets, and wetland functions. Although the Congo basin is considerably a freshwater-rich region, largely characterised by numerous water resources after the similitude of the Amazon basin, recent accounts of droughts in the basin are indications that even the most humid regions of the world can be affected by droughts and its impacts. Given the scarcity and limited availability of hydrological data in the region, GRACE (Gravity Recovery and Climate Experiment) observations are combined with model and SPEI (standardized precipitation evapotranspiration index) data to investigate the likelihood of such impacts on the Congo basin's surface water hydrology. By integrating multivariate analysis with support vector machine regression (SVMR), this study provides some highlights on the characteristics (intensity and variability) of drought events and GRACE-derived terrestrial water storage (TWS) and the influence of global climate on the Congo river discharge. The southern section of the basin shows considerable variability in the spatial and temporal patterns of SPEI and extreme droughts over the Congo basin appear to have persisted with more than 40% coverage in 1994. However, there has been a considerable fall in drought intensities since 2007 and coincides with periods of strong positive anomalies in discharge (i.e., 2007-010). GRACE-derived TWS over the Congo basin is driven by annual fluctuations in rainfall (r = 0.81 at three months phase lag) and strong inter-annual variations of river discharge (r = 0.88, α= 0.05). Generally, results show that changes in the surface water variations (from gauge and model output) of the Congo basin is a key component of the GRACE water column. The outputs of the SVMR scheme indicate that global climate through sea surface temperature anomalies of the Atlantic (r = 0.79, α= 0.05), Pacific (r = 0.79, α= 0.05), and Indian (r = 0.74, α= 0.05) oceans are associated with fluctuations in the Congo river discharge, and confirm the importance of climatic influence on surface water hydrology in the Congo basin.

Keywords: Surface water storage, River discharge, Rainfall, drought, Climate variability, Floodplains

1. Introduction

The knowledge of global climate influence on drought evolutions and freshwater availability is vital to drought risk mitigation, and evaluation of the cascading impacts of droughts on hydrological stores and agriculture (e.g., Agutu et al., 2019, Ndehedehe et al., 2019, Thomas et al., 2017). Drought events are increasingly becoming complex due to the combined effects of unmitigated climate change/climate variability, perceived human factors and other non-climatic factors such as the interference of water abstraction from underground reservoirs with the propagation process of drought characteristics and intensity (e.g., Ndehedehe, 2019, Ndehedehe et al., 2020a, Kubiak-Wójcicka and Bąk, 2018, Thomas et al., 2017, Van Loon et al., 2016). Understanding the impacts of climate on surface water hydrology is therefore required to predict consequences and implications on several freshwater habitats, ecological assets, and wetlands functions such as flood water storage, drought relief for wildlife, provision of shelter for fish and support for aquatic biodiversity, among others (e.g., Chen et al., 2014, Tockner et al., 2010, Gidley, 2009, Ozesmi and Bauer, 2002).

Furthermore, increased competition for freshwater as is now the case in some semi-arid African regions are some challenges that have been associated with its highly limited and shared water resources, which are considerably variable in time and space (e.g., Ndehedehe, 2019, Okewu et al., 2019, Freitas, 2013). The high variability of freshwater in these regions laced with considerable and disproportionate trans-boundary water sharing due to increase demand for freshwater create the propensity for inter-state tensions and rivalry. These conditions nonetheless, can be amplified by extreme and prolonged drought events, thus increasing the vulnerability of rural agro-communities to poverty and famine. While a broad range of socioecological impacts are imminent during such times, even distant populations that indirectly depend on the water resources of Africa could be subjected to far-reaching impacts of limited freshwater caused by extreme drought (Ndehedehe, 2019, FAO, 2016).

Moreover, the impacts of climate variability and/or climate change on agriculture and freshwater availability create several risks and key challenges for hydro-power production, water security, and a broad range of ecosystem services (see, e.g., Ndehedehe et al., 2018a, Ferreira et al., 2018, Van Loon et al., 2017, Agutu et al., 2017, Shiferaw et al., 2014, Spinoni et al., 2014, Schroth et al., 2016, Hall et al., 2014, Cenacchi, 2014). Indeed, the myriads of recent scientific reports on droughts and impacts of climate variability in the African subregion (e.g., Agutu et al., 2019, Ndehedehe et al., 2019, Agutu et al., 2017, Nkiaka et al., 2017, Hua et al., 2016, Epule et al., 2014) would only reinforce the notion of the continued influence of global climate on the continent. Although the Congo basin is considerably a freshwater-rich region, largely characterised by numerous water resources after the similitude of the Amazon basin, recent accounts of droughts in the basin (e.g., Ndehedehe et al., 2019, Hua et al., 2016, Zhou et al., 2014) are indications that even the most humid regions of the world can be affected
by extreme droughts and its impacts. For example, the impacts of prolonged and frequent droughts on the tropical Congolese rainforest systems will have compositional and structural changes on Congolese forest (Zhou et al., 2014).

In line with the need to assess global freshwater change, pioneering hydrological studies over the Congo basin found declines in Gravity Recovery and Climate Experiment (GRACE, Tapley et al., 2004) derived terrestrial water storage (TWS) while other reports have highlighted the key hydrological characteristics and uniqueness of the Congo basin's surface water hydrology and hydrodynamics (e.g., Becker et al., 2018, Ndehedehe et al., 2018b, Alsdorf et al., 2016, Lee et al., 2014, O'Loughlin et al., 2013, Conway et al., 2009, Crowley et al., 2006). Although extreme hydro-climatic events in Africa are generally dominated by natural variability and other important processes of inter-annual variability (Bahaga et al., 2019, Ndehedehe et al., 2019, Anyah et al., 2018, Nicholson et al., 2018), from a multi-satellite approach, surface water hydrology of the Congo basin is influenced by indices of oceanic variability such as the El-Niño Southern Oscillation (ENSO) (Becker et al., 2018, Ndehedehe et al., 2018b). However, recent changes in land water storage in some parts of the Congo basin have been linked to deforestation (Ahmed and Wiese, 2019). As some reports on the negative trends in TWS over the Congo basin converge, a broader perspective of surface water interactions with droughts could provide more understanding of the implications of extreme events (droughts flood) on biodiversity, and the hydro-ecological assets of the Congo basin.

Tropical rivers provide essential services and ecological functions for society and ecosystems such as regulating nutrient cycle, maintaining fishery production, water supply, recreation and tourism, generation of hydropower, and support for a range of terrestrial and aquatic biodiversity (e.g., Ndehedehe et al., 2020c,b, Tockner et al., 2010, Gidley, 2009, Zhao et al., 2012, Kennard et al., 2010, Keddy et al., 2009, Bunn et al., 2006). Process-based knowledge of the cascading impacts of extreme events such as drought on hydrology is crucial and can directly feed into management and policy frameworks. Because large scale hydro-climatic fluctuations and decadal-scale droughts impact hydrological regimes, a key focus of this chapter is to improve understanding on the response of freshwater ecosystem to extreme drought and the role of climate variability on the terrestrial hydrology of the Congo basin. This knowledge is important to help highlight the contributions of human activities such as deforestation and land cover change on surface water hydrology.

In other large watersheds and river basins, multiple lines of evidence confirm significant large-scale alteration of hydrological processes caused by several human activities, including surface water developments for agriculture and hydropower and water diversion (e.g., Ndehedehe et al., 2019, Wada et al., 2017). For instance, Lake Volta, the largest man-made lake contributed 41.6% to the observed increase in GRACE-derived TWS over the Volta basin during the 2002–2014 period when there was an apparent fall in precipitation (see, Ndehedehe et al., 2016, 2017a). Lake Victoria is the largest lake in Africa and as recently demonstrated, its water storage variability is dam controlled, contributing about 64% of TWS variability to its basin (Getirana et al., 2020). Arguably, the water resources in several river basins in Africa are generally being disturbed by natural variability, large scale ocean-atmosphere phenomenon, and a combined human-induced factors, e.g., land use changes and surface water schemes (e.g., Ngom et al., 2016, Moore and Williams, 2014, Redelsperger and Lebel, 2009, Descroix et al., 2009). The impacts of these interventions have always been altered surface water hydrology culminating in complex hydrological processes and or increased variability in these regions (e.g., Gal et al., 2017, Mahé and Paturel, 2009, Li et al., 2007, Mahé and Olivry, 1999).

Apparently, the Congo basin contains some of the largest areas of the world's tropical forests and wetlands, which are considerably important to global carbon and methane cycle (O'Loughlin et al., 2013, Achard et al., 2002). And within the context of global environmental change triggered by various human actions and climate variability, the Congo basin, which is home to the largest river in Africa and contains about 18% of the world's tropical forests (e.g., Becker et al., 2018, Ndehedehe et al., 2018b, Verhegghen et al., 2012, Achard et al., 2002) are also vulnerable to multiple influence of human actions and climate change. The main contribution of this study therefore is to improve contemporary understanding on the influence of climate variability on surface water hydrology in the Congo basin. Specifically, this study (i) investigates the characteristics of extreme events and land water storage using GRACE observations and multi-scaled indicators and (ii) predicts the influence of global climate on surface water hydrology by integrating multivariate analysis with support vector machine regression. Although in this era of the Anthropocene where combined climate and human actions are leading drivers of environmental change, global hydrological hotspots such as the Congo basin will experience more climatic disturbance due to the influence of the tropical oceans, physical mechanisms, and climate teleconnections. These factors regulate precipitation and the transport of moisture and will be the vehicle by which climatic extremes will be delivered across the basin and its environs. This chapter will therefore focus on exploring the interactions and links between land water storage (surface water hydrology) and global climate using sea surface temperature, GRACE-derived TWS, and standardized precipitation evapotranspiration index (SPEI) data. Further details on data, statistical analysis and modelling employed in this chapter are highlighted in subsequent sections.

2. Materials and method

2.1. Terrestrial water storage

This study used three GRACE mascon solutions from JPL, CSR and GSFC and was accessed from the Center for Space Research (CSR) at The University of Texas through its data portal (http://www2.csr.utexas.edu/grace/RL05_mascons.html). Generally, Mascons solves for monthly gravity field variations in terms of 120 km wide mascon block (Save et al., 2016, Wiese et al., 2016, Watkins et al., 2015). GRACE solutions based on the so-called mass concentration (mascon) from different processing centers at Center for Space Research (CSR), the Goddard Space Flight Center (GSFC), and Jet Propulsion Laboratory (JPL) were considered for estimating TWS fields. The CSR solution describes the global mass changes expressed in TWS solved for 40,962 cells in which each has an approximately 12,400 km2 with the average distance of about 120 km between the cells and finally resampled into 0.5∘-by-0.5∘ (Save et al., 2016). The GRACE GFSC mascon solution is solved for 1∘-by-1∘ equal-area grid blocks in which there are 41,168 mascon blocks covering the entire globe with mean area of 12,389 km (Luthcke et al., 2013). The JPL mascon solution solves for monthly gravity field variations in terms of 4,551 equal-area 3-degree spherical cap mascons covering the time of April 2002 to June 2017 and are also resampled into a fine resolution of 0.5∘-by-0.5∘ (Watkins et al., 2015).

2.2. Surface water storage hydrology

2.2.1. Surface water storage

Using hydrological models, Getirana et al. (2017a) decomposed the global terrestrial water storage (TWS) variability into its four major components: surface water storage (SWS), groundwater storage (GWS), soil moisture (SM) and snow water equivalent (SWE). Two state of-the-art models, the Noah land surface model (LSM) with multi-parameterization options (Noah-MP Niu et al., 2011) and the Hydrological Modeling and Analysis Platform (HyMAP) river routing scheme (Getirana et al., 2012, 2017b), are combined in order to represent the physical processes controlling TWS dynamics. Noah-MP is a multi-physics version of the community Noah LSM (Ek et al., 2003). As in most LSMs, Noah-MP maintains surface energy and water balances while simulating direct evaporation from soil, transpiration from vegetation, evaporation of interception and snow sublimation, and estimating key surface energy and moisture prognostics such as land surface temperature, snowpack, soil moisture and soil temperature. In addition, Noah-MP incorporates a three-layer snow physics component and a groundwater module with a prognostic water table (Niu et al., 2011). HyMAP is a state-of-the-art global scale river routing scheme capable of simulating surface water dynamics in both rivers and floodplains using the local inertia formulation (Getirana et al., 2017b, 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 backwater effects. Noah-MP and HyMAP are one-way coupled. This means that, at each time step, gridded surface runoff and baseflow output from Noah-MP are transferred to HyMAP and used to simulate spatially continuous surface water dynamics. No information is returned from HyMAP to Noah-MP. Several meteorological and precipitation datasets were used as model inputs, resulting in a 12-member ensemble model output. Here, the ensemble mean is used as the reference. The output from this model is used in this study as a surrogate for the surface water storage (SWS) over the Congo basin.

2.2.2. In-situ river discharge

Observed river discharge data for the Congo Kinshasa station was accessed from the GRDC (www.bafg.de/GRDC) archives and used to assess hydrological response of the Congo river to climatic fluctuations. The Congo river is one of the key rivers in the region as multiple sources of discharge from other tributaries within the Congo basin connect with this channel before reaching the Atlantic ocean. While the Congo river discharge encapsulates most of the flows within the basin (Ndehedehe et al., 2019), this river largely modulates the surface water hydrology of the Congo basin (e.g., Alsdorf et al., 2016, Ndehedehe et al., 2018b). The monthly river discharge data of the Congo river in Kinshasa station covering the period between 1980 and 2010 was used in combination with sea surface temperature to model the impacts of the surrounding oceans on temporal dynamics of Congo river discharge. But in assessing climate influence on surface water hydrology (i.e., TWS) over the Congo basin, the data covering the period during 2002-2010 was used.

2.3. Tropical Rainfall Measuring Mission (TRMM)

The TRMM 3B43 (Huffman et al., 2007, Kummerow et al., 2000) provides monthly precipitation estimates on a $0{:}25^{\circ}$ x $0{:}25^{\circ}$ spatial grids across the globe. The data was used in this study to assess the leading driver of GRACE-derive TWS and the spatial and temporal distributions of rainfall over the Congo basin.

2.4. Sea surface temperature products

This study used the global sea surface temperature (SST) data (Reynolds et al., 2002) covering the period between 1982 and 2015 and was accessed from NOAA's official earth system research laboratory portal (http://www.esrl.noaa.gov/psd/data/gridded/data. noaa.oisst.v2.html). Given that the influence of global SST anomalies on precipitation over tropical central Africa have been reported (see, e.g., Ndehedehe et al., 2019, Farnsworth et al., 2011), SST over the Atlantic, Pacific, and Indian oceans were used in this study to model climate influence on discharge. The global oceans modulate the zonal and local circulation patterns over Equatorial Africa (Pokam et al., 2014, Nicholson and Dezfuli, 2013), thus our motivation to examine the impact of SST on discharge.

2.5. Standardized precipitation evapotranspiration index

The standardized precipitation evapotranspiration index (SPEI) combines precipitation and temperature data in a water balance framework (see, Vicente-Serrano et al., 2010a,b). The SPEI used here was estimated based on a water balance approach as the difference between precipitation (*P*) and *PET* (potential evapotranspiration), i.e., δ = *P-PET*. As detailed by Vicente-Serrano et al. (2010b), the computed values of δ are cumulated on different time scales,

$$\delta_n^k = \sum_{i=0}^{k-1} \left(P_{n-1} - PET_{n-i} \right) n \geq k \; (10)$$

where *k* is the cumulated time scale and *n* is the calculation number. This cumulated time series are thereafter fitted with a log-logistic probability distribution function. The SPEI drought characterization here follows the thresholds defined by McKee et al. (1993), in which a drought condition is assumed to occur when the SPEI is consistently negative and reaches a value of -1. On a 12-month cumulation, this threshold supports hydrological drought characterization in the Congo basin.

2.6. Statistically analysis and modelling

The statistical analysis and decomposition of SPEI and TWS into temporal and spatial patterns were based on the principal component analysis (PCA, e.g., Jolliffe, 2002). The need to localize hydro-climatic signals is increasing due to growing multiple climate signals around the globe (e.g., Ndehedehe et al., 2017b). This has triggered numerous robust applications of multivariate methods in the spatio-temporal analysis of drought patterns and multi-resolution data (see, e.g., Agutu et al., 2017, Ndehedehe et al., 2016, Ivits et al., 2014, Bazrafshan et al., 2014). To understand the influence of global climate on Congo's hydrology, the support vector machine regression model (SVMR, Vapnik, 1995) was used to assess the influence of climate on the Congo basin hydrology. The support vector machine (Cortes and Vapnik, 1995) algorithm was extended by Vapnik (1995) for regression using an ε-insensitive loss function. The SVMR concept is based on the computation of a linear regression function in a high-dimensional feature space in which the input data (*xi*) are mapped through a non-linear function (e.g., Okwuashi and Ndehedehe, 2017). This mapping is warranted because most of the time, the relationship between a multidimensional input vector *x* and the output *y* is unknown and could be non-linear (e.g., Wauters and Vanhoucke, 2014). After finding a linear hyperplane that fits the multidimensional input vectors to output values, the SVMR predict future output values that are contained in a validation set (e.g., Okwuashi and Ndehedehe, 2017, Wauters and Vanhoucke, 2014, Smola and Schölkopf, 2004, Vapnik, 1995). Assuming the set of data points **X** = (x_i, p_i); *i* = 1.., *n* with x_i, being the predictand data point *i*, p_i the actual value and *n* the number of data points. The linear SVMR function *f*(*x*) takes the form (e.g., Vapnik, 1995)

$$f(x) = wx + b \quad 2$$

The assumed linear parameterization in Eqn 2 above bears similarity to a linear regression model. That is because the predicted value, *f*(*x*), depends on a slope *w* and an intercept *b*. However, the goal of the SVMR is to identify a function f(x) that has a maximum deviation *ε* from the target values p_i and has a maximum margin for all training patterns *xi*. In order words, a balance between learning the relation between inputs and outputs whilst maintaining a good generalization behaviour is targeted. As highlighted further in Wauters and Vanhoucke (2014) too much focus on minimizing training errors may lead to overfitting. Hence, a pre-specified penalty value (*C*) is introduced as a trade-off to create the balanced between generalization and good training. That is, *C* regulates the trade-off between the

regularization term ($½\|w\|^2$) and the training accuracy in the formulation below as (e.g., Wauters and Vanhoucke, 2014, Vapnik, 1995),

$$\varsigma = \frac{C}{n}\sum_{i=0}^{n} L_\varepsilon(p_i - f(x))\frac{1}{2}½\|w\|^2 \quad 3$$

where the compound risk caused by training errors and model complexity is given as ς. Eqn 2 provides the estimated values for *w* and *b* and comprises the empirical risk measured by the ε-insensitive loss function, L_ε and the regularization term $½\|w\|^2$, which describes the model complexity (Wauters and Vanhoucke, 2014, Cortes and Vapnik, 1995). Prior to modelling the response of discharge to climate using the SVMR, a regularization approach where the SST is compressed through a PCA-based orthogonalization was employed (e.g., Ndehedehe et al., 2018b, Bretherton et al., 1992, Barnett and Preisendorfer, 1987). This resulted in significant modes of SST variability from the respective oceans, which were then used as predictands in the SVMR model. Specifically, a linear SVM regression model was trained to fit the data. The SVMR technique evaluates each run of the experiment using regression, by partitioning the data internally into training, validation, and testing components (i.e., 65% of the total data). The remaining 35% of the observed data were thereafter used for forward prediction based on the hold-out method of cross-validation (e.g., Haley, 2017). The stratified partitioning of the data using this approach ensures that each partition includes similar amount of observations from each group. The predicted and observed discharge were then compared using Pearson correlation.

3. Results

3.1. Characteristics of extreme events in the Congo basin

Three leading modes of variabilities, accounting for a total of 34.5% were identified in the statistically decomposed SPEI patterns (1980-2015) over the Congo basin (Figs. 1a-f). From the joint interpretation of the spatio-temporal patterns of SPEI localised over the tropical south of the basin, the longest drought duration occurred during the 1992-1996 and 2003-2006 periods (Figs. 1a-b). During the 1985-1991 and 2007-2008 periods, the SPEI time series associated with this southern section of the basin were significantly wet. In terms of the total variability accounted for in the three SPEI modes over the basin, the southern section of the basin with considerable changes in rainfall show the highest (17%) SPEI variability (Figs. 1ab). We agree that the central regions and areas of the Congo basin below the equator are apparently and significantly wet in terms of rainfall amount and the presence of surface water and fluxes (Section 3.2.2). It is also true that the southern section experiences drought and dryer conditions more frequently compared to other regions (Figs. 1a-b). However, as with wet regions of the basin, the amplitudes of rainfall in the tropical wet-dry southern section are strong and show monthly averages of about 250 mm between December and February, consistent with rainfall amounts during the September-November period in the central region. There is considerable evidence in the literature regarding the distribution of rainfall in the south between December and March (e.g., Amy Creese et al., 2019, Ndehedehe et al., 2019, Alsdorf et al., 2016, Munzimi et al., 2015) and our spatio-temporal analysis of land water storage highlights this pattern in the wet-dry and temperate regions of the southern region (Section 3.2.1), given that rainfall is the main input to hydrological systems.

[Figure 1]
[Figure 2]

Moreover, there are few drought episodes in the south-western region of the basin (Figs. 1cd). The evolution of wet episodes in the south-western region suggests it appears to be wet most of the times (Figs. 1c-d). However, since 2010, the temporal patterns of SPEI in the southwestern region have been largely somewhat less than moderate (Figs. 1c-d). The decomposition of SPEI over the basin also shows that drought conditions of the early 1980s affected the northern section in Central Africa Republic (CAR) (Figs. 1e-f). The frequent episodes of droughts in CAR obviously are in sharp contrast to the wet episodes observed in the southeast region of the basin (SPEI-3, Fig. 1). Some moderately wet periods between 1995 and 2002 (Figs. 1e-f) are also noted in CAR region. The latter is a humid tropical wet and dry savannah ecosystem largely characterised by considerable changes in annual and seasonal rainfall that is in opposite phase with the southern section. Arguably, the nourishment of the Congo basin hydrology and freshwater ecosystems also emanates from the southern end of the basin where
extreme droughts tend to be more frequent (Figs. 1a-b). As this region is also characterised by high rainfall amounts, which occur all through the year except during the June-August period, a shift in hydrological regime of the Congo basin is more likely. Drought intensities over the Congo basin are conspicuously moderate or probably less. Droughts persisted between 1992 and 2001 with more than 40% coverage between 1994/1995 and early 2006 (Figs. 2a-b). The observed extreme drought between 2004 and 2006, one of the post 2000 period with widely acknowledged hydrological drought period in the basin reported in the literature also persisted, fluctuating between 25% in 2004 and more than 40% in 2006 (Fig. 2b). During the last few decades (between 1984 and 2011), reoccurring severe and extreme drought episodes have affected on the average at least 30% of the Congo basin
(Fig. 2). While the 1994 extreme droughts reached 50%, in other periods (e.g., 1992, 1999, 2004, 2005/2006), only about 30% of the basin on the average has been affected by extreme drought during the 1991-2011 period (Figs. 2a-b). This increasing intensity in extreme drought episodes is

consistent with the results indicated in Fig. 1. However, between 2012 and 2016, drought episodes and their intensities have diminished over the Congo basin (Fig. 2), consistent with the temporal SPEI patterns shown in Fig. 1. But the intensity of the well-known large-scale extreme droughts of the 1980s, which affected Africa are less and not wide spread in the Congo basin compared to other African sub-regions where drought-affected areas ranged from 70% to more than 90% (e.g., Ndehedehe et al., 2020a, 2019, Agutu et al., 2017, Masih et al., 2014).

3.2. Surface water hydrology of the Congo basin

3.2.1. Spatial and temporal patterns of land water storage

Linear trends from three GRACE-mascon solutions are summarized in Figs. 3a-c for the period between Jan 2003 and Dec 2015. Despite having a spatial resolution of 0.5◦ x 0.5◦ (CSR and JPL), the mass changes show the overall structures of the 3.0◦ x 3.0◦ native resolution and its suitability to capture hydrological patterns. The surface water hydrology of the Congo basin was assessed using time series of GRACE-derived TWS and model-derived SWS during the 2002-2017 period. Spatial distribution of trends in TWS obtained from three GRACE solutions (including TWS solutions that have been smoothen with a 150 km Gaussian filter) are generally consistent (Figs. 3a-f). The distribution of positive trends in TWS in the basin is weak unlike the surrounding regions (East and South Africa) where considerably rise in TWS is observed (Figs. 3a-c). The negative trends around the Cuvette central and northern section of the basin could result in a possible unfavourable hydro-climatology of the Congo basin if the trends persist (Figs. 3a-f). The root mean square error (RMSE) values summarizing the monthly errors (68% confidence level) in the aerial averaged time series are 23.70 mm, 22.84 mm, and 26.00 mm for CSR, GSFC, and JPL, respectively (Fig. 4). The linear rates over during the period (April 2002 to June 2017) were estimated using weighted least-squares method (including their uncertainties). These linear rates show mass changes of approximately 0.33±0.94 mm/yr (CSR), 0.73±0.95 mm/yr (GSFC), and 1.95±0.93 mm/yr (JPL) but they are statistically insignificant (Figs. 4a-c). Overall, the temporal variations of TWS and their corresponding RMSEs observed over the Congo suggest low uncertainties amongst products. From the averaged TWS time series for the Congo basin (Fig. 4), the three mascon solutions depict the same overall seasonality while the error bars represent the monthly uncertainties
of TWS and was estimated following Scanlon et al. (2016). First, the residual series were considered as the difference between the observed TWS series and the best fit considering constant, trend, annual, and semi-annual terms. Secondly, the residual series from the previous step were smoothed using a 13-month moving average, which was considered as the monthly errors for the GRACE series. The RMSE of the smoothed residual series is approximately 23.70 mm, 22.84 mm, and 26.00 mm for CSR, GSFC, and JPL, respectively. This suggests the GSFC GRACE product is relatively better over the Congo basin. The time temporal patterns summarizing the overall mass changes within the Congo basin are indicated in Figs. 4a-c and show a slight rise between 2012 and 2016, though not significant.

[Figure 3]

[Figure 4]

[Figure 5]

Apart from estimating trends in TWS, the leading orthogonal modes of TWS changes over the Congo basin were also identified to understand the spatial and temporal variability and key hydrological drivers of TWS. Apparently, the first mode of TWS over the Congo basin is considerably dominated by annual signal and accounts for about 78% of the total variability (Figs. 5a-b). This leading mode of TWS over the Congo basin is driven by annual fluctuations in rainfall because of the observed strong correlation (r = 0.81, α= 0.05) between TRMM-based precipitation and dominant temporal patterns of TWS (Figs. 5a-b) at three months phase lag. This relationship is further supported by the spatial patterns of TWS (Figs. 5a-b), which show strong inter-hemispheric dipole configuration patterns similar to those of spatial distribution of TRMM-based rainfall. It should be noted that the direct correlation of TWS-1 with rainfall showed no significant relationship (r = 0.002, p = 0.98) unlike the direct correlation of rainfall with the second mode of GRACE hydrological signal (TWS-2) (r = 0.52, p = 0.000). The second GRACE-hydrological signal represents multi-annual variation in TWS changes (approximately 12% of the total variability) over the northern sections where rainfall is largely bimodal (Figs. 5c-d). This GRACE-hydrological signal is moderately associated with rainfall (r = 0.52, p = 0.000), it is largely driven by the strong inter-annual variations of river discharge and surface water in the Congo basin (r = 0.88, α= 0.05). The GRACE-hydrological signal in the third mode, which accounts for 2.7% total TWS variability represents mostly multi-annual variations resulting from considerable rise in TWS over the region (Figs. 5e-f). This signal clearly corresponds to the hydrology of the surrounding East African lakes (Lakes Tanganyika, Edward, and Kivu) though the decline in between 2003 and 2005 in the Congo basin is also captured (Figs. 5e-f).

[Figure 6]

3.2.2. Climate influence on surface water hydrology

The response of surface water hydrology to climate variability was evaluated by comparing the leading SPEI temporal series (Figs. 1a and c) with normalised discharge time series (Congo river discharge). The temporal patterns of Standardised Runoff Index (SRI) and SPEI tend to be consistent except during the drought periods between 1995 and 1999 (Fig. 6a). SRI indicated positive values (except 1998) contrary to SPEI, which showed drought condition. SPEI temporal pattern is poorly correlated with SRI during the 1980-2010 period (r = 0.22 at α = 0.05). But as shown in Fig. 6a, the temporal relationship between SRI and SPEI are relatively better in some periods. For example, SPEI is better correlated with SRI between 1980 and 1987 (r = 0.46; α= 0.05) and the post 2000 period (r = 0.46; α= 0.05). A recent assessment of global multi-scale climate influence on historical drought events over the Congo basin (Ndehedehe et al., 2019) showed that SRI and SPI were largely correlated during the 1931-1990 and 1961-1990 (r = 0.69 and 0.64, respectively at α= 0.05) periods unlike the 1991-2010 period (r = 0.38). While this suggests rainfall was the main driver of hydrological conditions of the basin between 1903 and 1990, that appears to have changed as droughts and human activities can impact on the rainfall-discharge relationship in ways that further complicates our understanding of natural climate processes in the region.

[Figure 7]

[Figure 8]

Temporal variability in discharge is expected to be driven by changes in precipitation patterns and other land surface conditions, including land cover change. Considerable variability in the Congo river's discharge between 1960 and 1995 was reported by Alsdorf et al. (2016), consistent with a 21% increase in the Congo river discharge during the same period. Ultimately, this would imply that increased rainfall led to a rise in the Cong river discharge. But the time series of SPEI and SRI were largely inconsistent during most parts of the 1990s when extreme drought was observed (Fig. 6a). For instance, SRI indicated wet episodes for most of the period after 1995 until 2000 (except 1998) and even during the post 2000 period while SPEI was largely characterised by drought episodes in between these periods (Fig. 6b). Further, it is shown here that the surface water of the Congo basin is key component of the GRACE water column indicating significant association with river discharge and SWS (Fig. 6b). The multi-annual variations of TWS (Figs. 5a-b) observed around the Congo Cuvette central is dominated by the Congo river discharge (r = 0.88 at α= 0.05) (Fig. 6b). The response of the Congo river discharge to climate variations was predicted using the leading modes of SST anomalies of the surrounding oceans (Atlantic, Indian and Pacific) as predictands in an SVR scheme. The output of the linear SVMR show that global climate through SST anomalies of the three oceans are associated with fluctuations in the Congo river discharge (Figs. 7a-c). Given the moderately strong correlation (r = 0.79, p = 0.0000) between the observed and predicted (Figs. 7a-b), SST of the Atlantic and Pacific are relatively stronger predictors of river discharge compared to SST of the Indian ocean, which indicated a moderately strong correlation (r = 0.74, p = 0.0000) (Fig. 7c). From the SVMR model, the first SST mode (annual) from the Pacific and Indian oceans had the strongest coefficients (second mode of Atlantic SST had the highest coefficients out of the five predictors). However, while the first and second SST modes of the Indian ocean showed strong coefficients, the fifth mode of the Pacific SST showed the second highest coefficients. Overall, the weight of coefficients of the predictands in the SVMR model confirm the importance of slow oceanic and climate signals (e.g., ENSO) from global SST anomaly on hydrological changes and surface water hydrology in the Congo basin. Furthermore, there is significant difference in the spatial distribution of SWS during extreme drought (2004) and wet (2007) periods in the basin (Figs. 8a-h, cf. Fig.1). Generally, strong spatial patterns of SWS and total inundation are restricted to the Congo river channel with values reaching 200 mm in the September-October period (Figs. 8a-h). With a gradual rise in rainfall during the November-December period, surface water storage extends to the Curvette central and is perhaps stored as floodplain waters. During the 2004 drought period (Figs. 8e and g), this floodplain waters around the Curvette central area of the Congo basin in November-December period are not as noticeable as the wet period in 2007 (Figs. 8f and h). There is a significant difference in the SWS spatial and temporal patterns shown for the wet and dry periods (Figs. 8a-h) and a wider distribution of surface water during the former is observed. This is expected for the Congo basin as diminished flow under limited rainfall condition would be normal. Additional analysis based on observed spatial trends in SWS were also undertaken. These short terms trends of SWS were estimated for specific drought (e.g., 2005-2005) and wet (e.g., 2006-2007) periods and they are consistent with the aforementioned results.

4. Discussion and conclusions

4.1. Understanding drought variabilities, intensities, characteristics and drivers

Although the Congo basin is one of the most humid regions of the world similar to the Amazon basin, droughts and its impacts are unavoidable. Drought variability and frequency tend to be higher in the southern part of the Congo basin where seasonal rainfall amount is highest during the December–March period in the basin areas. Although extreme droughts affected more than 40% of the basin between 1992 and 2001, drought episodes and their intensities diminished over the Congo basin after late 2006 when the basin became extremely wet because of strong changes in rainfall. Generally, there is consistency between the results here and the global scale analysis by Spinoni et al. (2014), who showed prolonged and severe droughts during the same period (1991-2010) over the Congo basin. While the degree of intensity or impacts of extreme droughts might be different due to catchment characteristics, land cover change, topography and land surface conditions, water deficits caused by prolonged climate-induced, below average rainfall could have implications on freshwater variability and availability. For example, evolutionary patterns of standardised precipitation index and discharge

show that these variables have considerable linear relationships in the Congo basin (e.g., Ndehedehe et al., 2018c, 2019). Consistent with this study, we have noticed a rise in SWS of the basin in areas below the equator during wet periods. Similarly, a fall in SWS was observed during the 2004 drought period, confirming the critical role of climate variability on changes in surface water hydrology.

Land surface conditions and human induced climate change are other possible drivers of surface water hydrology in the Congo basin. Evapotranspiration losses caused by significant declines in soil moisture and droughts (e.g., Ndehedehe et al., 2018c, Jung et al., 2010) can alter hydrological regimes in the Congo basin. Strong land-atmosphere interactions and feedbacks and the importance of the Congo forest to its local hydrology and precipitation (Bell et al., 2015, Koster et al., 2004), could indeed induce considerable changes in hydrological regimes of the Congo basin. Even though the physiographic characteristics of rivers connecting to the Congo river do have complex drainage systems that could create a non-stationary relationship between surface water flow and rainfall (e.g., Ndehedehe et al., 2019), the terrestrial hydrology of the Congo basin is directly regulated by the prolonged seasonal rainfall within the Congo basin. For example, rainfall patterns over the Congo basin are linearly correlated with the Congo river discharge (e.g., Conway et al., 2009). But from a sub-regional analysis that included West Africa, the river discharge explained a considerable proportion of GRACE-terrestrial hydrological signal in the Congo basin (Ndehedehe et al., 2018b). Arguably, this relationship gives the notion that sink terms (runoff and evapotranspiration) in the basin are also key drivers of surface water hydrology other than rainfall. Locally recycled precipitation caused by the combined influence of the nearby ocean and evaporation from the Congo basin (Sorí et al., 2017, Dyer et al., 2017) are further evidence supporting the argument of other hydrological drivers in the basin. Moreover, the observed change in hydrological response of the Congo river to strong deviations in rainfall suggests non-linear interactions and complex hydrological processes in the basin. For instance, changes in the temporal series of discharge do not completely reflect those of observed land water storage. Although it is less debated that the waters of the Congo basin are directly supplied by rainfall, changes in the surface water of the basin contributes significantly to variations in GRACE-hydrological signals. Multi-satellite assessments of the Congo terrestrial hydrology from recent studies (Becker et al., 2018, Ndehedehe et al., 2018b) agree that this is the case.

Extreme negative anomalies in rainfall impacts surface water hydrology through a trickle-down effect that culminates in soil moisture and hydrological droughts. While processes such as seasonality effects, catchment and climate characteristics tend to influence drought propagation, strong precipitation deficits in tropical climates would normally result in reduced alimentation and temporary decrease in stream flows, storage reservoirs, and freshwater stocks (e.g., Ndehedehe, 2019, Kiem et al., 2016, Van Loon et al., 2014). However, it has recently been shown that this was not the case in the Congo basin (1995-2010) as most drought episodes were inconsistent with discharge anomalies during the period (Ndehedehe et al., 2019). One wonders if there are known physical and ecological processes that play key roles in drought propagation in the Congo basin. But the basin's catchment stores (e.g., swamps, lakes, reservoirs, soil column, groundwater, etc.), which could create a prolonged reservoir memory in the hydrological system could be a determinant in the delayed propagation of drought signals or even its absence in the discharge anomalies. It has been reported that the Congo basin is the only river basin that seconds the Amazon river in terms of average yearly discharge (i.e.,
about 40,200 m3 s^{-1}), and surface water storage (111 km^3) (see, Lee et al., 2011, Alsdorf et al., 2010). This storage capacity could increase catchment response time to drought events, and arguably create a non-linear relationship that results in an asymmetric response of surface water dynamics to a drought signal (e.g., Ndehedehe et al., 2019, Loon, 2013). Although antecedent conditions could exist, this relationship can be disturbed or altered in the event of strong human footprints (e.g., deforestation), land surface conditions, and increased frequency in drought events triggered by changes in atmospheric circulation patterns. In other words, rainfall may not be the only driver of hydrological conditions and fluxes in the Congo basin. Earlier studies have recognised rainfall as a key indicator regulating the hydrology of the region. However, river basin physiography and properties (e.g., topography, streamflow characteristics, etc.) and several ongoing human actions such as the effects of land use change and deforestation in the Congo basin drive variability in river flows and surface water availability.

4.2. Surface water hydrology of the Congo basin and the role of climate

Aerial averaged time series of TWS over the Congo basin between 2002 and 2017 showed no significant trend. But within the basin, leading spatio-temporal mode of TWS accounting for about 78% of the total variability is considerably dominated by annual signal, which coincides with annual fluctuations in rainfall. While the Congo river signal is also identified in the GRACE-hydrological signal over the Congo basin, there was a fall in TWS between 2003-2005 and a subsequent rise during the 2006-2017 period. These trends, though spatially explicit, are very consistent with both temporal drought patterns and the percentage of drought affected areas observed during the same periods. In fact, there was a relatively higher distribution of surface water inundation within the Cuvette central and floodplain corridor of the Congo basin during wet years unlike dry years when rainfall was restricted. TWS variability are mostly characterised by strong annual changes and multi-annual signals. There is also a significant surface mass variation emanating from the hydrology of the surrounding East African rivers and lakes (Lakes Tanganyika, Edward, and Kivu), which share boundary with the Congo basin. Considering the spatial patterns of observed GRACE-hydrological signal over this area,

there is a possible indication of significant exchange of fluxes within the various watersheds of the Congo basin. These of fluxes among freshwater bodies may contribute to flow dynamics and lead to considerable amplitudes in surface storage of the Congo floodplain and the Cuvette central. This argument is consistent with an earlier insinuation by Tshimanga and Hughes (2014) that the hydrology of this region and other surrounding large floodplain wetlands are expected to contribute to downstream flow regimes of the Congo river. Furthermore, the surface water hydrology of the Congo basin has considerable connections with the surrounding oceans. Predictive scheme based on a linear SVMR show that global climate through SST anomalies of the three oceans (Atlantic, Indian, and Pacific) have linear relationships with fluctuations in the Congo river discharge. The SST of the Atlantic and Pacific are relatively stronger predictors of river discharge compared to SST of the Indian ocean. Overall, the weight of coefficients of the predictands in the SVMR model confirm the importance of slow oceanic and climate signals from global SST anomaly on hydrological changes and surface water hydrology in the Congo basin. Previous studies have reported the links between Congo discharge and SST of the surrounding oceans. The study by Materia et al. (2012), which confirmed the effect of freshwater on SST, suggests an interplay involving river discharge, sea surface salinity and temperature. While these factors could be significant to the interannual variability observed in the region, recent diagnostics study shows that ENSO-related equatorial Pacific SST fluctuations have been identified as a key climate variability index associated with land water storage (Ndehedehe et al., 2018b). Additional evidence from a recent satellite-based assessment of surface water dynamics in the Congo basin confirm the influence of ENSO on its surface water hydrology (Becker et al., 2018).

Moreover, the implications of persistent droughts events on tropical rainforest systems was stressed by Zhou et al. (2014). They argued that the continued drying of the basin could lead to compositional and structural changes in the Congolese forest. Other than the well-known influence of climate variability on fluxes and terrestrial hydrology of the Congo basin (Becker et al., 2018, Ndehedehe et al., 2018b, Conway et al., 2009), recent findings on drivers of TWS in the basin suggest the critical role of human actions (Ahmed and Wiese, 2019). The conversation around human-induced changes in TWS of the Congo basin is important and requires further details. This is because as home to the world's second largest rainforest block (e.g., Oslisly et al., 2013), it is critical to advance knowledge on long term effects of intense human-actions such as deforestation on TWS dynamics. This will build on existing compendium of knowledge highlighting the sensitivity of climate to the loss of the Congo basin

rainforest and other ecological disturbance in the region (e.g., Bell et al., 2015, Malhi et al., 2013, Verhegghen et al., 2012). Moreover, it has recently been reported that the knowledge of surface hydrology in major large river channels have implications on the duration and extents of flood that sustain globally important floodplain and wetland ecosystems (Carr et al., 2019). As the Congo basin's rainfall climatology is very significant to global tropical rainfall during transition seasons (e.g., Ndehedehe et al., 2018b, Washington et al., 2013), this again reinforces the importance of the Congo basin hydro-climatology to global climate change. Hence, key hypothesis future assessment and consideration is to understand if the depletion of the Congo forest through uncontrolled logging and deforestation impacts on the global water cycle.

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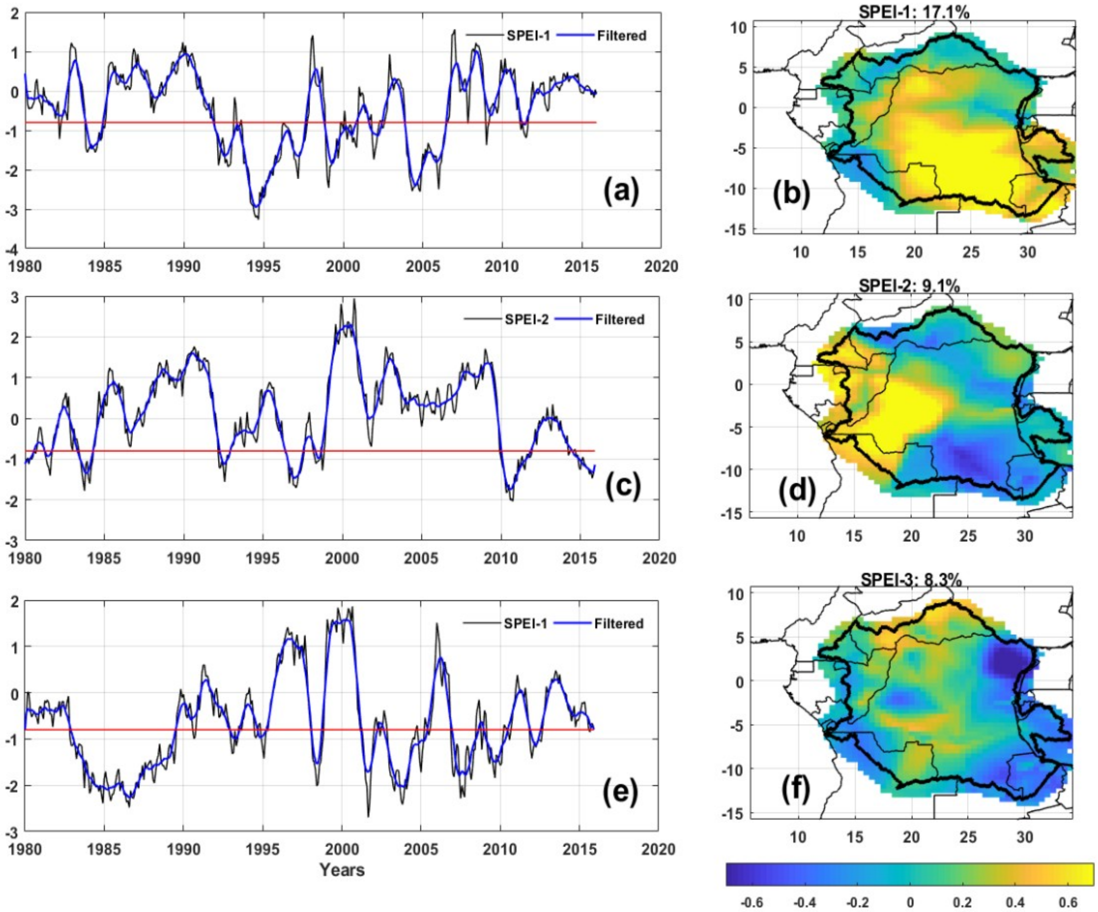

Figure 1: Spatio-temporal SPEI patterns of the Congo basin using 12-month gridded SPEI values (a-f). Localised spatial SPEI patterns (right) corresponds to the temporal evolutions (left) and actual SPEI values to be used for drought classification (drought threshold is in red) are jointly derived from the spatial and temporal patterns. The SPEI time series (blue) are filtered to cushion the effect of residual short-term seasonal signals and also for better representation.

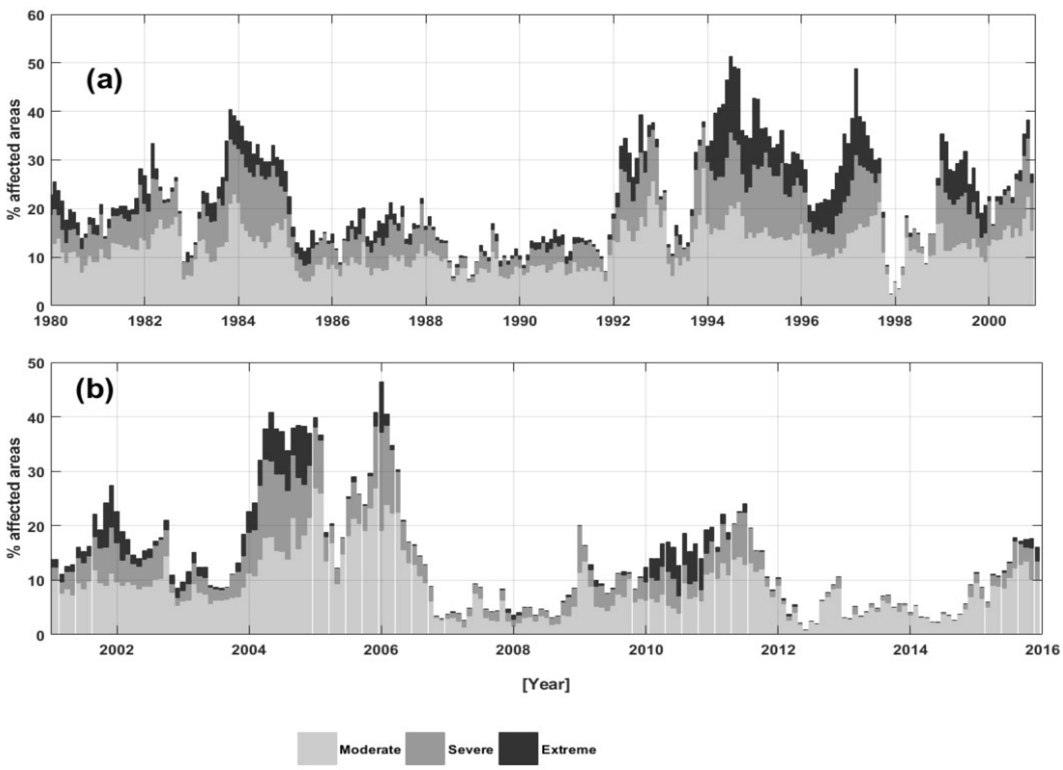

Figure 2: Estimated areas affected by various drought intensities (extreme, severe, and moderate) over the Congo basin during 1980-2000 (a) and 2001-2015 (b) periods. The SPEI-derived drought affected areas (%) are characterized based on the classification thresholds defined in McKee et al. (1993) and Ndehedehe et al. (2019). Note this SPEI is based on a 12-month aggregation.

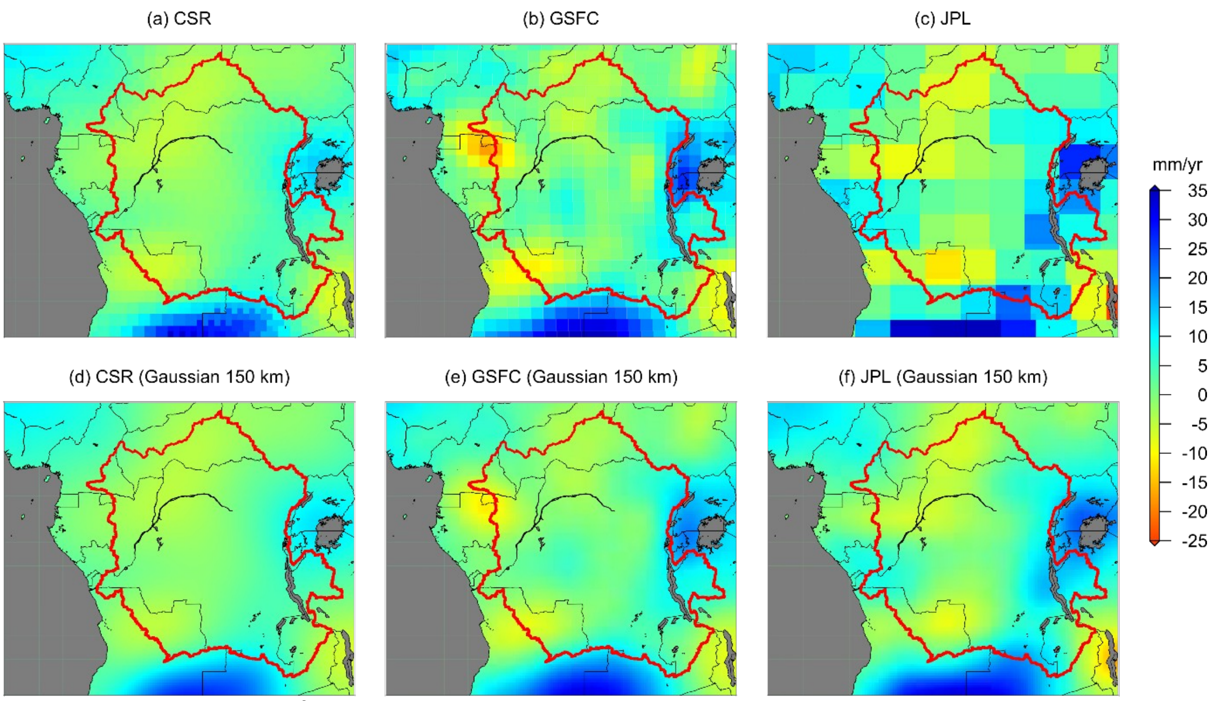

Figure 3: Spatial distribution of trends in GRACE-derived TWS (2002- 2017) over the Congo basin. Panels (a)-(c) show the linear rates of TWS changes over the study area in the Congo basin delineated by the red line. Panels (d)-(f) show the trend map smoothed with a Gaussian filter using 150 km radius for visualization.

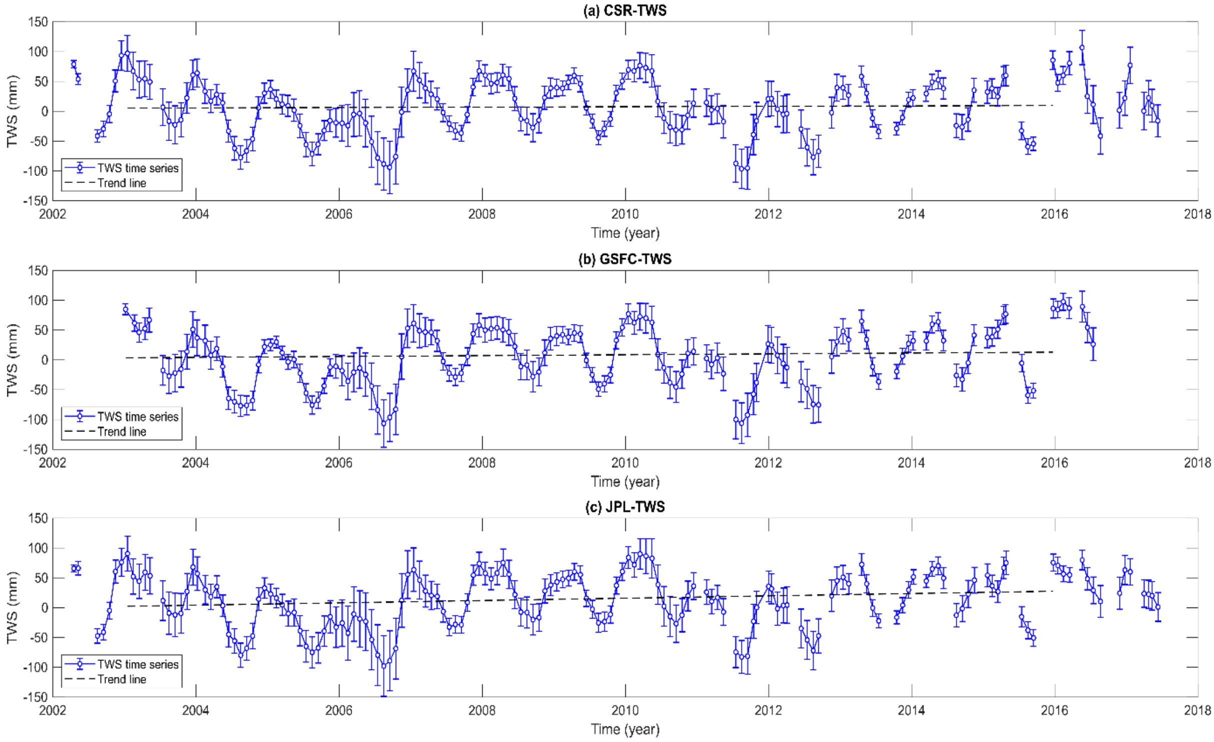

Figure 4: Aerial averaged temporal series of TWS (2002-2017) estimated from three different GRACE mascon products. Gaps in the time series are periods with missing data. The TWS time series based on mascon solutions provided by CSR (a), GSFC (b) and JPL (c) within the Congo Basin and their respective linear trends depicted by the dashed lines. The error bars show the respective monthly errors for each solution.

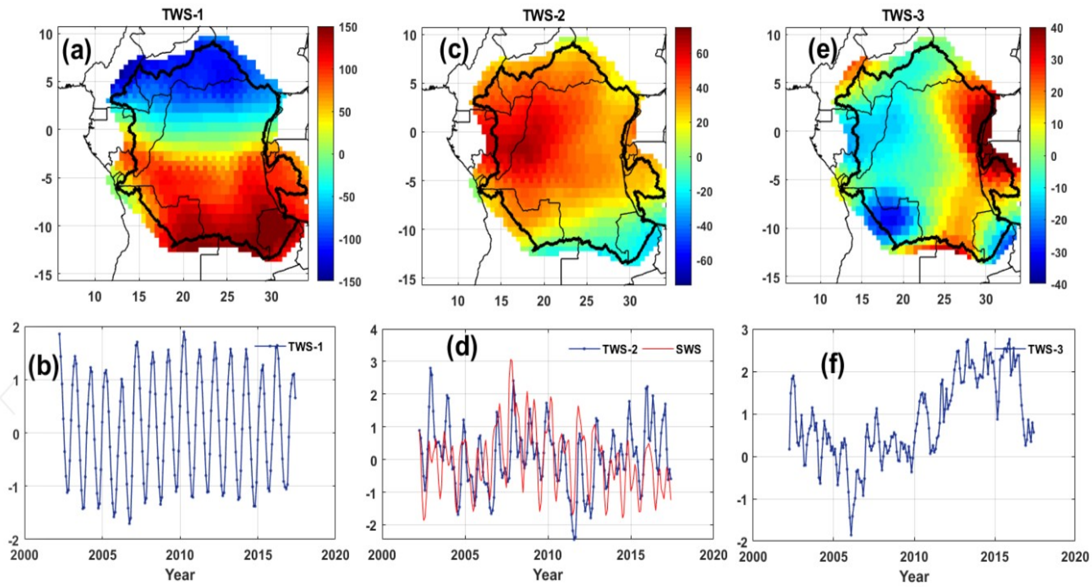

Figure 5: Leading modes of TWS (2002-2017) over the Congo basin. Averaged spatial patterns (a, c, and e) corresponds to the temporal series (b, d, and f). The observed correlation value between TWS and surface water storage is significant at α= 0.05.

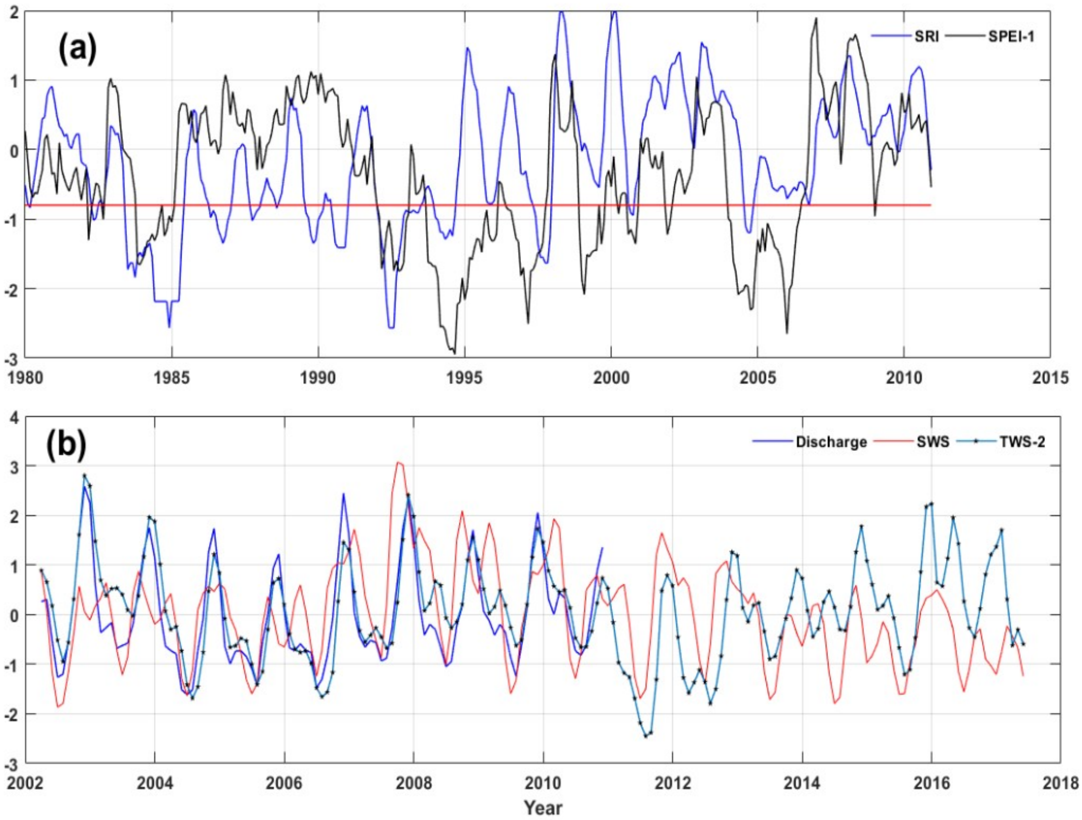

Figure 6: Assessing climate influence on surface water hydrology over the Congo basin. (a) Relationship between river discharge and SPEI, and (b) relationship of Congo river discharge with TWS and surface water storage. TWS here is the GRACE-hydrological signal in the second orthogonal mode (TWS-2, Fig. 5).

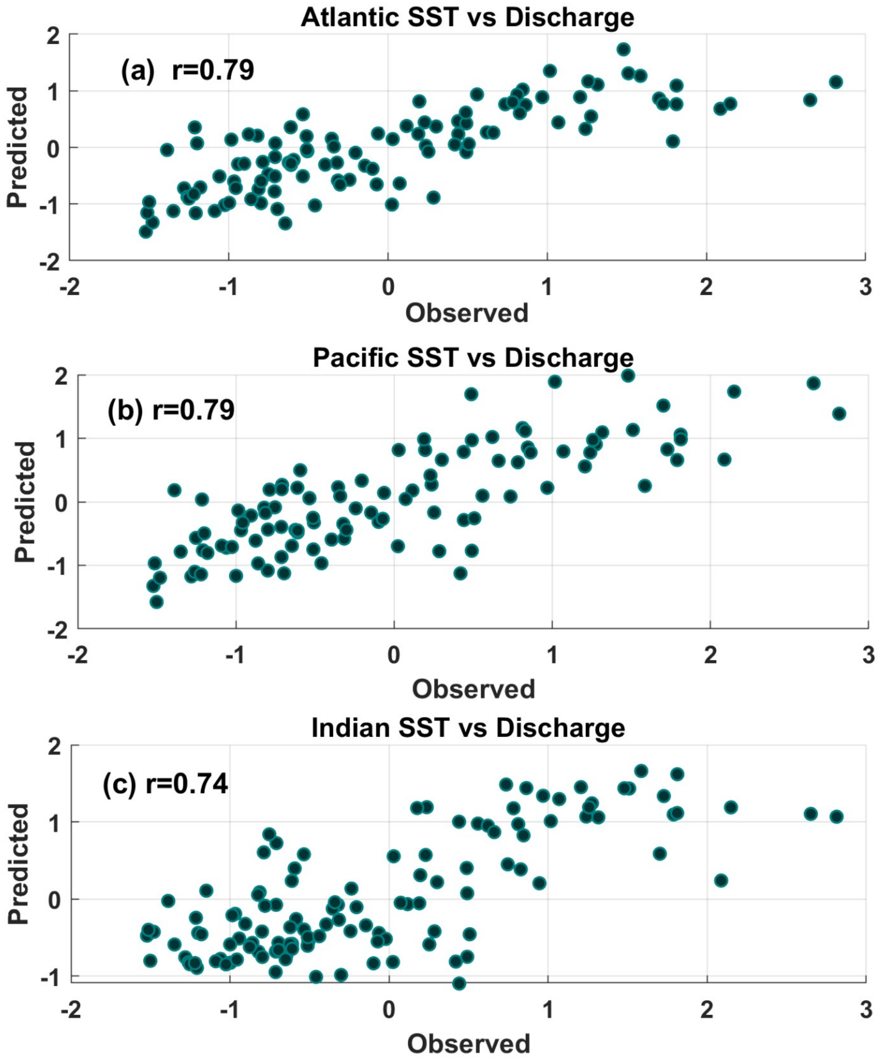

Figure 7: Modelling the temporal dynamics of Congo river discharge (1980-2010) using dominant patterns of (a) Atlantic, (b) Pacific, and (c) Indian SST anomalies in the SVM regression scheme.

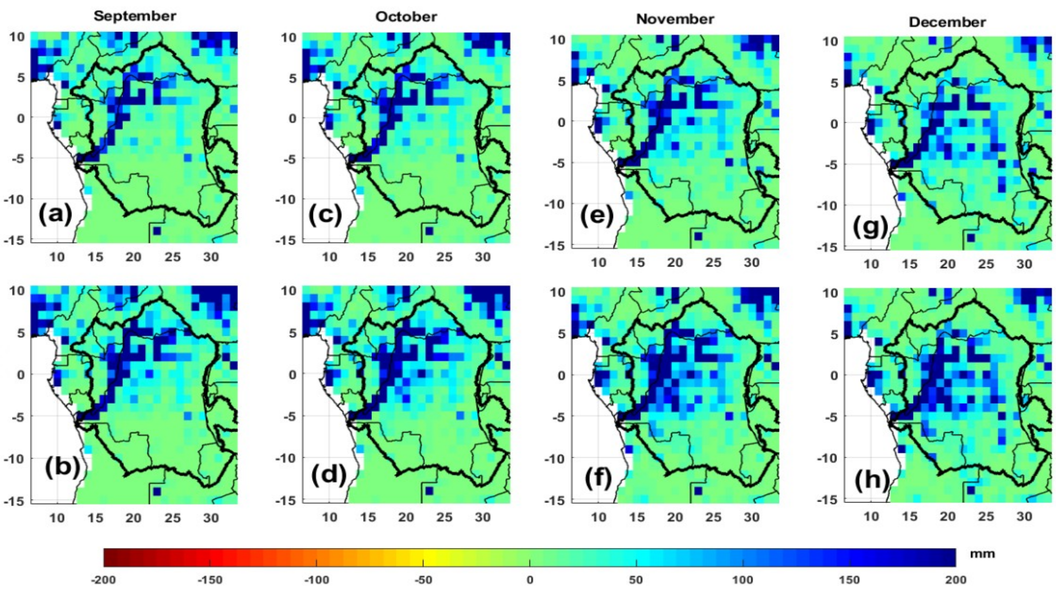

Figure 8: Surface water storage over the Congo basin during the extreme drought period of 2004 (a, c, e, and g) and the 2007 wet episodes (b, d, f, and h).