



Water Resources in Africa: The Role of Earth Observation Data and Hydrodynamic Modeling to Derive River Discharge

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Abstract

For more than a century, river discharge has been measured indirectly through observations of water level and flow velocity, but recently the number of gauging stations worldwide has decreased and the situation is particularly serious in African countries that suffer more than others from discontinuous and incomplete monitoring. As one of the most vulnerable regions in the world to extreme weather events and global warming, African countries need adequate and reliable monitoring. Decades of available Earth Observations data represent a tool complementary to the hydro-monitoring network and, in recent decades, they have demonstrated their potential, especially for data-poor regions. In this paper, a review of methods for hydrological and hydraulic modeling and for estimating river discharge by the use of satellite data, specifically radar altimetry and optical sensors, is provided, with particular focus on their role in the climate changes monitoring. More emphasis is placed on their relevance on African basins highlighting limits and advantages.

Keywords Remote sensing · Radar altimetry · Discharge · Hydrological models · African basins · Hydraulic models

Abbreviations

ADCP	Acoustic Doppler current profiler
ANN	Artificial neural network
BAM-AMHG	Bayesian at-many-stations hydraulic geometry Manning

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CC	Climate change
CCI	Climate change initiative
CNES	Centre National d'Etudes Spatiales (French Space Agency)
DEM	Digital elevation model
ENSO	El Nino Southern Oscillation
ENVISAT	Environmental satellite
EO	Earth observation
ERS	Earth remote sensing satellite
ESA	European Space Agency
GCM	Global climate model
GCOS	Global Climate Observing System
GeoSFM	Geospatial streamflow mode
GIEMS-2	Global Inundation Extent from Multi-Satellites
GR4J	Modèle du Génie rural à 4 paramètres Journalier
GRACE	Gravity recovery and climate experiment
GRDC	Global Runoff Data Center
H	Height
HBV	Hydrologiska Byråns Vattenbalansavdelning
ICESat-2	Ice, cloud and land elevation satellite-2
IND	Niger inner delta
IOD	Indian ocean dipole
Landsat	Land remote sensing satellite
LSM	Land surface model
MERIS	Medium resolution imaging spectrometer
MGB	Modelo de grandes bacias
MNDWI	Modified normalized difference water index
MODIS	MODerate resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDWI	Normalized difference water index
NIR	Near-infrared
NRT	Near real time
NSE	Nash–Sutcliffe efficiency
OLCI	Ocean and land colour instrument
P	Precipitation
Q	Discharge
RC	Rating curve
RS	Remote sensing
SAR	Synthetic aperture radar
SRTM	Shuttle radar topography mission
SWAT	Soil and water assessment tool
SWOT	Surface water and ocean topography
TMPA	TRMM multi-satellite precipitation analysis
TRMM	Tropical rainfall measuring mission
TWS	Terrestrial water storage
UKSA	United Kingdom space agency
VS	Virtual station
WL	Water level
WMO	World Meteorological Organization

Article Highlights

- African countries are vulnerable to extreme weather events and global warming, and suffer from incomplete monitoring of river discharge
- Decades of Earth Observations data represent a tool to compensate for the reduction in the hydro-monitoring network and to model physical processes
- A review of methods is provided for hydrological and hydraulic modelling, and for estimating river discharge, by using satellite data in Africa

1 Introduction

As a result of the changes observed in the climate over the years, such as rising temperatures and shifting precipitation patterns, rivers have undergone and are undergoing major changes, locally increasing the hydrological stress. The risk of catastrophic floods or droughts has increased, threatening public health, weakening economies, decreasing the quality of life in many places and interfering with ecosystems (Besada and Werner 2015). For some decades, the Global Climate Observing System (GCOS 2016) has established the importance of river flow in the hydrological cycle, considering it among the essential climate variables, due to its role in linking atmospheric, oceanic and terrestrial processes. Environmental, and especially fresh water, monitoring is therefore a key component in addressing various aspects, such as understanding continental hydrology and the water cycle, managing water supplies, assessing flood risks and hydropower generation, to name a few. For the hydro-meteorological monitoring, instruments, such as stream gauges, represent an irreplaceable resource for measuring river discharge in situ, thanks to their high quality, reliability and consistency. They remained the primary means of observation until the end of the twentieth century (Fekete et al. 2015). However, the in situ monitoring network is not evenly distributed all over the world, and some territories are better sampled than others. Moreover, with increasing modeling and sensing capacities together with local and global phenomena knowledge (Addor et al. 2020), initiatives have been launched to tackle this issue and build cooperation networks (Beven et al. 2020; Dixon et al. 2020). This uneven distribution of the in situ network is particularly flagrant in Africa, which presents a consequent deficit of gauges when compared to Northern Hemisphere territories. This is mainly due to (i) the high cost of in situ network installation and maintenance, (ii) security and political instability issues, (iii) transboundary basins, due to the lack of international cooperation agreements in many regions and (iv) lack of qualified staff able to ensure the maintenance of existing gauges or those recently installed in the frame of international programs. Hence, capacity building must be leveraged out together with any improvement of the in situ monitoring network. This is the aim of the international WMO-HYCOS program (<https://hydrohub.wmo.int/en/world-hydrological-cycle-observing-system-whykos>). The insufficient sampling of African watersheds, and more generally of watersheds on the tropical belt (GRDC 2021), is a real issue for understanding climate change (CC) impacts on freshwaters and ensuring a safe, conscient and shared use of inland waters. The advent of satellite remote sensing of surface hydrological variables has brought new complementing capabilities. Earth Observations (EO) derived from remote sensing platforms play a central role to fill the gap of ground observations (Santos da Silva et al. 2014), and allow to track the human impacts on the environment from a new perspective (Abdalla

et al. 2021). For the past two decades, hydrology in general has benefited from the succession of the different satellite missions and the extensive and temporally continuative availability of the remote sensing data. The traditional approaches have been adapted and tailored to make the most of EO data. Therefore, modern hydrology faces a major dilemma between the unprecedented availability of data with a large spatial–temporal coverage and their difficult diffusion and acceptability to users and stakeholders for use in specific applications. Regardless, it is undoubted the availability of a large number of different sensors (characterized by low to high spatial resolution and wide temporal coverage) that satellite measures can offer especially in areas with scarce measurement networks (Famiglietti et al. 2015; Papa et al. 2022, this issue). The use of satellites for the discharge assessment, especially in data-scarcity contexts, is of paramount interest not only for scientific applications but also for problems related to water resource management and flood risk prevention.

In this paper, we critically investigate the current methods for modeling and estimating river discharge, focusing on the support provided by satellite data, the main advantages to be expected from them, and the aspects related to the future roadmap even in consideration of climate changes. In particular, more emphasis is placed on their relevance on African basins highlighting difficulties and benefits.

This paper is organized as follows: Sect. 2 provides an overview on the methods used to estimate river discharge by ground and satellite observations; Sect. 3 contains a review of the river hydraulic models applied in the African basins and with the use of remote sensors. Section 4 provides some examples for investigating the dynamic of the river flow in African rivers in a context of climate change. Section 5 discusses conclusions and future perspectives.

2 River Discharge by Ground and Earth Observation: A Working Combination?

River discharge is defined as the volume of water flowing through a river channel in a unit time (cubic meter per second). For more than a century, river discharge has been indirectly estimated in rivers through ground measurements of water depth, water flow velocity and channel cross section width at different measuring points (bathymetry). Only in recent years, new techniques and approaches are involving satellite observations as a supporting tool to ground observations. In this section, an overview is given on the use of traditional in situ stream gauges and different satellite using radar and optical sensors data.

2.1 Estimation of River Discharge at In Situ Stations

In situ stations traditionally deliver daily or sub-daily estimates of river discharge at chosen locations. Such estimates are conversions of water level readings or measurements (by stream gauges or level loggers) through a previously inferred stage/discharge relationship. However, establishing a rating curve at a given cross section is not straightforward, because of: i) the possible non-univocity of the height/discharge (H/Q) relationship depending on the type of the control and morphology of the river, ii) the difficulty of retrieving H/Q pairs in extremely low and high flows, iii) the natural heterogeneity and the possible changes of the cross section shape, iv) the multiple possibilities for the mathematical formulation of the rating curve, and v) the technological changes for measuring H/Q pairs.

The hydraulic characteristics of stream channels, i.e., depth (d), width (w) and velocity (v), are measured quantitatively at ground observation stations, and these parameters vary with discharge as simple power functions at a given river cross section. Consequently, the structure primarily used for river discharge measurements is the channel cross section. The total instantaneous water flux (Q), in m^3/s or ft^3/s , through the cross section, approximated as rectangular, can be estimated using Eq. (1).

$$Q = w \cdot d \cdot v \quad (1)$$

All discharge measurements rely on this simple relation. However, in natural channels, measuring discharge remains a challenge, as the variations of w , d and v with Q are uncertain. Hence, a single discharge measurement actually comes from the discretization of the cross section into elementary stripes, where those are considered homogeneous and an integration, along the cross section, of the elementary discharges. The measurement of this discretized stripes can be made whether from current-meter or by ADCP (acoustic Doppler current profiler). While current-meters imply strong hypothesis on the distribution of horizontal velocities within the cross section, on the direction of the flow and on its steadiness during the measure, the ADCP allows a finer representation of the cross section in a shorter timeframe which ensures the stability of river discharge during the measurement (Mueller et al. 2009). Thanks to the ADCP method, unique features of rivers were revealed, as the 220 m depth and 4 m/s flow velocity in the lower Congo (Oberge et al. 2009) and it permitted the manutention of in situ rating curve on large rivers along the time.

Despite the growing need of information on surface water availability fostered by the populational increase, the number of gauges has drastically decreased worldwide in the last decades (GRDC 2021). This is also true in Africa, where the GSIM database (Do et al. 2018) accounts for more than 900 hydrometric stations before the 1960s, only half with data until the year 2000 (among which the majority is in South Africa) and only one hundred with data after 2015. This sparsity and unequal distribution over the African continent raise issues for understanding climate change impact on surface water and designing flood early warning systems or hydraulic structures. Given this rarefaction of in situ gauges, remote sensing approaches for estimating discharge have been leveraged out in the last decades. As expressed above, in a given section the discharge is a function of local hydraulic variables that can partially be measured from space. However, an attempt to leave out any of the parameters contributes to an error in the final estimate of discharge. Therefore, a satellite multi-mission approach with the capability of estimating w , d and v could be the ideal option. Yet, depending on channel properties and visibility from space, approaches based on approximations can provide accurate estimates of discharge. The accuracy requirement is also a function of the basin of interest and the purpose of the use of satellite data. Consequently, the acceptable assumptions and simplifications will vary geographically.

2.2 Hydro-Monitoring Network in Africa

Based on the recent report of GRDC (2021), the number of stations on the hydro-monitoring networks is decreasing in the recent years. If this can be a global problem, for the African countries the situation is exacerbated by the already low density of active monitoring network and by the lack of funds to maintain the hydrological services and train the technical staff (Hanna et al. 2011). However, recently, Trambly et al. (2020) collected data of 1529 stations from GRDC and SIEREM database (Dieulin et al. 2019) in a unique dataset with minimum 10 full years of daily river discharge data in the period 1950 and

2018. This represents the largest ever built database of daily discharge data in Africa, and it can be considered here as the only source of data currently available and updated over the African continent. Because the strict conditions related to the national authorities, the sharing of original and real time data is not possible (Do et al. 2018), while it is allowed to distribute hydrological indices (e.g., minimum, mean and maximum daily streamflow, baseflow magnitude, slope of flow duration curve, to cite a few), that have been collected in ADHI, African Dataset of Hydrometric Indices (Tramblay et al. 2021). These metadata can be proficiently used in the modeling of different hydrological processes or for basin classification in Africa, for example. In terms of river discharges, the stations are quite well distributed (see Fig. 1) in the West and South Africa, whereas over the Congo and Nile basins, in which the mean flows represented by circles are quite large, the gauged stations are in a limited number. Looking at the climate of African countries these stations include most of the variety of climate types. According the Köppen–Geiger classification, most of the stations, 687, are located in the west and central Africa, in the Savannah area (Aw), whereas the Sahel region and Southern Africa are included in 207 stations over the Steppe-hot (Bsh) climate zone. A number of stations is located in the temperate with dry winter classes (Cwa and Cwb) related to the southern region (187 and 125 stations) and in the Desert-hot class (Bwh) of the northern and southern boundaries of the Sahara Desert (98 stations). Mediterranean climate of north and south Africa is represented by 87 stations under a temperate climate with dry hot summer. The diversity of climates zones sampled by the in situ stations indicates that CC studies may be undertaken based on such database. However, a strong limitation to that end is the length of records. Indeed, the WMO recommends the use of a 30-year period to define climate normals, and such a long period is accessible only on a fraction of the database. Moreover, WMO also recommends that long-term CC impacts assessment is computed over the 1961–1990 period, period for which the decline of the in situ monitoring network had already begun.

In this context, EO from space can help bridge the gap between past observations and current climate and surface water availability. Furthermore, most of sensors now offers records long enough to estimate trends and perform CC studies, at the condition of being brought in a compatible manner to that of in situ measurements.

2.3 Radar Altimetry for Understanding the River Flow: Past, Current and Future Missions

To date, the most widely used technology for estimating river discharge from space is radar altimetry. Altimeters provide the water level (WL) above a certain reference (see Papa et al. 2022 for more details) that is used as in the traditional discharge monitoring, to derive river discharge through a rating curve, established by fitting a Manning's like power-law to multiple simultaneous estimates of WL and discharge. Once the rating curve is established, the water levels measured by satellite can be converted into discharge. Generally, the WL derived from radar altimetry is available at a virtual station (VS, defined as the intersection between the satellite ground track and the river) not located in correspondence of in situ discharge measurements. This implies that methods are needed to estimate discharge at the VS location on a time span that overlaps with the one of the satellites. The most straightforward method is using distributed hydrological models (see §4.1). The main advantages of satellite altimetry WL when compared to traditional in situ networks are that satellites do not see boundaries and that the observations are all made in an absolute reference system, that makes hydraulic studies possible (see §4.2). After decades of research,

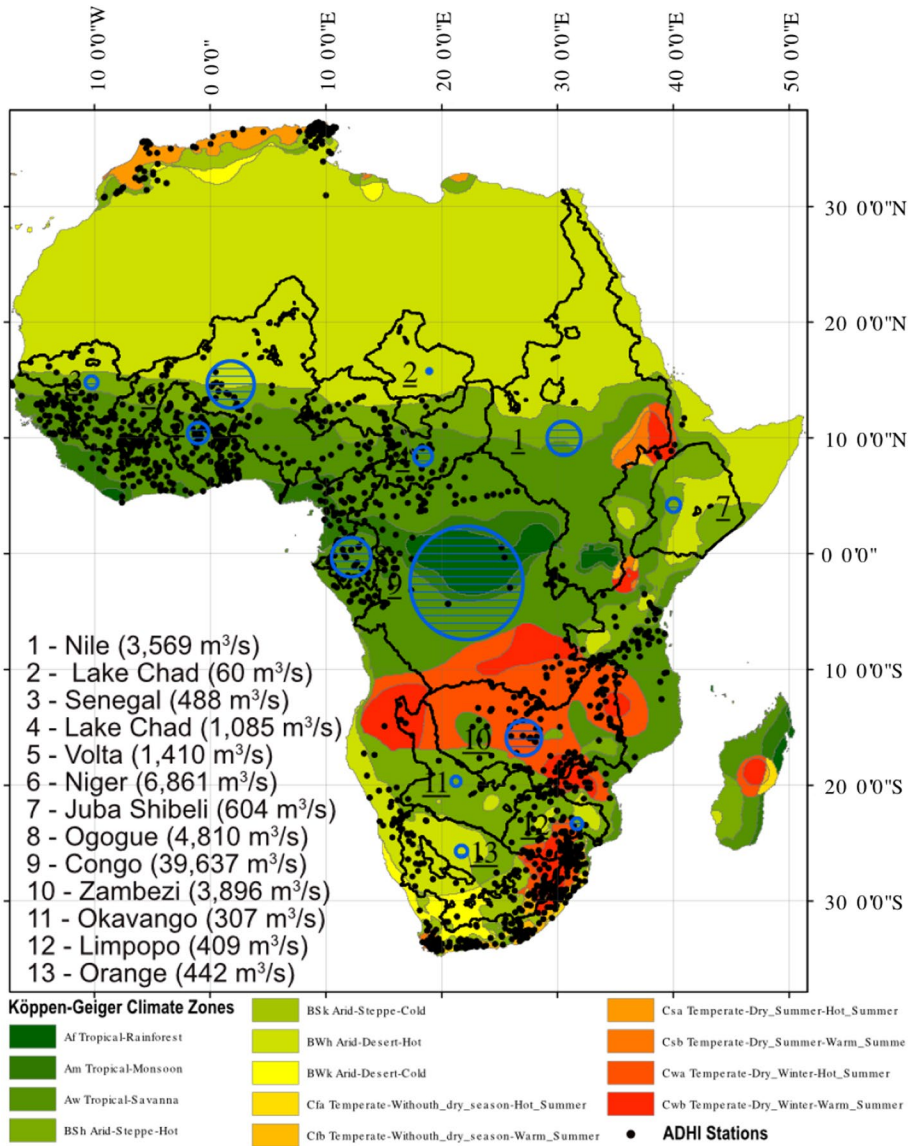


Fig. 1 Climatology of Africa according to the Köppen–Geiger climate zones classification and location of the stations included in the ADHI database (Tramblay et al., 2021). The circles represent the mean flows (reported on the left) based on HydroAtlas database (Linke et al., 2019)

the satellite altimetry constellation now entered the operational era, with ESA’s Copernicus program, with promises of long-term monitoring of inland waters from space.

WL data derived from a single mission will at best give a temporal resolution of 10 days, i.e., Jason-3, at worst 27 days (for the current flying missions). The number of VSs is also directly linked to this temporal resolution, with an inverse relationship (the shorter the revisit time, the bigger the spatial distance between each ground track, see

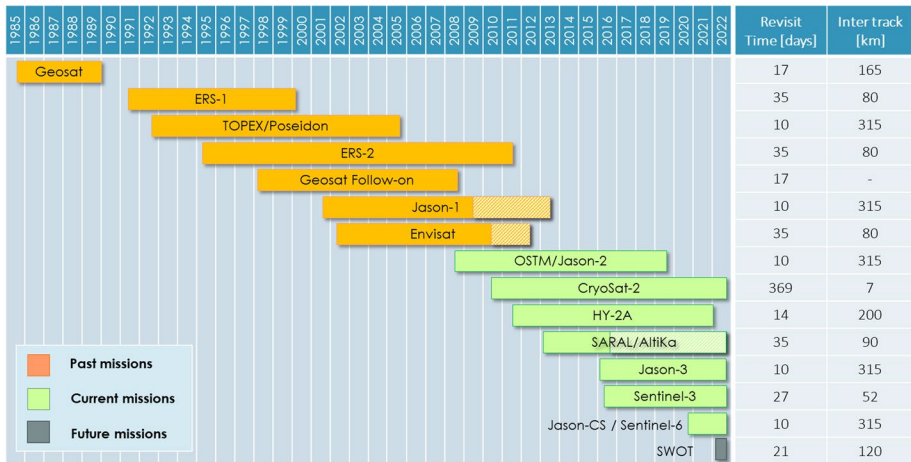


Fig. 2 Timelines for the past (in orange), present (in green) and future (for SWOT) altimetry missions. On the extreme right, the revisit time of the satellite mission and the inter track of the orbit at equator

Fig. 2). Altogether, there are now almost thirty years of WL from satellite altimetry. This forms a unique archive of observations of continental waters, even though several challenges are still to overcome (see Papa et al. 2022). An ensemble of the past, current and future altimeter missions summarized in Fig. 1 can potentially improve the temporal resolution and spatial coverage of the resultant WL data. Therefore, a multi-mission approach is key to increase the acceptability among users and the possibility of merging with in situ databases of altimetry derived river discharge. Schwatke et al. (2015) developed a method that is based on an extended outlier rejection and a Kalman filter approach that incorporates cross-calibrated multi-mission altimeter data from Envisat, ERS-2, Jason-1, Jason-2, TOPEX/Poseidon, and SARAL/AltiKa. An automated selection of raw data based on physical criteria is employed in Hydroweb (Crétaux et al. 2011; Santos da Silva et al. 2010) together with bias estimates to provide coherent multi-mission estimates of WL (mainly for Jason-2, Jason-3 and Sentinel3-A and B missions). Thanks to these methodologies, a number of studies have employed the satellite multi-mission databases to estimate river discharge (since the pioneering study in an African basin from Coe and Birkett 2004 on Lake Tchad basin, to recent ones such as Papa et al. 2010; Paris et al. 2016; Tourian et al. 2016; 2017; Bogning et al. 2018; Scherer et al. 2020; Pujol et al. 2020; Malou et al. 2021). Despite the huge contribution provided by multi-mission approaches, the combination of different altimetry measurements represents still a challenge because of the inter-satellite biases (Normandin et al. 2018) which impede a straightforward combination of water level measurements (Tourian et al. 2022). The inter-satellite bias depends not only on the mission but also on the atmospheric corrections (Fernandes et al. 2014) or the retracker algorithm (Kitambo et al. 2021), and therefore it cannot be considered global, but it needs to be estimated at regional scale. For rivers, a hydraulically and statistically merging (Tourian et al. 2016) can be considered a solution to solve the inter-satellite bias and to improve the temporal resolution even if accuracy may be compromised. In particular, the study of Tourian et al. (2016) uses auxiliary measurements of average river width and slope, within a simple empirical hydraulic equation (based on Bjerklie et al. 2003) to estimate the average flow velocity and the time lag (due to streamflow between the altimetric virtual stations and

the selected location along the river). Each measurement is shifted of the estimated time lag and stacked at the selected location. The stacked time series is normalized between the 3rd and the 85th percentiles and the outliers are removed by Student's *t* test with a monthly a sliding time window. The time series is finally rescaled according to the statistical water level distribution of the selected location.

Once dedicated to ocean monitoring, satellite altimetry is now taking the direction of continental waters monitoring, thanks to the advent of spatial hydrology. This change is materialized by the NASA/CNES/ASC/UKSA SWOT mission to be launched in late 2022, whose objective is to observe all rivers whose width exceeds 100 m (requirement, with a goal of 50 m). An intense activity is ongoing that involves researchers from different research laboratories to find methods that jointly use satellite derived water level, slope and river width for the final objective to estimate river discharge estimation also in ungauged river basins (Biancamaria et al. 2016).

Meanwhile, a number of ESA projects (FDR4ALT, Cryo-TEMPO, HYDROCOASTAL, St3TART) is aiming to re-process past missions with up-to-date algorithms and corrections and/or elaborating current missions (Sentinel-3 and Cryosat-2) focusing on inland waters to guarantee a continuous and consistent monitoring of rivers. These activities represent a valid and tangible support for non-expert altimetry users intended to employ satellite data for hydrological and hydraulic applications.

2.4 Optical and SAR Sensor Data as Tools for Supporting the River Flow Estimations

Besides the use of satellite altimetry, optical and the SAR imagery sensors can serve the purpose of detecting and measuring surface water. The use of sensors as MODIS, Landsat or Sentinel-1 and 2 is becoming more and more widespread on this topic, due to high data availability, as well as suitable spatial and temporal resolutions, increasing the number of algorithms and techniques properly developed to emphasize their quality with respect to the other source of remote measures (Huang et al. 2018).

Optical remote sensing imagery offers the possibility to easily discriminate water from land due to the lower reflectance of water, compared to that of other land cover types, in infrared channels. This simple concept has been implemented in numerous methods for extracting water areas both by using infrared band to derive a water map (Frazier and Page 2000) or through the use of water indices. The latter are calculated from two or more bands, to identify the differences between water and non-water areas, e.g., normalized difference water index NDWI (McFeeters 1996), or modified NDWI (mNDWI; Xu 2006). These indices are largely applied to extract surface water areas, flood inundation extent or width of the river. There is a well-known relationship between flow volume and inundation extent (Frazier et al. 2003; Frazier and Page 2009), and several studies have been carried out to develop empirical relationships between water extent remotely observed and ground observed river discharge (Leauthaud et al. 2013; Ogilvie et al. 2015; Overton 2005; Sagin et al. 2015; Townsend and Walsh 1998; Smith & Pavelsky 2008; Gleason and Smith 2014).

Although the combination of in situ and satellite observations is successful, river discharge estimation is critical for many sites due to the scarcity and sometime absence of gauge stations, making difficult the monitoring of surface water variation. From space, it is possible measure water levels, channel width, channel slope and flow velocity, but it is still necessary to develop accurate models or specific relationships between these variables to estimate river discharge (Bjerklie et al. 2003).

A different concept is studied by Brakenridge et al. (2005) who found a strong correlation between river discharge and MODIS band 2 (NIR band) radiance ratio, suggesting another approach for discharge estimation. Following this approach, Tarpanelli et al. (2013, 2017, 2019) extended and deepened the analysis demonstrating the big effectiveness to calculate the reflectance ratio between a land pixel, C, located near the river in an area free of surface water even during high flooding and a water pixel, M, located in the bank of the river in an area subject to liquid surface enlargement. The ratio (C/M) was employed as a sensitive and consistent measurement of surface water and has been tested for several satellite sensors, e.g., MODIS, MERIS, OLCI, Sentinel-2 (Tarpanelli et al. 2020; Sahoo et al. 2020; Hou et al. 2020; Shi et al. 2020).

The combination of remotely sensed data with in situ data has the main advantage to help water monitoring transfer from point-based to region-based. This is the case of the study of Tarpanelli et al. (2017) in Niger-Benue River in which the relationship between the reflectance ratio calculated several km upstream, allowed to accurately predict the discharge at the Makurdi station. The use of daily MODIS products guarantees a continuity suitable to address the operational activities and provides accurate results with a lead-time of four days, that is a sufficient time to warn the population and plan the evacuation of the settlements. This example is valid and reproducible only in large basins when the concentration time is longer than the lead-time.

Concerning the use of SAR imagery, a few studies investigated how the geometric variation of the flow areas or river width extracted by the SAR images can be used for estimating the river discharge (Smith et al. 1995, 1996). The concept is again built on the relationship between the physical variable (width or surface area) that changes during the high/low flows and the advantage with respect to the optical sensors, is the availability of the images also during flood peak in cloudy sky or during night time. However, the complexity of the processing does not foster the use of SAR for temporal analysis.

2.5 Multi-Sensor Approaches for River Discharge Estimation

Nowadays, the large availability of satellite data coming from several sensors represents an unprecedented opportunity to observe and monitor the rivers and hydrological processes. The characteristics of the various sensors sum to explore combined products able to observe the Earth under different aspects, e.g., improved resolutions, improved sampling frequencies, monitoring ungauged areas (Jung et al. 2013). The combination of optical and altimetry data is particularly powerful to derive useful information of river discharge. Sichangi et al. (2016) developed two simplified empirical formulas to derive river discharge by the exploitation of river width from MODIS and river stage from altimetry (Envisat and Jason-2). The analysis over 14 gauged stations from 8 major rivers resulted with the combination of both (NSE ranging between 0.60 and 0.97).

The combination of MODIS and radar altimetry is analyzed by Tarpanelli et al. (2015) and Tarpanelli et al. (2019) through two different methods based on physical and machine learning approaches, respectively. In the physical approach, the radar altimetry is used to derive water level, whereas the reflectance ratio from MODIS is used as proxies of flow velocity (Tarpanelli et al. 2020). The two variables are used in the traditional formulation of hydraulic to determine the river discharge along the Po River, making the exercise to know or not the bathymetry of the river cross section. Errors of 36% and NSE equal to 0.75 are in line with similar studies showing that the method can provide good results also in absence of bathymetry. In the machine learning approach, the MODIS and MERIS

reflectance ratio are used along with a temporal series of altimetry (ERS-2, Topex/Poseidon, Envisat, CryoSat-2 and Jason-2) to train and test two independent artificial neural networks (ANN) for the Po River (at Pontelagoscuro) and the Niger River (at Lokoja). The validation results confirm that the more sensors that are involved, the better is the obtained performance.

Different applications are carried out by Huang et al. (2018) that tested the potential of satellite sensors combination to derive river discharge in the Upper Brahmaputra River characterized by narrow river channels in the high-mountain. They extracted river width from Landsat, Sentinel-1 and Sentinel-2 (1237 images) and water level from Jason-2/3 and SARAL/AltiKa satellite altimetry and retrieved values of discharges through three different procedures: two power function equations by using single satellites and a third equation considering the combination of both. Results again confirm the higher accuracy of the combination of several hydraulic variables compared to considering single variables.

3 Complementarity of EO Datasets and Hydrological/Hydraulic Modeling for Understanding River Dynamics in Africa

As expressed before, hydrological and hydraulic models are powerful tools to i) have a basin-scale vision of freshwater availability, ii) link physical on site processes to EO datasets, iii) help managing the watersheds and iv) design mitigation solutions for future climate change impacts on continental waters. With the increasing computational capacity and availability of EO observation, the number of local and regional initiatives have exponentially grown. In this section, we illustrate the way EO datasets are being used in and/or together with hydrological and hydraulic models for the study of continental waters in Africa, especially regarding river discharge estimation, and highlight the strengths and perspectives of such tools.

A number of scientific publications, accessible to the public and research communities, have been carried-out in the last years involving both modeling and EO datasets for a better understanding of African Rivers. Figure 3 provides a geographic view of the major African basins where discharge estimates were performed using hydrological or hydraulic models and EO datasets, whether for model set-up, calibration or validation. This figure illustrates the basins where, to our best knowledge, more than two publications exist and are available in the public domain, and is not representative of all the studies led with EO datasets (in particular, several studies on flood mapping from space exist and can be found in Papa et al. 2022). The absence of publicly available studies can be related to several reasons, such as a dense in situ network and/or strongly anthropized basin (in South Africa, for example), turning EO datasets not necessary or hydrological time-scales difficult to be reached by RS observation (as for small basins with a fast hydrological response). It is also evidenced in Fig. 3 that EO datasets are most commonly used for model set-up (in that case, static datasets like DEM and Land Cover datasets are the most used) and that hydrological/hydrodynamic and hydraulic models are a versatile tool widely used for improving knowledge of African basins.

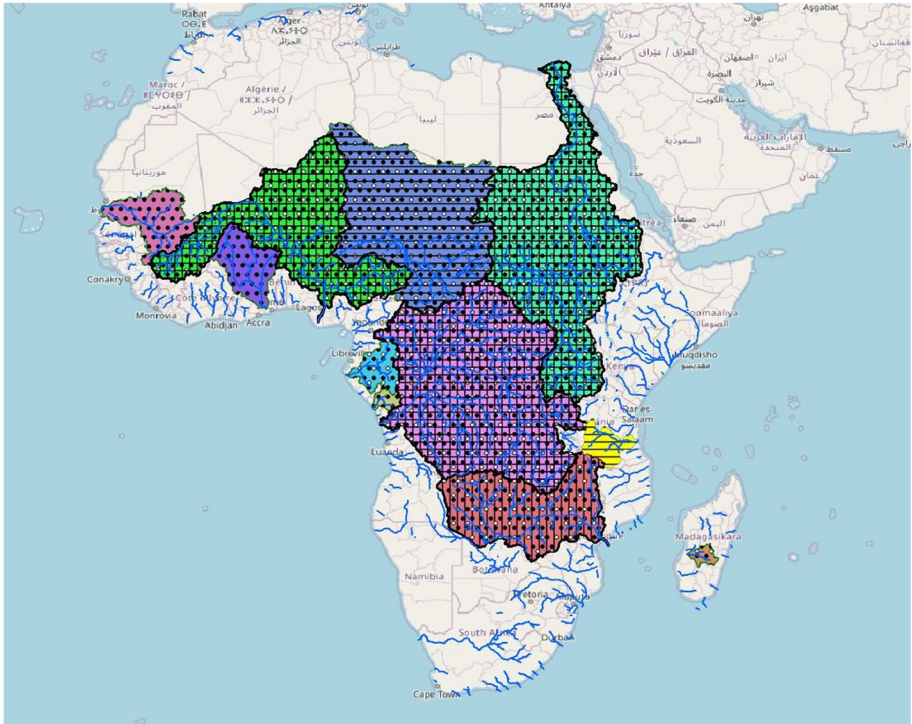


Fig. 3 Main watersheds where studies of hydrology and hydraulics modeling making use of EO datasets have been undertaken; Colored basins are those where a hydrological or hydrodynamic model was set-up using EO data; vertical black lines indicate those basins where a hydraulic modeling was employed; Black dots provide the basins where EO data were used for model set-up; white dots provide the basins where surface water observations were used; horizontal lines indicate that other RS variables have been used

3.1 On the Use of EO Datasets for Building Large Scale Hydrological Models and Deriving River Discharge

The increase of computational capacity in the last decades has fostered the use of local to large scale hydrological and hydrodynamic models for deriving river discharge in several areas of application. The range of possible applications for such models is wide, spreading from the understanding of local flood events and wetland management to transboundary water resources management. Population growth leads to an increase in water resources used, such as wetlands, lakes and rivers for agriculture, fisheries (Sakané et al. 2011; McLean et al. 2014; Leemhuis et al. 2016), transportation (Damania et al. 2016; Solomon et al. 2021) and hydropower (Falchetta et al. 2019). Adequate yet data-demanding, hydrological models allow modeling past and present behavior of surface waters, and also possible impacts of climate change on those resources. Whether physically based or conceptual-based models can be used to represent surface water flows and understand their link with climate and human activities, and EO datasets allow their application in data-scarce regions (Brocca et al. 2020; Dile et al. 2020, among others).

However, the studies on hydrological processes have been slowed down by the lack of resources and data (Hughes et al. 2015) while in the last two decades the understanding of

African watersheds has been improved thanks to the advent of RS. Climate variables (precipitation, air temperature, etc.) are now routinely derived from space and efficiently complement the lack of the traditional in situ data. As the main driver of hydrological extremes (Karamage et al. 2018), precipitation plays an important role in these new EO datasets. Satgé et al. (2020) provided an in depth analysis of 23 precipitation datasets, highlighting the importance of the very few rainfall gauges to improve RS precipitation products. Several studies have made use of those precipitation datasets for basin-scale hydrological modeling. Bodian et al. (2016) used the GR4J model to evaluate TRMM 3B42 3-hourly satellite precipitation over the upper part of the Senegal basin, with simulated hydrographs very similar to observed ones. In their study of a Malagasy river (the Tsiribihina), Andriambelosom et al. (2020) use the long term ARC2 rainfall as an input of the distributed MGB model to link past observation and present datasets. In their study, Dos Santos et al. (2022) investigated the impact of precipitation uncertainty (through the analysis of several precipitation datasets) for hydrological modeling of the Congo Basin using the SWAT model. Daily TMPA 3B42 rainfall was used in the MGB model set-up over the Niger basin by Fleischmann et al. (2018) to better understand the model's response to hydrodynamics in the Niger Inner Delta (IND). In this study, an estimate of channel width within the IND was also obtained from LANDSAT optical imagery. The aforementioned studies also used DEM (STRM) and land cover from space, such as ECOCLIMAP (Masson et al. 2003) and ESA CCI LC (ESA 2017), as ones of the model's static inputs. SRTM DEM was also used by Kwakye et al. (2020) as a basis for basin description into the conceptual HBV model. In such set-ups, EO datasets are also frequently used as a validation of model results. Hulsman et al. (2020) made joint use of satellite altimetry WL and GRACE data to constrain a distributed hydrological model in the Luangwa River basin in Zambia, one of the major tributaries of the Zambeze River. They concluded that besides their different resolution, satellite altimetry and GRACE data can be combined in order to better identify adequate parameters sets of large scale hydrological models in data scarce regions. Jung et al. (2017) used several EO datasets to investigate the accuracy of their coupled LSM-flow routing model set-up in the upper Blue Nile basin. Bader et al. (2011) built and calibrated a water balance model of Lake Tchad using satellite altimetry WL and LandSat imagery. In their studies, Munzimi et al. (2019) and Paris et al. (2022) used several EO products for set-up and calibration of two hydrological models, the GeoSFM model and the MGB model, respectively. EO datasets provided critical information that permitted better calibrations of the models. Satellite altimetry was especially used by Fleischmann et al. (2018), Bogning et al. (2021), Paris et al. (2022) and Datok et al. (2020) for means of model validation, hence filling the gap of the in situ databases. The strength of such studies is to convert discrete and localized datasets with different time resolution into daily distributed information of discharge. They provide an applicable framework for hydrological studies and for inferring hydrological state of African watersheds from space.

Beside climate change impact mitigation, the most critical aspect involving surface waters in Africa remains the day-to-day use that is made of rivers -navigation, electricity and human consumption- and the consequences of extreme events. Africa recently suffered several droughts (e.g., the 2021 global drought in eastern Africa) and floods (e.g., Niger River in 2020 and Ubangui River in 2019) that affected populations living in the surrounding of the rivers. Attempts have been made to provide simple methodologies merging hydrological models and free and open-access satellite data that could provide decision-makers intelligible and valuable information on unmonitored catchments. As pointed out by Trambauer et al. (2013) and Hawker et al. (2020), regional to continental-scale hydrological models have the potential to provide useful information for drought and flood

monitoring and even forecasting. However, continental and global models have important limitations regarding their capacity to faithfully represent local phenomena, regional ones, informed with EO data, represent a valuable alternative. The global model GLOFAS (Harrigan et al. 2020) is one of the global models used routinely to provide operation discharges all over the world. Informed with global EO datasets, it provides long term discharge time series of African rivers. However, the lack of in situ data and the uncertainty lying within satellite data still turns difficult the use of such global models for analyzing large scale trends (Harrigan et al. 2020). Some studies have been undertaken to take advantage of the recently reached—after decades of research—operational status of the last satellite altimeters Sentinel3A&B (COPERNICUS program) and Jason-CS (NASA/CNES) that promise to deliver WL observations from space in NRT and with insurance of data continuity for the upcoming decades. Based on this, tools were developed to convert EO observation into discharge in NRT, thus fulfilling some of the gaps of deficient in situ observational networks. Applying a methodology first built upon the Amazon basin experience, Bogning et al. (2021) built “altimetric stage/discharge rating curves” where the stage is WL derived from satellite altimetry and the discharge is simulated discharge from MGB model, bringing back to life the historical observation at Lambarene gauge (Ogooué River, Gabon). A similar approach was successfully applied to a smaller watershed, namely the Tsiribihina River watershed, in Madagascar. In this watershed, not monitored anymore for decades, Andriambelosom et al. (2020) managed to re-activate the monitoring thanks to RCs built from modeling and satellite altimetry. In those two basins, due to unfavorable sizes and configurations, few RCs were estimated and the re-monitoring was successful only for the downstream part of the basin. However, the configuration was different in the Congo River basin. In their study, Paris et al. (2022) successfully estimated hundreds of RCs located all over the basin. The WL time series were taken from Hydroweb, and the discharges were simulated with MGB model. Since WL are provided in NRT (i.e., few hours to days after the satellite overpasses the river), it is possible to have an estimate of discharge and equivalent depth (through the RC parameters) all over the basin in NRT. In mean, those RCs provide more than 26 observations of CRB surface water every day. Such a simple framework could be applied in all African basins suffering from a lack of observational data in order to provide a spatialized view of water resources in NRT, without the need of any model run (beside the previous one used for inferring the RCs). It could be deployed with few efforts within a simple framework and would also be a good basis for more refined methods. A proposal of workflow would be: 1) run and calibrate a hydrological model on the target watershed (on a period overlapping with the altimetry era and with some in situ data available) to obtain distributed discharges; 2) extract WSE time series from altimetry in the basin; 3) compute stage / discharge relationships everywhere. At this step, each new WSE observation provide an estimate of discharge and depth, with no need of running any model. They can even be used, for sub-watersheds with a concentration time of some days to weeks, as a basic flood early warning system. Yet, the solution can be improved when not performing well enough (see possible reasons in Paris et al. 2016), in particular with the ancillary datasets from EO as exposed above. In case of particular local problematics, the framework can be completed as shown hereafter: 1) use of other EO datasets to derive discharge from space or/and 2) implement an assimilation system that will propagate the discrete daily estimates of discharge from space all over the basin or/and 3) use the estimated discharge as an informer for a locally relevant hydraulic model (see an application of such framework in Malou et al. 2021) that will convert level and discharges into flood risk and areas or in refined depths.

Also, the density of VSs now makes it possible to infer a priori RCs at newly monitored locations, such as VSs of future missions. In the aforementioned studies, the RCs were deliberately built on as little data as possible, namely only WL at VSs and corresponding simulated discharge. The discharges estimated through this methodology will probably gain in performance when using WL together with slopes and widths, as provided by the forthcoming SWOT mission. In fact, in addition to the use of the official river discharge product, SWOT will provide water surface elevation, slope and width measurements to be used 1) for evaluating independent discharge estimates 2) for model calibration and validation and 3) in assimilation systems to improve models outputs (Andreadis et al. 2007; Biancamaria et al. 2011; Li et al. 2020). With the proliferation of global datasets on river hydraulic structures, waterfalls and global simulations of river hydraulics (Yamazaki et al. 2011) the idea of use SWOT measurements even for hydraulic models at global scale seems quite close. Some studies have focused on the impact of assimilation SWOT data for operational use (see Munier et al. 2015, on the upper Niger River basin) while other focused more on maximizing the use of the data (e.g., Revel et al. 2019, on the Congo River basin). In their study, Haile et al. (2016) successfully calibrated the HEC-HMS model with TMPA rainfall data in the Benue river basin (Niger river tributary) in order to build a flood-forecasting system fed by EO data (climate and rainfall). They recommend that riparian countries improve their data-sharing policies and that climatic predictions are improved.

All the aforementioned studies have provided an interesting insight on how to adequately use EO to infer discharge from space in order to better understand the large scale behavior of African watersheds and the possible impacts of CC on water availability and distribution, and also to provide NRT estimates of discharges in poorly monitored basins. However, one common limitation of the aforementioned large scale hydrological models is their incapacity to adequately represent all the very local processes that can originate flood events or the fine scale variations of hydrodynamics and cross section areas, turning necessary the use of more refined hydraulics (Trigg et al. 2016; Archfield et al. 2015; Alfieri et al. 2021). Hydraulic models have then been used stand-alone or coupled with hydrological models for applications on representing floods in terms of levels or extents.

3.2 Informing Regional to Local-Scale Hydraulic Models with EO Datasets

If remote sensing and in particular Satellite Earth Observations have enabled large-scale hydraulic modeling to take place in Africa, the move toward using remote sensing for hydraulic modeling started with the release of the Shuttle Radar Topography Mission or SRTM (Farr et al. 2007). SRTM is the most widely used digital elevation model and reduced the need for expensive manual surveys. However, while SRTM addressed one of the key inputs required in hydraulic modeling, it did not useful for monitoring of water levels that is key in ensuring that hydraulic models are accurate. In Africa, obtaining historical information on water levels and or discharge is extremely difficult for a large number of reasons; however, Earth Observations are able to alleviate this problem through satellite altimetry and observation of inundation extents. One of the first applications of satellite altimetry to calibrate and or validation hydraulic model in Africa was in the Niger River Basin (Neal et al. 2012). Neal et al. (2012) used the ICESat laser altimeter to obtain water level information that was otherwise not available, in both the calibration and validation of a hydraulic model for the Niger inland delta. Schumann et al. (2013) also used the ICESat laser altimeter to calibrate a hydraulic model for the lower Zambezi River; however, they also used optical imagery from Landsat to produce inundation maps to evaluate the

accuracy of their model. Komi et al. (2017) used inundation extents for MODIS to validate the outputs from a hydraulic model for the Oti River basin. O'Loughlin et al. (2020) calibrated a hydraulic model for the middle reach of the Congo River using water elevations estimate from both ERS-2 and Envisat radar altimeters. Haque et al (2020) compared the inundation extents from a hydraulic model built for the Niger Inland Delta to inundation extents obtained from MODIS imagery. In a recent study, Kittel et al. (2021) used Cryo-Sat2 WL observation to calibrate a steady-state hydraulic model on several reaches of the Zambezi River basin. Recently, Lamine et al. (2021) merged satellite altimetry together with optical and DEM data through BAM-AMHG properties to retrieve discharges in a 30-km reach around Niamey (Niger), highlighting the applicability of their methodology for poorly monitored reaches of African rivers.

Despite their importance for people and climate, large African rivers are among the most insufficient monitored systems in the world. Hydrologic and hydraulic modeling, constrained and informed by EO datasets, have enabled the study of those river systems, the understanding of freshwater distribution and the adequate representation of regional to local hydrological processes. This opens a wide path for hydrological studies of climate change impacts on African rivers and permits a better understanding of recent extreme events in a CC point of view.

4 EO and Models for Understanding Dynamics of Fresh Water in African Rivers in a Changing Climate

4.1 Combination of EO Datasets for Deriving Large Climate Trends

As a key resource for sustaining life and society, fresh water is among the most important components of the water cycle and the rising of average temperatures affects the rate of evaporation and precipitation patterns, contributing to intense and frequent storms, with increased runoff and hence, frequent flooding as well as intensify drought-affected areas. African countries are among the most affected by climate changes, because of high rates of population growth and the high declines in agricultural production, as well as the low resilience to the natural hazards, i.e., floods and droughts. Floods may destroy farmlands and crops, causing undernourishment and starvation (Tosam and Mbih 2015), and in the extreme cases can hit settlements causing fatalities and affected people. Standing water may increase the incidence of malaria and dengue fever. Droughts affect hygiene as preference is given to cooking water and little is left for washing and cleaning facilitating the spread of infectious diseases.

Therefore, climate change mitigation is a crucial task of the first order, as well as politically and ethically complex. For the health sector, the challenge involves identifying the primary health threats posed by climate change and ensuring that strategies are developed to mitigate the risk (McMichael 2013). Water management falls entirely under this umbrella and requires urgent measures to manage the water resource through the adoption of climate change adaptation strategies. The first major step is the adoption of an independent, continuous, and reliable monitoring system to control the past and current conditions of rivers and lakes. Unfortunately, the traditional hydro-monitoring network in Africa underlines the scarcity in data (see §3.2). By the study of Crochemore et al. (2020), African countries appear among the most suffering in terms of data availability and this lack avoid routine flood forecast evaluations (Lavers et al. 2019). The lack of data is certainly

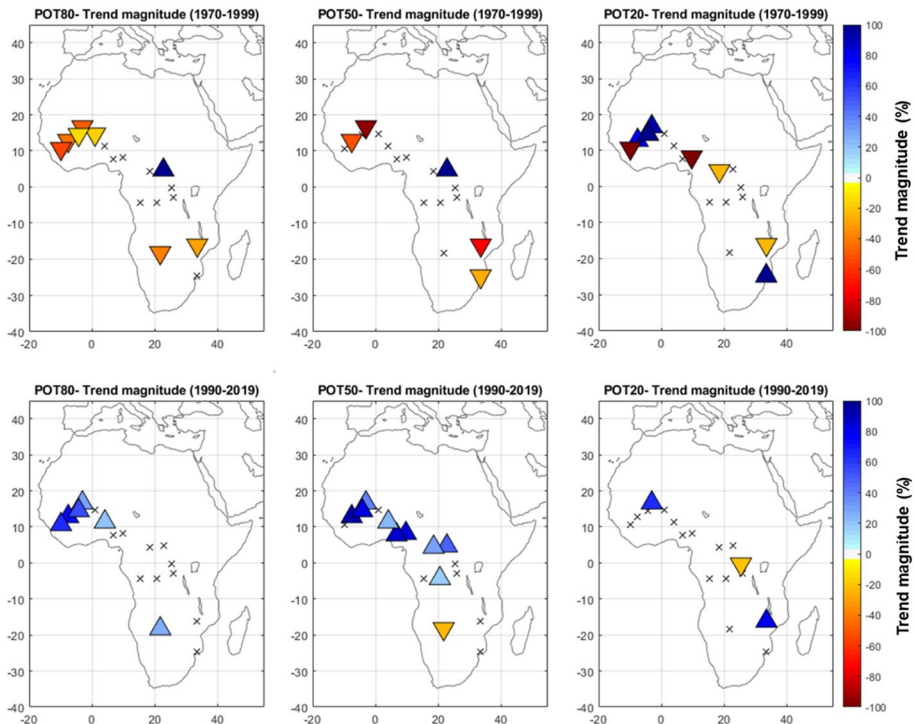


Fig. 4 Trend analysis of peak over threshold, POT. Columns illustrate the trend magnitude of high flow events (80th percentile), median flow (50th percentile) and low flow (20th percentile) for 1970–1999 and 1990–2019 periods. The crosses in the images indicate sites with no significant trend; red and blues triangles indicate sites with significant negative or positive trend, respectively (based on Fig. 15 in Belloni et al., 2021)

detrimental to an objective assessment of change. However, the use of radar altimetry represents a very important resource for the evaluation of the dynamic of fresh water in African rivers (Becker et al. 2018). For example in the study of Kitambo et al. (2021) the intense activities of monitoring carried out by the collaboration with the regional partners of the Congo Basin Water Resources Research Center (CRREBaC) and the Environmental Observation and Research project (ORE HYBAM, <https://hybam.obs-mip.fr/fr/webseite-under-development-2/>) allowed to demonstrate the benefits of using in situ and earth observation datasets (i.e., radar altimetry and Global Inundation Extent from Multi-Satellite, GIEMS-2) to improve our understanding of the water flow in the Congo River basin. This study will permit to infer whether the trends in the Congo basin, revealed from in situ data by Laraque (2015), are stable, increasing or decreasing.

The knowledge of the dynamics of the water heights of the river and their analogy with the river discharge enables us to extract information about climate trends. Specifically, in the studies conducted by Gudmundsson et al. (2019) and Crochemore et al. (2020) the West Africa experienced before 1980 a decreasing trend in the high and medium flows (80th and 50th percentiles of river discharge), and an inverse positive trend pattern in the recent period (from 1990 to 2019) also confirmed by the study of Trambly et al. (2020). This last period corroborates the already known “Sahelian Paradox”

(Descroix et al. 2013) according to which the increasing of river discharge is not linked to the increasing rainfall that in the same period seems to decrease, rather to the land use change. The same conclusions are obtained by the use of satellite altimetry data carried out by Belloni et al. (2021) over the same area (Fig. 4). Satellite altimetry water level data are set to update and fill long discharge datasets over different sites with the purpose to obtain long time series for the evaluation of climatic trend. The availability of several altimetry missions and several algorithms coming from different laboratories (DAHITI, THEIA) guaranteed an independent analysis that has been able to reach the same conclusions of the ground monitoring network, demonstrating the potential of the altimetry data also for climate change evaluation in rivers.

4.2 Understanding Recent Outstanding Events and Possible Future Trends Thanks to EO Datasets and Modeling

Given the decline of the in situ observational network, there is a strong need of using hydrological models to infer and understand possible impact of climate change on major African basins. The several studies aforementioned have highlighted the difficulties in estimating basin-scale hydrological state in a data-lack situation. To overpass this difficulty, one of the most straightforward solutions is to update model's estimates through data assimilation. WL from satellite altimetry was used by Khaki and Awange (2020) to estimate water storage variations. These variations were assimilated in a hydrological model of the Nile River and consequently improved the surface water simulations, and, by indirect feedbacks, the other components of the model. Consequently, EO data assimilation was used by Khaki and Awange (2021) to understand the 2019–2020 abnormal increase in Lake Victoria's level. In their study, they used satellite altimetry and terrestrial water storage from GRACE-FO to understand and model the effect of large-scale ocean indices of Lake Victoria's hydrology. They concluded that the 2019–2020 rise was triggered by the Indian Ocean Dipole (IOD) that caused an increase in TWS, leveraging changes in surface waters. The link between regional and global climate and surface waters was also investigated by Bogning et al. (2020) in the Ogooué River basin (Gabon). They used satellite altimetry to calibrate and validate the MGB hydrological model, and found that the inter-annual variations of ENSO (El Niño Southern Oscillation) plays a major role on river discharges in the basin. These conclusions could help understand the impact of CC on surface waters in this region. In their study, Näschen et al. (2018) used the SWAT model to infer the impact of vegetation change on basin hydrology.

They estimated the land use change from Landsat images between 1970 and 2014 in the Kilombero floodplain (Tanzania) and evidenced severe shifts in water balance due to these changes, emphasizing the fact that such interactions should be taken into account for ensuring that economic and population growth does not harm future food production capacity. The hydrological response to CC was also investigated by Aloysius and Saiers (2017). In their study, they forced the SWAT model of the Congo River basin, prepared with EO DEM data, with temperature and rainfall from 25 GCMs (global climate models). The outcome of their study is that most models predict a positive change in precipitation, P , subsequently leading to an increase in Q , in the equatorial regions, and a negative trend in P and Q in headwater catchments. This could consequently affect the compound hydrograph at Kinshasa and affect electricity and food production.

5 Conclusions and Future Perspectives

In this paper, we reviewed the methods currently used to estimate and model river discharge with the support of satellite data focusing on applications in Africa and in a climate change context. The overview offered in the paper emphasized the great advantage of having satellite data that are freely available, continuous over time, with a wide spatial coverage, and independent of any political aspect. The multiple applications reviewed in this paper tried to provide an overview of the possible way to analyze and manage the satellite data, from the direct use in the empirical formulas or the ingestion into more complex hydrological or hydraulic models with the final target to derive useful information about the flow in scarce data areas. In these situations that are typical of developing countries such as those in Africa, satellite data represent a rich source of data, sometimes exclusive, sometimes complementary to the existing in situ hydro-monitoring network. In fact, monitoring networks often suffer from problems of data availability and sharing and are not sufficient to monitor the increasing number of extreme events that hit African countries, thus becoming the most vulnerable in the world. The main causes are linked to the low levels of socioeconomic growth and the lack of resources to mitigate and to recover from the effects of climate changes. A prioritized task for Africa is to improve climate resilience to achieve sustainable and equitable development and to guarantee quality of life of the people. The water availability has a central role in this aspect and the monitoring becomes one of the essential tools to manage the water resources and assess the flood and drought risks. A better understanding of the hydrological regime of the sub-region would be very instrumental in helping policy makers and water resource managers to make important decisions on investment, development and management. The role of satellite and in situ data, together with the modeling and the data assimilation techniques, can offer a large support on this aspect and with the future perspective of high-resolution products the reproducibility of the implemented approaches for large basins to small regions appears increasingly feasible.

The ongoing initiative by the scientific community on existing or future satellite missions, as well as the exploration of new techniques and the recent advances in the machine learning methods, represents good opportunities:

- to improve the understanding of hydrological processes at various spatial and temporal scales,
- to play a determining role in the decision-making activities, and
- to maintain a long-term archive of hydrological data.

Moreover, the promotion and the dissemination of remote sensing is important for the process of developing and strengthening the skills, the processes and resources that African organizations and communities need to survive and adapt to the climate change.

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