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Hydropower dam operation strongly controls Lake Victoria's freshwater storage variability

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Abstract

River impoundments strongly modify the global water cycle and terrestrial water storage (TWS) variability. Given the susceptibility of global water cycle to climate change and anthropogenic influence, the synthesis of science with sustainable reservoir operation strategy is required as part of an integrated approach to water management. Here, we take advantage of new approaches combining state-of-the-art computational models and a novel satellite-based reservoir operation scheme to spatially and temporally decompose Lake Victoria's TWS, which has been dam-controlled since 1954. A ground-based lake bathymetry is merged with a global satellite-based topography to accurately represent absolute water storage, and radar altimetry data is integrated in the hydrodynamic model as a proxy of reservoir operation practices. Compared against an idealized naturalized system (i.e., no anthropogenic impacts) over 2003-2019, reservoir operation shows a significant impact on water elevation, extent, storage and outflow, controlling lake dynamics and TWS. For example, compared to Gravity Recovery and Climate Experiment (GRACE) data, reservoir operation improved correlation and root mean square error of basin-wide TWS simulations by 80% and 54%, respectively. Results also show that lake water storage is 20% higher under dam control and basin-wide surface water storage contributes 64% of TWS

variability. As opposed to existing reservoir operation schemes for large-scale models, the proposed model simulates spatially distributed surface water processes and does not require human water demand estimates. Our proposed approaches and findings contribute to the understanding of Lake Victoria's water dynamics and can be further applied to quantify anthropogenic impacts on the global water cycle.

Keywords: Reservoir operation, human impacts. river routing scheme, lake water dynamics, radar altimetry, terrestrial water storage, GRACE

Highlights:

1. Computational models are used to quantify human impacts on Lake Victoria dynamics
2. Dam operation raised lake water elevation by ~7m and averaged water storage by 20%
3. Averaged water extent increased by 9%, flooding an additional ~8000km^2
4. Dam operation largely dominates basin-wide terrestrial water storage (TWS)
5. Lake Victoria contributes 64% of basin-wide TWS variability

1. Introduction

In the past several decades, more than 50,000 dams have been constructed globally (ICOLD, 2007), regulating more than half of the world's large river systems (Nilsson, 2005). Such a dam construction booming is mainly driven by an increased demand for electric power, water and infrastructure, as a result of population growth and socio-economic development. The downside of dam construction on natural wetlands and biodiversity are enormous and includes declined ecosystem health caused by flow variability, poor water quality, and disruption of migration routes for fish and other higher order consumers (Bunn et al., 2006; Wu et al., 2019). River impoundments also impact land-atmosphere interactions by increasing evaporation rates from extended water surfaces and changing the local and regional climate (Degu et al., 2011; Hossain et al., 2012; Pokhrel et al., 2012), and promote an increase in greenhouse gas (e.g., methane and carbon dioxide) emission from immerged organic matter (Deemer et al., 2016). Indeed, understanding and quantifying the impacts of river impoundments and reservoir operation on the global water cycle is crucial from a resource planning and management standpoint.

In Africa, the deleterious impacts of climate change on water availability in lakes, rivers, and reservoirs hamper economic development, contributing to increased poverty, famine, and intense social-cultural conflicts arising from droughts and competition in limited shared transboundary water resources (Agutu et al., 2017; Ndehedehe et al., 2020). As with other global freshwater ecosystems, the considerable variability in climatic conditions will impact the water storage in African lakes and rivers. For instance, extreme droughts in West and East Africa have negative impacts on water storage changes in lakes and their ecosystems (Awange et al., 2008a; Ndehedehe, 2019; Ndehedehe et al., 2016). Such impacts will arguably affect aquatic biodiversity and food security. With the rise in human population in Africa, the largely agrarian communities in the continent will be more vulnerable to water availability and extreme climate conditions (e.g., droughts) in the immediate future. Given that several African lakes and reservoirs have strong economic potential as they are largely dedicated income-generating hydropower schemes, climate-induced variations and extreme droughts are expected to cause disparity in the level of national income amidst other social challenges (e.g., limited power supply and migration). Indeed, the specific contribution of surface water resources in Africa to social and economic development and food security cannot be over-emphasized. While more

than 60 million people rely on freshwater fisheries for their livelihood in emerging economies, reservoir fisheries in Africa contribute about 15,000 tons (10%) to the overall inland fishery consumed in the continent (Abobi and Wolff, 2019). Impacts of climate variations on surface water hydrology may disrupt the global food production chain, particularly to regions depending on African resources.

Lake Victoria, located in Eastern Africa, is the world's second largest freshwater lake, after Lake Superior in the U.S., and the largest lake in Africa, spanning ~66,600km^2 over Uganda, Tanzania and Kenya. The Lake Victoria basin is a major source of the Nile River, draining an area of approximately 262,900km^2, and plays a key role in the socio-economical sustainability of the region, economically supporting over 400 million inhabitants and supplying major urban centers with water. From an ecological stand point, Lake Victoria has experienced profound ecological degradation. This is evident in the probable extinction of more than 500 different species of endemic cichlid fishes (Verschuren et al., 2002). Apart from the significant impact of land use on freshwater biodiversity of the region, an average loss of 10.8% in species richness has recently been reported (Soesbergen et al., 2019). With the projected negative impacts of limited and highly variable freshwater resources induced by climate change and rising population on per capita food production in East Africa (Agutu et al., 2019), long-term monitoring is therefore crucial to understand the complexity of ongoing ecosystem changes and the impact climate and human disturbance on the lake's hydrology.

Since 1954, Lake Victoria has been controlled by the Nalubaale hydropower dam, located at its only outlet on the White Nile River (see Figure 1b), providing an estimated 90% of Uganda's hydropower, and a significant fraction for Burundi and Rwanda. Fully understanding the Lake's water dynamics is fundamental, in view of its aforementioned socio-economic importance, in addition to its role in modulating the regional climate and possible impacts of recurring climate patterns, such as the El-Niño/Southern Oscillation and the Indian Ocean Dipole (Awange et al., 2013). Earlier studies provide an overview of Lake Victoria's hydrology (Piper et al., 1986; Yin and Nicholson, 1998), indicating that the attempts to reproduce its water budget and water level change from observed precipitation at a limited number of gauge stations and evapotranspiration estimates generally resulted in water imbalances. Although case-specific studies within a global context demonstrate the susceptibility of surface water hydrology to climate change (Arnell et

al., 1990; Awange et al., 2008a; Oyebande, 2001), a rise in water demand due to industrialization, population pressure, and urbanization is obviously inevitable. The integration of science with sustainable reservoir operation strategy is therefore required as part of an integrated approach to water management and future development of water infrastructures.

Nevertheless, progress in remote sensing techniques has allowed a better understanding of Lake Victoria's water balance and dynamics by correlating available multi-satellite estimates of gravimetry-based terrestrial water storage (TWS) anomalies, radar altimetry-based water level change and other hydrological variables, such as precipitation and evapotranspiration (Awange et al., 2008b; Khaki and Awange, 2019; Longuevergne et al., 2013). On the other hand, satellite-based water balance estimates present two disadvantages: (i) due to the unavailability of satellite data in the pre-dam construction era, one cannot isolate the impacts of dam operation on the lake's water storage dynamics and contributions to the water storage variability in the region; (ii) satellite-based water balance estimates often result in residuals (i.e., water imbalance) due to their multi-sensor nature. Such limitations can be resolved through numerical modeling, since they preserve the water balance and allow us to build scenarios under specific natural events and those impacted by anthropogenic activities. The current state of literature suggests that an evaluation of dam operation impacts on Lake Victoria's water storage and flux dynamics has not been performed. Studies evaluating global scale human activity impacts mostly focus on streamflow, neglecting other hydrological variables (Döll et al., 2009; Haddeland et al., 2006; Hanasaki et al., 2006; Yassin et al., 2019) and the majority neglects the Nalubaale hydropower dam. In a global scale analysis using a hydrological model, Döll et al. (2009) found that regulating Lake Victoria increases low flows, as a result of a temporal streamflow homogenization allowing for hydropower production, flood protection or water supply.

A recent study has demonstrated that surface water storage (SWS) is a major component of TWS variability in the tropics, along major rivers flowing over arid regions, and at high altitudes and latitudes, in particular, over the Amazon and Nile River basins, accounting for ~28% of TWS (Getirana et al., 2017a). In that study, however, global hydrological processes were represented in the absence of river impoundments. Such limitations, as highlighted in their work, restricts the appropriate simulation of the global water cycle and a proper decomposition of TWS components, generally defined in modeling systems as the summation of SWS, soil moisture,

groundwater, snow water equivalent and canopy water interception. In this sense, their results might have been negatively impacted by the absence of such key processes, in particular, large controlled lakes and reservoirs. Although progress has been made towards an improved numerical representation of such anthropogenic impacts on the global water cycle in the past two decades (Döll et al., 2009; Haddeland et al., 2006; Hanasaki et al., 2006; Meigh et al., 1999; Yassin et al., 2019), most of these studies are limited to quantifying reservoir operation impacts on river flow through simplified methods neglecting both backwater effects and spatiotemporal water storage variability. That said, a global modeling system that takes into account both natural and anthropogenic processes in a physically-based manner is highly needed and required for optimizing monitoring frameworks of freshwater systems.

As mentioned above, TWS changes within the Lake Victoria basin are attributed to climatological conditions (Awange et al., 2013). While this is a reasonable explanation for inter-seasonal variabilities and long-term trends, our hypothesis is that dam operation also plays a synergetic role on TWS variability in the region. In this sense, our goal is to combine state-of-the-art computational models and a proposed satellite-based reservoir operation scheme in order to understand and quantify the impact of dam operation on Lake Victoria's water dynamics. In our modeling system, lake water elevation, observed by radar altimeters onboard satellites, is used to inform a large-scale hydrodynamic model on the amount of water that should be stored or released over time, as a proxy of dam operation practices. Numerous studies found in the literature focus on the development of satellite-based reservoir monitoring techniques (e.g., Chen et al., 2014; Gao et al., 2012; Getirana et al., 2018; Kim et al., 2020; Okeowo et al., 2017; Van Den Hoek et al., 2019). These techniques mostly focus on reservoir water level, extent and storage. Reservoir outflow can be obtained by combining hydrological model outputs or ground-based observations with satellite data (e.g., Hossain et al., 2014). Other approaches are based on empirical equations or water management models coupled with hydrological models (e.g., Döll et al., 2009; Haddeland et al., 2006; Hanasaki et al., 2006; Mateo et al., 2014; Michailovsky and Bauer-Gottwein, 2014; Shin et al., 2019; Zhao et al., 2016). Hydrological models and reservoir operation schemes proposed in these studies vary in their complexities in representing physical processes and human intervention. The proposed reservoir operation scheme is an improvement on those in current literature because it is simultaneously (1) fully based on satellite data, not requiring ground-based or empirical operation rule information and (2) fully coupled with a river

routing scheme based on the local inertia formulation, allowing a dynamic spatial and temporal representation of water storage, extent and depth of the lake, in addition to its outflow. Reservoir operation schemes proposed by Mateo et al. (2014) and Shin et al. (2019) are similar to that presented here in the sense that they represent backwater effects and the inertia of large water mass of deep flow through the local iertia formulation (Bates et al., 2010). However, such approaches require outflow estimates derived from empirical equations and could result in innacurate representations of the water storage and flux dynamics of reservoirs. Using radar altimetry data as a proxy for reservoir operations minimizes errors added to the modeling system, in particular over large water bodies where altimetric accuracy is relatively high.

2. Modeling framework

The modeling framework was designed for the Lake Victoria basin using the NASA Land Information System (LIS; Kumar et al., 2006). The Noah Multi-Physics (Noah-MP; Niu et al., 2011; Yang et al., 2011) land surface model (LSM) and the Hydrological Modeling and Analysis Platform (HyMAP; Getirana et al., 2012, 2017b) hydrodynamic model are coupled within LIS in order to represent the hydrological processes within the basin. Noah-MP and HyMAP are one-way coupled, which means that, at each time step, gridded surface runoff and baseflow simulated by Noah-MP are transferred to HyMAP and used to simulate spatially continuous surface water dynamics, but no information is returned from HyMAP to Noah-MP. The proposed satellite-based reservoir operation scheme is coupled with HyMAP in order to represent the anthropogenic impacts on the lake water dynamics. Figure 2 shows a flow chart of the modeling system, where a naturalized system scenario is represented by coupling Noah-MP and HyMAP, and the reservoir operation scenario includes the reservoir operation features, shown in red. Model parameters were processed using the Land surface Data Toolkit (LDT; Arsenault et al., 2018a). The models, as well as the experimental design, are described below.

HyMAP

HyMAP is a state-of-the-art global scale hydrodynamic model capable of simulating surfacee water dynamics, including both stage and discharge in-stream, as well as floodplain inundation. HyMAP uses the local inertia formulation (Bates et al., 2010; Getirana et al., 2017b), accounting for a more stable and computationally efficient representation of river flow diffusiveness, which

is essential for a physically-based representation of wetlands, floodplains, tidal effects and impoundments. The Courant–Freidrichs–Levy (CFL) condition is used to determine HyMAP's optimal sub time steps for numerical stability. Rivers and floodplains interact laterally and have independent flow dynamics, with roughness and geometry derived from land cover characteristics, topography and river parameterization (Getirana et al., 2013, 2012). Hypsographic curves, i.e., the relationship between water elevation (H) and storage (S) are derived from the available topographic information. The H×S relationship is derived for each grid cell from a pre-processing step where high resolution topography is upscaled to the model spatial resolution. HyMAP has been extensively evaluated in the Amazon basin (Getirana et al., 2013; Getirana and Peters-Lidard, 2013) and successfully applied over North America (Kumar et al., 2019, 2016), Africa (Jung et al., 2017; McNally et al., 2019), the Middle East (Getirana et al., 2015), and globally (Getirana et al., 2017a).

In this study, HyMAP parameters at 0.1 degrees were derived from the Multi-Error-Removed Improved-Terrain (MERIT; Yamazaki et al., 2017) digital elevation model (DEM) at 3-arcsec spatial resolution. Over the Lake Victoria basin, the MERIT DEM is based on the NASA Shuttle Radar Topography Mission (SRTM; Farr et al., 2007) processed with successive correction of absolute bias, stripe noise, speckle noise, and tree height bias from using multiple satellite data sets and filtering techniques. As a result, the MERIT DEM provides a more reliable representation of floodplains and wetlands. A ground-based bathymetry was used to correct the DEM in order to more accurately represent the lake water elevation, extent, storage and dynamics. The 3-arcsec spatial resolution bathymetry was generated by applying an ordinary kriging interpolation to ~4 million points collected by the Lake Victoria Regional Hydro-acoustics Working Group (Hamilton et al., 2016) and is available in the Africa Lambert Conformal Conic projection. The bathymetric depths were converted to the EGM96 geoid elevation based on the reference height of 1137.77m on the Lake Victoria shoreline, matching MERIT's vertical datum. The converted elevation values were used to replace DEM pixels within Lake Victoria. Cross-sectional profiles of the lake with both original and corrected DEMs are shown in Figure 1c. Based on this bathymetric dataset, the lake's maximum depth is, approximately, 80.77m. The topography used to generate the hypsographic curves results from the combination of the observed bathymetry and MERIT.

Reservoir operation scheme

A satellite-based reservoir operation scheme was designed to integrate radar altimetry data into HyMAP as a proxy of the reservoir operation rules. Figure 3a illustrates two ways hydrological models can represent a river reach in the presence of a dam: first, the naturalized system, neglecting human activities (i.e., absence of a dam); second, for not being a natural process, the hydrological model needs to be informed about the dam operation through a reservoir operation module. Using a satellite-based reservoir operation scheme, altimetric data can inform models on the actual reservoir water levels, which, in turn, combined with a DEM-based floodplain elevation profile, can be coonverted into the actual reservoir water storage (or satellite-based storage, S') through the hypsographic curve ($H \times S$). The proposed approach represents reservoir operations as follows: once identified the grid cell *i* where the dam is located, the observed water elevation (H_{obs}) at time step *t* is determined by a temporal linear interpolation of available radar altimetry observations. At the end of *t*, after HyMAP simulates the naturalized downstream elevation (H_o), outflow (Q_o) and storage (S), the differential water storage dS needed to fill or empty *i* is determined by subtracting S from the satellite-based storage derived from the combination of H_{obs} with the hypsographic curve. Then, the following rule is applied in order to obtain the updated water storage (S'), elevation (H'_o) and outflow (Q'_o) at grid cell *i* and time step *t*:

$$if (Q_o - Q_{min})dt \geq dS \qquad (1)$$

$$S' = S + dS$$

$$Q'_o = Q_o - (dS/dt)$$

$$H'_o = H_{obs}$$

$$if (Q_o - Q_{min})dt < dS \qquad (2)$$

$$S' = S + (Q_o - Q_{min})dt$$

$$Q'_o = Q_{min}$$

$$H'_o = f[S', (H \times S)]$$

where *dt* stands for the time step interval and Q_{min} is the minimum reservoir outflow, which was defined here as zero, due to data unavailability. Figure 3b illustrates how rules defined in Equations (1) and (2) impact water storage and fluxes within a grid cell controlled by a dam.

Using the local inertia formulation, water elevation, storage, and flow in upstream grid cells will be backwatered in the following time steps, reproducing the temporally continuous and spatially distributed dynamics of the reservoir. Satellite-based water elevation time series for Lake Victoria is available from the Hydroweb database (http://hydroweb.theia-land.fr). It is composed of data derived from multiple sensors (e.g., Topex-Poseidon, Jason series, Envisat, GEOSTAT Follow-On, Saral and Sentinel 3A) spanning 1992 to present and corrected to solid Earth tide, pole tide and ionospheric delay, resulting in an estimated accuracy of 2-3cm over large lakes (Crétaux et al., 2011). The dataset is available on the GGMO2C geoid (Tapley et al., 2005) and was converted to EGM96 to match the vertical datum of the other datasets. Because of its multi-sensor composition, time intervals vary over time, from one to 30 days. The full 1992-2019 radar altimetry record is provided in Figure 1d.

Noah-MP

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

Forcings

In order to take into account the uncertainty introduced by meteorological datasets used to force Noah-MP, our modeling system was forced with four datasets: the NASA's Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2, or simply M2; Reichle et al., 2017), spanning 1980 to present; the NCEP's Global Data Assimilation System (GDAS; Derber et al., 1991; Kalnay et al., 1990), available from 2000 to present; and global, operational analysis products from the European Center for Medium-range Weather Forecast (ECMWF; Molteni et al., 1996), available from 2003 to present; an additional dataset was generated by replacing M2 precipitation fields with precipitation from the Climate Hazards group InfraRed Precipitation with Stations version 2.0 (CHIRPSv2; Funk et al., 2015), named here MERRA-2 + CHIRPSv2 (M2C). The reason for combining MERRA-2 with CHIRPSv2 is to reproduce the meteorological dataset used to force the Famine Early Warning System Network (FEWS NET) Land Data Assimilation System (FLDAS; McNally et al., 2017). CHIRPSv2 has been widely used in monitoring water availability and forecast in Africa (Getirana et al., 2020a; Jung et al., 2017; McNally et al., 2019; Shukla et al., 2019).

Experimental design

In order to quantify the impacts related to the Nalubaale hydropower dam operation on Lake Victoria's water storage and fluxes, two experiments were designed based on the proposed modeling system (see Figure 2): (i) a naturalized system, i.e., a hypothetical scenario where the lake is not controlled by a dam, and (ii) reservoir operation, a scenario representing the existing system where the lake is controlled by the dam. Experiments were run for 17 years, from 2003 to 2019, where all meteorological datasets overlap, on a 15-min time step (or shorter in HYMAP, with time steps automatically adjusted by the CFL condition) and 0.1-degree spatial resolution. The spatial and temporal resolutions adopted here are sufficiently fine to represent large-scale physical processes of interest and have been widely used in the literature (e.g., Arsenault et al., 2018b; Mateo et al., 2014). Experiments were repeated using the four meteorological datasets, totaling eight model runs, and spun up for 100 years, allowing the models' water storage components to stabilize.

Evaluation procedure

The evaluation was performed using the median of the 4-member ensemble of each experiment. Model outputs were quantitatively evaluated against satellite-based observations of water elevation, water extent and TWS variability. A quantitative streamflow evaluation was unfeasible due to the unavailability of recent observations over the region. To make up for this, we conducted a qualitative evaluation of dam operation impacts on lake outflows. The impact of reservoir operation on TWS variability was evaluated against TWS anomalies derived from the Gravity Recovery and Climate Experiment (GRACE; Tapley et al., 2004) and GRACE Follow On (GRACE-FO) missions. We used the monthly 0.25-degree gridded Mascon solution Version RL06 processed by the University of Texas at Austin's Center for Space Research (CSR; Save et al., 2016). GRACE and GRACE-FO data is available from April-2002 to August-2019 with an 11-month inter-mission gap between July-2017 and May-2018. Even though the CSR GRACE mascons are natively estimated at 120-km wide mascon blocks and resampled to finer grids, the actual resolution of its solution is about 250–300 km along the equator. Mascon-based products have been shown to have a somewhat higher signal-to-noise ratio and reduced errors than products based on spherical harmonics (Rowlands et al., 2010; Save et al., 2016). Simulated water extent was evaluated against monthly Landsat-based water extent time series. Water extent information was obtained following the technique presented in Van Den Hoek et al. (2019) processing all available Landsat surface reflectance imagery from 2000-2019 over Lake Victoria. The Modified Normal Water Difference Index (MNDWI; Xu, 2006) is computed for 4,837 images over 16 Landsat WRS-2 path-rows after cross-calibration and removal of cloud and cloud shadows. Pixel-level cloud masking was performed using CFMask (Version 3.3.1), a commonly used cloud and cloud shadow detection algorithm with approximately 90% accuracy (Foga et al., 2017). A MNDWI threshold of 0.1 was used to classify 'water' in each image, and monthly composites were generated by mosaicking water/non-water maps within a given month. To address missing data in a monthly water map due to persistent clouds and cloud shadows, we performed an additional infill based on historic water frequency maps.

Simulated water elevation, water extent and TWS time series were evaluated using the root mean square error (RMSE), the Nash-Sutcliffe (NS) coefficient, correlation (r) and standard deviation ratio (γ), also called variability ratio, between simulation (s) and observation (o). RMSE, NS and γ are defined as follows:

$$\mathrm{RMSE} = \left[\frac{\sum_{t=1}^{nt}(s_t - o_t)^2}{nt}\right]^{1/2} \quad (3)$$

$$NS = 1 - \frac{\sum_{t=1}^{nt}(o_t - s_t)^2}{\sum_{t=1}^{nt}(o_t - \bar{o})^2} \quad (4)$$

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

where *t* is the time step in months, *nt* the period length, $\bar{o}$ the mean value of the observations and σ the standard deviation of TWS time series. RMSE ranges from zero to ∞, where zero is the optimal case. NS ranges from –∞ to 1, where 1 is the optimal case, while zero means that simulations represent observed signals as well as the average of observations. γ ranges from zero to ∞, where 1 means that simulated and observed time series have identical variabilities. *r* ranges from -1 to 1, where 1 is the optimal case.

The spatially-distributed impact of each water storage component on TWS was determined by applying the impact index *I* (Getirana et al., 2017a). *I* is defined as a function of each water storage component contribution (*C)* to TWS. *C* is defined as the sum of absolute monthly anomaly values:

$$C_i = \sum_{t=1}^{nt}\left|S_{i,t} - \bar{S}_i\right| \quad (6)$$

$$I_i = \frac{C_i}{\sum_{i=1}^{nc} C_i} \quad (7)$$

where *i* is the index of water storage components, and *nc*=3, corresponding to the three water storage components (*S*) considered here: surface water storage, groundwater and soil moisture. Snowfall is zero in the Lake Victoria basin and canopy interception is negligible (Getirana et al., 2017a). The sum of all I_i equals one.

3. Results

Water fluxes within the Lake Victoria basin

Precipitation shows a wide variation at the basin scale among selected meteorological datasets, with temporally averaged values varying from 2.9mm/day (ECMWF) to 5mm/day (GDAS). The median value for all four datasets is 3.4mm/day, which is very close to both M2 and M2C

averages, which are composed of reanalysis (M2) and merged satellite and ground-based observations (CHIRPSv2, used in M2C). Such a difference in precipitation estimates is more pronounced between 2009 and 2019 (Figure 4a), resulting in a wide range of total runoff rates (Figure 4b), as simulated by Noah-MP, with mean GDAS-based total runoff (2mm/day) being ~3.5 times ECMWF estimates (0.6mm/day). Evapotranspiration is less impacted by precipitation estimates (Figure 4c), with mean values varying from 2.3mm/day (ECMWF) to 3mm/day (GDAS). As the total runoff is used as input in HyMAP, the wide variation of its estimates is a major source of uncertainty in simulating surface water dynamics, directly impacting streamflow simulation and lake outflow.

Surface water dynamics

Based on radar altimetry data over Lake Victoria, a steep water elevation decline is observed from 1998 to 2007, totaling a ~2.5-meter drop, and since 2007, the lake has experienced a continuous replenishment, returning to water levels observed in the late 90's. These two distinctive trends are likely due first to the extension of the Nalubaale dam and then high precipitation rates over prolonged periods of time (Awange et al., 2013, 2008b). The modeling system accurately reproduces the observed water elevation variability, nearly matching observations throughout the study period (Figure 5a). Exceptions are the underestimated elevations occurring during periods where lake water levels steeply rise, indicating that total runoff rates could be insufficient to fill the lake during these periods. In particular, ECMWF shows the poorest performance fast-filling the lake among all datasets, while GDAS matches observations during most of the period. This is consistent with the difference in total runoff rates, previously discussed. Naturalized water elevation is, on average, about seven meters below observations and, although some changes are in agreement with radar altimetry data, it shows a general disagreement in terms of both timing and amplitude (i.e., low correlation and standard deviation ratio). GDAS highly overestimates the naturalized water elevations, when compared to the ensemble median, in particular after 2007. On the other hand, ECMWF shows an overall underestimation.

Similar patterns are observed in the temporal variability of simulated water extents. Lake Victoria's ensemble median water extent time series under dam operation averages 66,400km^2, with a 470-km^2 variability, and a positive trend of ~64km^2/year over the 2003-2019 period. That

average is within previous estimates found in the literature, varying from 59,947km^2 to 68,800km^2 (Hamilton et al., 2016; Piper et al., 1986; Yin and Nicholson, 1998), and consistent with Landsat estimates (66,700km^2), which also shows a positive, but not as steep, trend (~30km^2/year), and a lower variability (33km^2). The averaged water extent under naturalized conditions is ~9% lower (60,900km^2) than Landsat estimates, with higher variability and trend.

Lake outflow

So far, results indicate that the modeling system accounting for dam operation using a satellite-based scheme is capable of accurately reproducing Lake Victoria's water dynamics. Based on outputs from both experiments, lake outflows are significantly impacted by dam operation, in terms of both timing and amplitude. As shown in Figure 3c, although long term averages of ensemble medians are similar for both experiments (1422-1482m^3/s), lake outflow under dam operation has a high variability of 1440m^3/s, which is about 3.5 times the naturalized outflow variability (401m^3/s). Low streamflow generally occurs when water elevation steeply rises, strengthening the suggestion that simulated total runoff may be insufficient to fill the lake during these periods, reducing lake outflow to zero, which is the value adopted for Q_{min}. The Global Runoff Data Centre (GRDC) makes available annual streamflow observations at Jinja for the 1946-1970 period (see Figure 6). A clear break in the time series is noted in 1962, explained by an increased precipitation over the basin (Piper et al., 1986). Using the 1962-1970 averaged streamflow observations (1390m^3/s) as 'best guess', we can conclude that long-term averages of lake outflow simulations are consistent with observations. Figure 5c also shows that GDAS highly overestimates outflow, when compared to the other meteorological datasets, which is explained by the heavier rainfall during most of the study period, while ECMWF, the lowest line in the plot, generally underestimates streamflow for opposite reasons. Our results diverge from findings presented in Döll et al. (2009), where the authors showed that controlling Lake Victoria generally increases low flows. Due to the unavailability of ground-based observations, the accuracy of these results remains inconclusive. However, as discussed above, considering that the bathymetry and satellite-based water elevations are precise enough to provide us with accurate lake water storage dynamics, divergence in lake outflows could be attributed to high uncertainty in total runoff simulations.

Terrestrial water storage variability

Under dam operation, Lake Victoria water storage is, on average, 2369km^3, corresponding to a 20% increase in lake water storage, if compared to a naturalized system (1985km^3). Using the same bathymetric dataset, Hamilton et al. (2016) suggests that Lake Victoria's water storage is 2424km^3, which is 2% higher than our estimates. This slight difference could be explained by the fact that ours is based on a 17-year average, while Hamilton's et al. is based on a static water elevation. Under the influence of the dam, the lake water storage variability was ±28km^3, with minimum (2310km^3) and maximum (2430km^3) extremes, occurring in Oct-2005 and Jun-2015, respectively (Figure 5d). Under naturalized conditions, the lake water storage variability is reduced to less than half, i.e., ±12km^3. Such an impact is reflected on the basin's surface water storage variability, which doubles under dam operation. Compared to GRACE at the basin scale, SWS variability under dam operation (SWS_{RES}), corresponds to 72% (or γ=0.72) of observed TWS variability (Figure 5e). They are also highly correlated, with r=0.89. Both the variability ratio and correlation are not as high between SWS under a naturalized system (SWS_{NAT}) and observed TWS. The variability ratio, in particular, is only 36%. As shown in Figure 5f, simulated soil moisture and groundwater combined (SM+GWS) are not as correlated with TWS observations (r=0.69) and also show a lower variability (43% of GRACE estimates). It is important to note that SM+GWS remains the same for both experiments, since models are one-way coupled. Simulated TWS_{RES}, which is obtained by combining the unbiased SWS_{RES}, SM and GWS time series, shows a high agreement with observations (Figure 5g), with low unbiased RMSE (ubRMSE=36.77mm), as well as high unbiased NS (ubNS=0.91), correlation (r=0.96) and variability ratio (γ=0.98). TWS_{RES} shows a positive trend (Δ) of 16.12mm/year during 2003-2019, which is very close to the observed trend (Δ=17.9mm/year) and a significant improvement when compared to the naturalized TWS (TWS_{NAT}) trend (Δ=8.95mm/year). TWS_{NAT} also shows a higher error, with a much higher ubRMSE (80.5mm) and lower ubNS (0.56), correlation (0.75) and variability ratio (0.69). Compared to these coefficients, including reservoir operation in the system increased accuracy in 54%, 80%, 84% and 94%, respectively.

Figure 7 shows the spatially distributed impact of each TWS component, demonstrating that SWS highly dominates TWS variability over the Lake Victoria basin. Under dam operation, the impact of spatially averaged SWS (I_{SWS}) is 0.64 (or 64% of TWS variability), which is about twice groundwater storage (I_{GWS}=0.11) and soil moisture (I_{SM}=0.25) impacts combined. I_{SWS} is

particularly dominant over the lake and major tributaries, while SM dominates TWS variability elsewhere in the basin. Under naturalized conditions (Figures 7d-f), the basin-wide I_{SWS} (0.44) is still dominant, but not as high as the scenario under dam operation.

4. Summary

Based on state-of-the-art models coupled with a proposed satellite-based reservoir operation scheme, we investigated the impacts of dam operation on the Lake Victoria water dynamics and storage variability. Our results demonstrated that surface water strongly controls freshwater water storage variability within the basin. In particular, we show that accounting for dam operation is essential for properly representing Lake Victoria's water elevation, extent and storage variability, which also has a significant impact on lake outflow and water availability in the region. The proposed satellite-based reservoir operation scheme can be useful to improve the representation of anthropogenic impacts on the global water cycle, since it does not require additional information on water use and dam operation practices.

Africa's water problems are multivariate in nature. Population increase drives water scarcity in some regions while highly variable climatic conditions restricts agricultural production because of reliance on rainfall. The impacts of drought frequency on regional income and livelihood, and the lack of field-based hydrological observations to track the various processes of interannual variability associated with drought episodes complicates these problems (Agutu et al., 2017; Ndehedehe et al., 2020). Since agriculture in Africa uses an estimated 88% of the continent's water resources (Oyebande, 2001), sustainable water resources development in the region can be perceived as part of risk-based decisions and mitigation strategies to ensure food security. While such efforts are challenged because of the increased vulnerability of the continent to the impacts of extreme droughts, climate-induced severe drying conditions in the south African-sub region triggered some management decisions that led to water supply disruption in Botswana and hydroelectric load shedding in Zambia (Siderius et al., 2018). Given the paucity of data on existing water infrastructures, the improved computational representation of reservoir operation, as demonstrated here, will have a particularly high contribution to water scarcity monitoring and early warning systems used for decision making in Africa and elsewhere (Getirana et al., 2020b; McNally et al., 2019, 2017; Sheffield et al., 2014). Integrating the proposed scheme into operational water monitoring systems lacking surface water components, such as the widely used

North American (NLDAS; Xia et al., 2012) and Global (GLDAS; Rodell et al., 2004) Land Data Assimilation Systems, will greatly benefit the scientific community and water managers, providing a more comprehensive spatial and temporal distribution of water fluxes and availability. The proposed approaches can also be adopted in climate and atmospheric modeling in order to better represent the impacts of human-induced surface water extent variability on land-atmosphere interactions, that will further impact the local and regional climate. Because of its high accuracy in representing reservoir dynamics, outputs from this approach could also be used to initialize hydrological forecasts under anthropogenic impacts. That, however, would require a real-time or near real-time altimetric data availability. Ultimately, a key outcome anticipated from this work is an improved faithfulness of climate and hydrological models and their capacity to reproduce realistic hydro-climatology and land surface conditions.

A downside of the proposed satellite-based reservoir operation scheme, however, is that it can only be used for water monitoring of past and near real time events. Forecasts and hypothetical scenarios can only be performed with actual reservoir operation rules, which could be obtained either from the operator or through empirical parameterizations based on water use (e.g. irrigation, hydropower generation, navigation, water supply) as those suggested in the literature (Döll et al., 2009; Hanasaki et al., 2006; Yassin et al., 2019). In order to overcome this limitation, the user must provide reservoir water level forecasts or estimates, which could be derived, for example, from statistical models based on long-term satellite observations. Due to the unavailability of recent observations, impacts of dam operation on outflow variability remains inconclusive. It is important to note that both models considered in this study, HyMAP and Noah-MP, are physically-based and use global parameterizations. Combined, these models are capable of explicitly representing backwater effects in surface waters, essential for a proper spatially distributed simulation of the impacts of river impoundments, and groundwater storage and variability. We acknowledge the limitations of using global scale datasets and physically based models, as opposed to customized datasets and fully calibrated models, which could result in inaccurate simulations of hydrological processes. These errors have not been considered in this study, but could have an important impact on total runoff generation and lake outflow. This means that results could be further improved with additional parameter refinement and data assimilation (Arsenault et al., 2018b; Getirana et al., 2013; Kumar et al., 2012; Nearing et al., 2016). However, using such datasets and models permits us to reproduce the procedure globally.

In this sense, next steps of this effort include expanding its application to the global scale, towards a more comprehensive inclusion of anthropogenic impacts on global surface water dynamics (Getirana et al., 2017a). That effort will highly benefit from the future Surface Water and Ocean Topography (SWOT) mission, planned to be launched in 2021, which will provide unprecedented information on surface water dynamics, including two-dimensional water level and extent time series. For example, as discussed above, lake outflows might be inaccurate due to the uncertain total runoff simulations. Using SWOT data in optimization (e.g., Brêda et al., 2019; Getirana, 2010) or data assimilation (e.g., Munier et al., 2015; Paiva et al., 2013; Pereira-Cardenal et al., 2011) schemes , the model could be informed with both lake level change and streamflow downstream the dam, improving not only the lake dynamics, but also outflow simulations.

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Figures

Figure 1: (a) Eastern Africa, (b) geographic location of Lake Victoria and the Nalubaale dam, (c) cross-sectional elevation profile in meters at 0.75°S latitude of the lake using the satellite-based topography and ground-based bathymetry, and (d) lake's radar altimetry time series, in meters, for 1992-2019. The dataset is composed of measurements from multiple sensors onboard Topex-Poseidon, Jason series, Envisat, GEOSTAT Follow-On, Saral and Sentinel 3A. In (b), the black line delineates the Lake Victoria basin and the yellow line is the cross-sectional profile. Both bathymetric and altimetric datasets are in meters [EGM96 vertical datum].

Figure 2: Flow chart of the adopted modelling system: black represents the naturalized system and red the implementation of the proposed reservoir operation scheme.

Figure 3: Visual representation of the satellite-based reservoir operation scheme within a model grid cell: (a) hypothetical river reach in a naturalized system (left) and under reservoir operation (right); and (b) rules defined in the reservoir operation scheme and its impacts on water storage and fluxes.

Figure 4: Basin-averaged monthly anomaly time series of (a) precipitation, (b) total runoff and (c) evapotranspiration rates in mm/day, as simulated by Noah-MP forced with three meteorological forcings: MERRA-2 (M2), MERRA-2 + CHIRPSv2 (M2C), ECMWF and GDAS.

Figure 5: Lake Victoria (a) daily water elevation, and monthly (b) extent, (c) outflow and (d) storage time series; basin-averaged monthly time series of (e) surface water storage (SWS), (f) combined soil moisture and groundwater (SM+GWS), and (g) terrestrial water storage (TWS). Results are provided for two experiments: reservoir operation (Reservoir) and naturalized system (Natural). Light colored lines represent model runs using different meteorological datasets, dark colored lines represent ensemble medians, and black dots stand for satellite-based observations. Lake elevation, water extent and TWS observations are derived from radar altimeters, Landsat and GRACE, respectively. Metrics are provided for the ensemble median over 2003-2019. Units differ for each variable, as informed in the boxes.

Figure 6: Annual Lake Victoria outflow [m^3/s], at Jinja, in the White Nile River. Red lines are long-term averages for the 1946-1962 and 1962-1970 periods.

Figure 7: Spatially distributed impacts of (a,d) surface water storage (SWS), (b,e) soil moisture (SM) and (c,f) groundwater storage (GWS) on terrestrial water storage (TWS) variability under reservoir operation (Reservoir) and naturalized system (Natural).

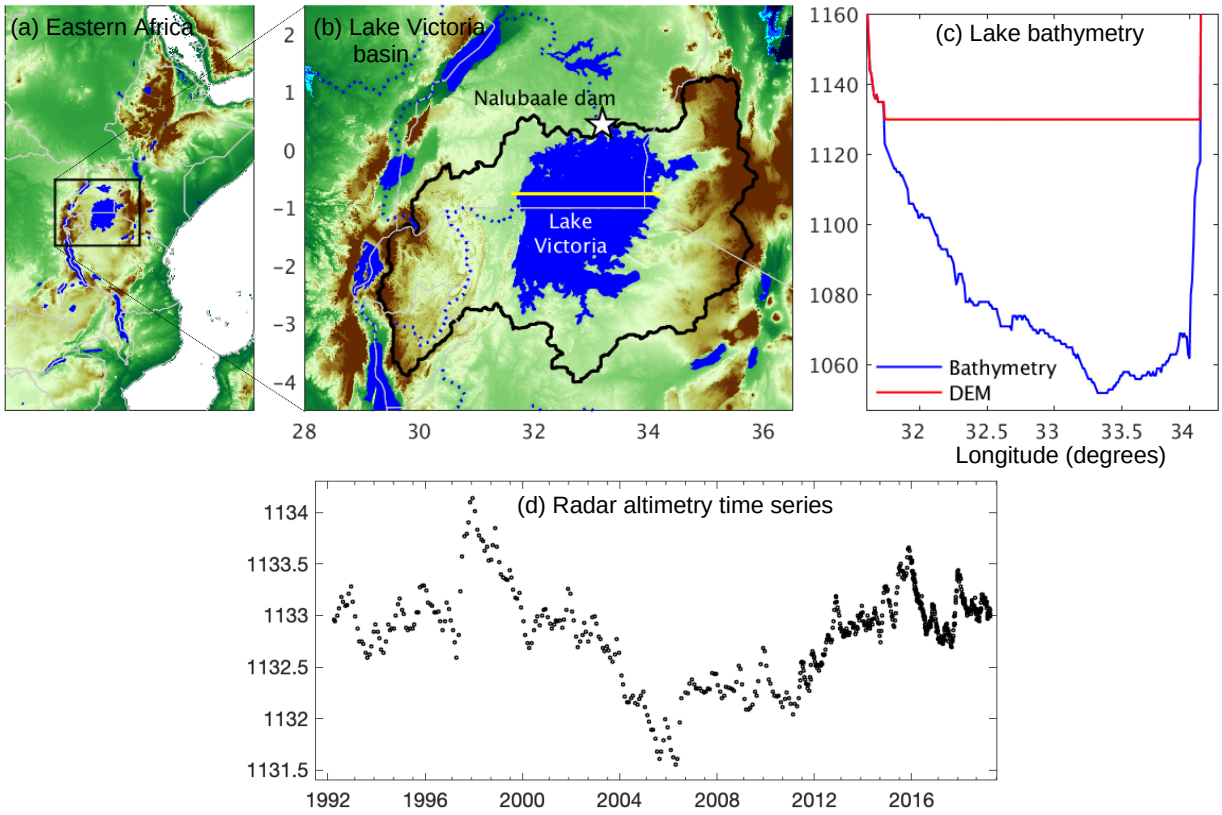


Fig. 1

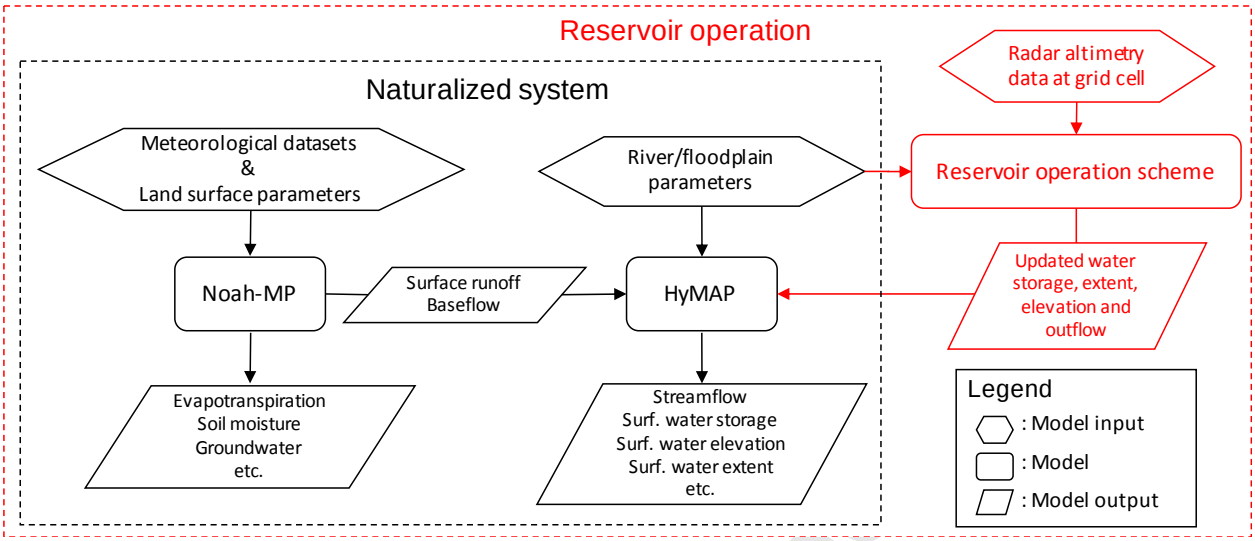
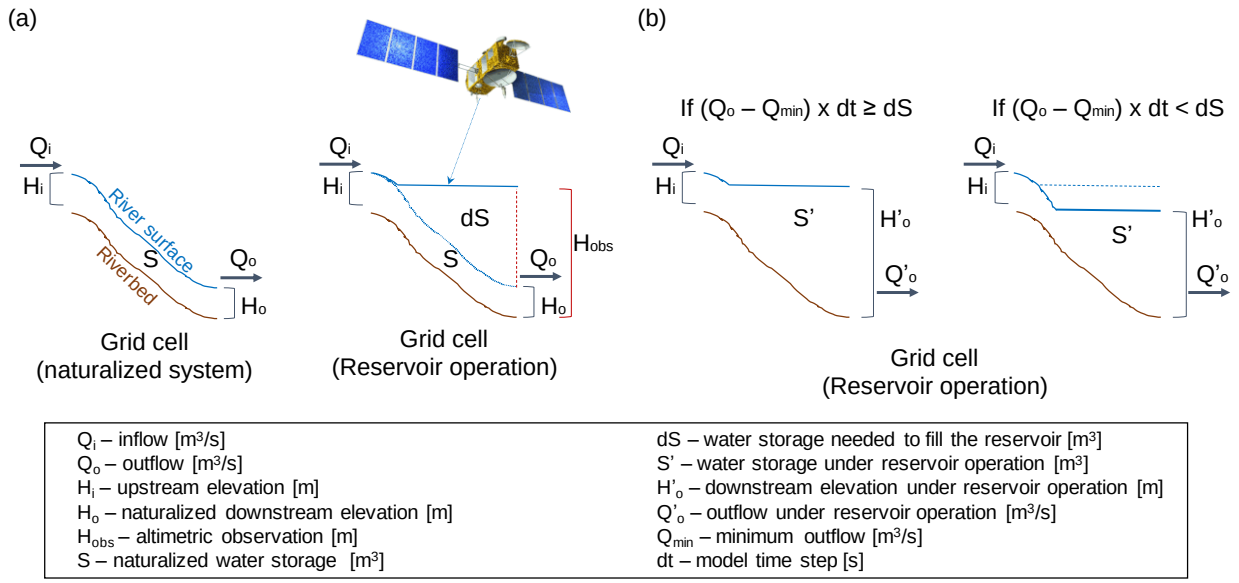


Fig. 2



Q_i – inflow [m^3/s]	dS – water storage needed to fill the reservoir [m^3]
Q_o – outflow [m^3/s]	S' – water storage under reservoir operation [m^3]
H_i – upstream elevation [m]	H'_o – downstream elevation under reservoir operation [m]
H_o – naturalized downstream elevation [m]	Q'_o – outflow under reservoir operation [m^3/s]
H_{obs} – altimetric observation [m]	Q_{min} – minimum outflow [m^3/s]
S – naturalized water storage [m^3]	dt – model time step [s]

Fig. 3

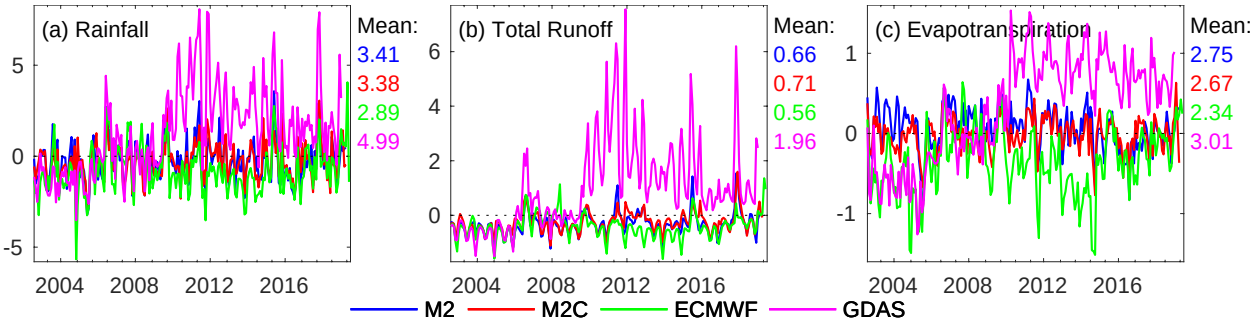


Fig. 4

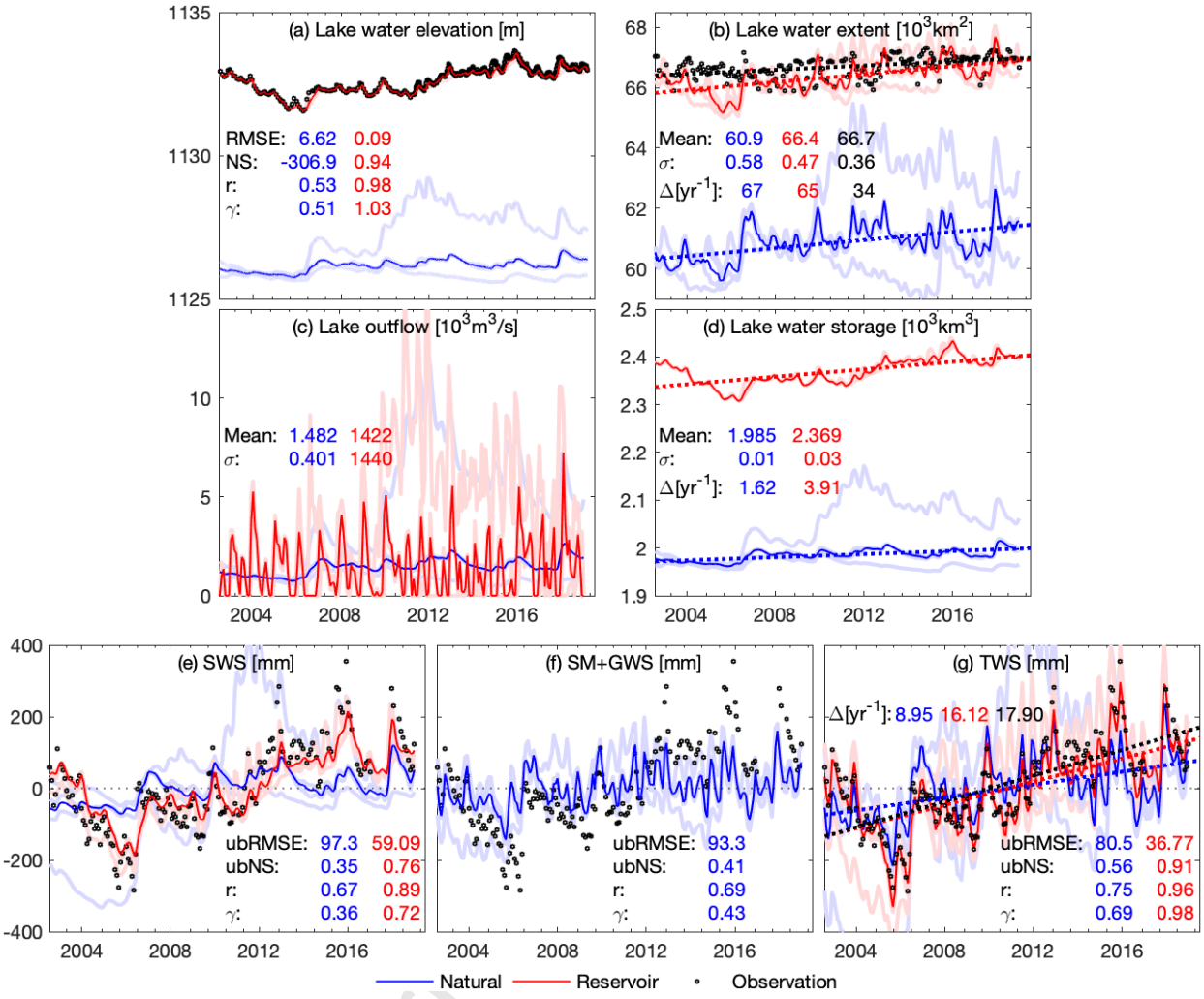

(a) Lake water elevation [m]
RMSE: 6.62 0.09
NS: -306.9 0.94
r: 0.53 0.98
γ: 0.51 1.03
(b) Lake water extent [10^3km^2]
Mean: 60.9 66.4 66.7
σ: 0.58 0.47 0.36
Δ[yr^-1]: 67 65 34
(c) Lake outflow [10^3m^3/s]
Mean: 1.482 1422
σ: 0.401 1440
(d) Lake water storage [10^3km^3]
Mean: 1.985 2.369
σ: 0.01 0.03
Δ[yr^-1]: 1.62 3.91
(e) SWS [mm]
ubRMSE: 97.3 59.09
ubNS: 0.35 0.76
r: 0.67 0.89
γ: 0.36 0.72
(f) SM+GWS [mm]
ubRMSE: 93.3
ubNS: 0.41
r: 0.69
γ: 0.43
(g) TWS [mm]
Δ[yr^-1]: 8.95 16.12 17.90
ubRMSE: 80.5 36.77
ubNS: 0.56 0.91
r: 0.75 0.96
γ: 0.69 0.98
Natural
Reservoir
Observation

Fig. 5

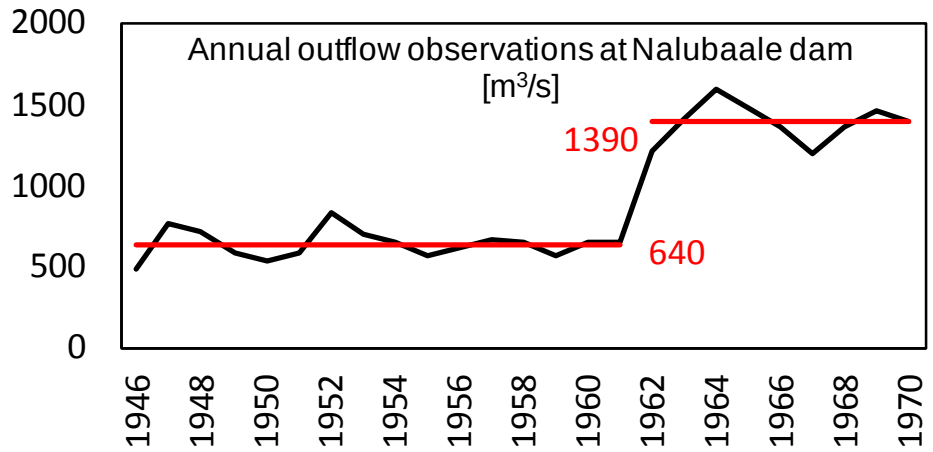


Fig. 6

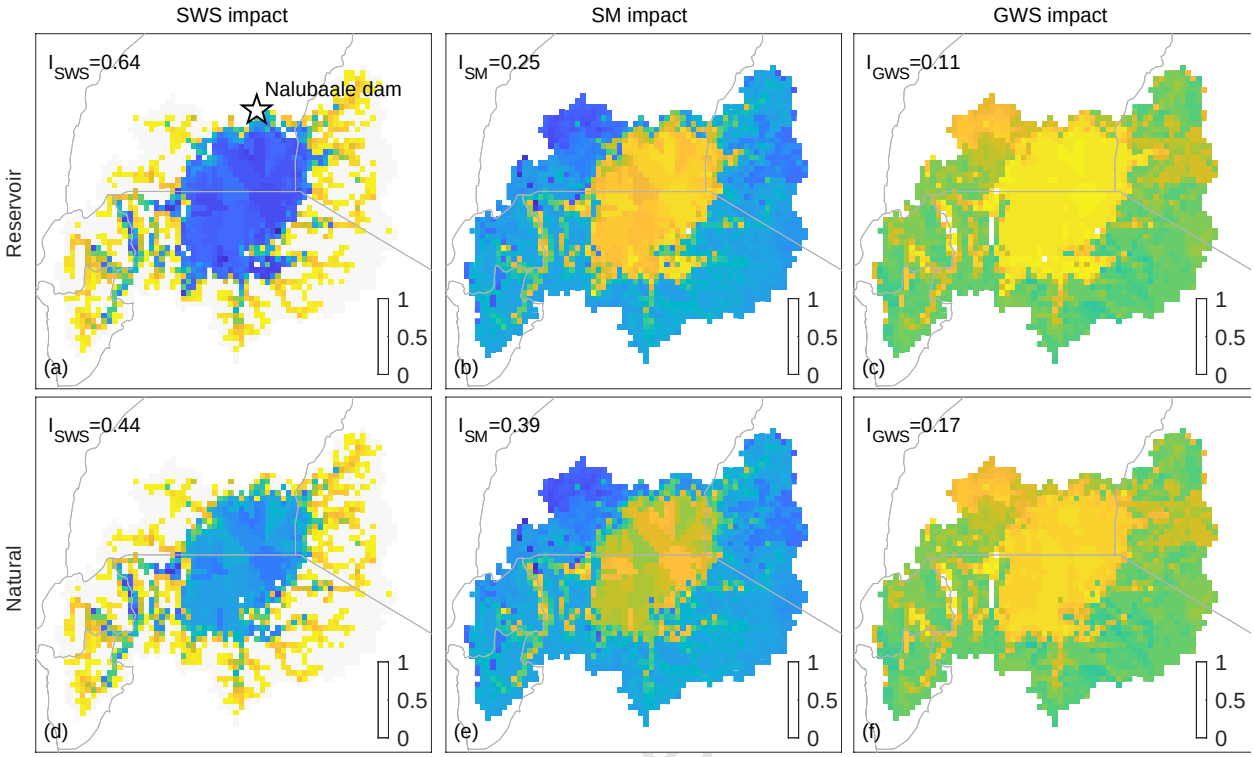


Fig. 7

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Graphical abstract