



Inland Surface Waters Quantity Monitored from Remote Sensing

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Abstract

In recent decades, water availability, water use, water sharing and freshwater supply for basic human and economic needs have become central scientific and humanitarian issues. With increasing water scarcity in many regions and increasing frequency of extreme flooding in other regions, there is a need to improve predictive capacity, to collect a large amount of information on key hydrological variables such as flows or water stocks in lakes and floodplains and to best combine these data with hydrological and hydrodynamic models. Most of the world's water demand relies on continental surface waters (rivers, lakes, wetlands and artificial reservoirs) while less on underground aquifers and seawater desalination. However, ground-based hydrological survey networks have steadily and drastically decreased worldwide over the last decades. In this context, current remote sensing techniques have been widely used by several countries for water resource monitoring purposes. In this paper, we present such remote sensing techniques, in particular satellite altimetry and imagery, and discuss how they became essential for the study of the water cycle and hydrological phenomena on a broad range of spatial and temporal scales. Large lakes, rivers and wetlands play a major role in the global water cycle and are also markers, integrators and actors of climate change at work on Earth. We show several examples chosen from the literature that perfectly highlight both current scientific and societal issues, as well as the crucial role of space techniques to monitor terrestrial surface waters.

Keywords Radar altimetry · Satellite imagery · Rivers · Rating curve · Floodplain · Lakes

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Article Highlights

- A review study on applications of satellite techniques for studying continental surface waters
- Floodplain monitoring at global scale
- Lake storage changes and their linkage with the water cycle
- River discharge estimation at basin scale from satellite data

1 General Introduction on Surface Water Issues

The Earth is commonly called the "Blue Planet" because of the abundant presence of liquid water on its surface, 70% of which is covered by oceans. The volume of the Earth's hydrosphere is estimated at about 1.45 billion cubic kilometers, but it is very unevenly distributed. Indeed ~97% is present as salt water in the oceans and seas, while freshwater represents only a small part (3%) of the total amount of water present on Earth (Chahine 1992; Shiklomanov and Rodda 2003). Two-thirds of this volume is stored as ice in the polar ice caps and glaciers (2% of the total amount). Finally, continental waters represent less than 1% of the total volume of water on Earth (Stephens et al. 2020).

Despite its relatively small quantity, continental water plays a vital role for the environment, terrestrial life, biosphere functioning and human activities (Kundzewicz et al. 2007). Continental water is stored in different reservoirs: snow cover, glaciers, aquifers, root zones and surface waters, which include rivers, lakes, reservoirs, wetlands and flooded areas. These components interact continuously with the oceans and the atmosphere and are continually recycled by precipitation, evaporation, changes in continental water stocks and outflow to the sea, all of which form the hydrologic cycle. Quantifying these components and understanding their interaction with all other components of the climate system is essential to better characterize the hydrological cycle and the variability of the water resource from short to long time scales. Even though they represent only 5% of the total surface area of ice-free land, continental waters play a primary role in hydrological and biogeochemical cycles on a global scale with direct interactions with the atmosphere and oceans (through evapotranspiration, river flow, temperature modulation) (Bousquet et al. 2006; Raymond et al. 2013; Getirana et al. 2017; Papa et al. 2008; Bullock and Acreman 2003; Dorigo et al. 2021). Besides, although the increasing concentration of greenhouse gases in the atmosphere is mainly attributed to fossil fuel combustion, agriculture and land use, surface waters (lakes and wetlands) are also a source and sink of carbon dioxide (CO₂) with net contributions that are still poorly understood (Richey et al. 2002, Williamson 2009, Raymond et al. 2013). Despite their importance, a detailed overview of continental surface water variability and fluxes and their dynamics is still not available (Alsdorf et al. 2007, 2003), leaving open many questions related to the continental water balance: How do different surface water stocks vary from daily to multi-year time scales, from local to continental scales? What are the spatiotemporal variations of water resources and their response to the joint influences of climate variability and anthropogenic effects? These questions are of primary importance in the current context of global change. Climate and hydrological cycles are indeed strongly linked, through direct effects and feedbacks, and climate variability can translate into significant impacts on the global hydrological cycle and on water resources (Chahine 1992; Vörösmarty et al. 2000). It is now generally accepted that climate change is having an increasing influence on both the frequency and intensity of

extreme hydrometeorological events (Katz and Brown 1992; Trenberth 1999; Seneviratne et al. 2006) resulting in millions of people being affected by droughts or floods every year around the globe. The latest report of the International Panel on Climate Change (IPCC 2021) is very clear on this issue. The importance of climate variability and change, in particular their impacts on continental hydrology, with an intensification of the global water cycle (Durack et al. 2012) and of the hydrological cycle on the continents (Huntington 2005), is clearly recognized. An increase in river flow of 540 km³/year over the period 1994–2006 has already been reported (Syed et al. 2010). In addition, over the last decade, exceptional hydrological events have affected many regions of the world, e.g., a succession of droughts and floods of great intensity in the Amazon basin since 2005 (Marengo et al. 2008a; 2008b, Jimenez-Munoz et al. 2016). More frequent and intense extreme events are expected to have significant consequences on a global scale (Hirabayashi et al. 2013).

In addition, hydrological cycles can be directly disrupted by human activities and population growth, increasing the vulnerability of the water resource (Vörösmarty et al. 2000, 2010; Alcamo et al. 2007; Oki and Kanae 2006). Nearly 80% of the world's population is exposed to a high level of risk on water scarcity (Vörösmarty et al. 2010). Among the human activities that impact all continental freshwater reservoirs (Wada et al. 2010a,b, van Beek et al. 2011), we note the significant water withdrawals for agriculture, economic activities and daily consumption (surface water, aquifers), the construction of dams, the drying of surface water (wetlands, etc.) (Wada et al. 2010a, 2017; Prigent et al. 2012). The combination of climate variability and anthropogenic pressure thus threatens the global water resource, and this threat is expected to be exacerbated in the coming decades. Characterizing the processes at work in the continental water cycle and recent changes thus remains a key challenge for the scientific community. One of the major problems is the lack of historical and operational observational networks. Some comprehensive and global hydrological measurement systems to measure water reservoirs and fluxes on Earth exist (for soil moisture, river discharge, lake level changes for example) but data are not always released operationally, while decline of the observing networks has moreover been observed. As example, the GRDC (Global Runoff Data Center, https://www.bafg.de/GRDC/EN/01_GRDC/13_dtbse/database_node.html) which gathers river runoff data worldwide suffers from increasing difficulties to collect up-to-date data over the large river basins (U. Looser, Personal communication). Because of their specific characteristics (topography, heterogeneity, morphology, climate) and given their great diversity, the study of continental hydro systems is complex (Rodda et al. 1993). The estimation, at the scale of a catchment area, of the distribution of water resources, their volume and their variations, requires the collection and the spatiotemporal follow-up of a broad quantity of information, such as water levels of lakes and rivers. In the past, many regional, national, or international networks of hydro-meteorological parameters measurements have been deployed, e.g., river discharge stations. However, the installation and the maintenance of such networks and infrastructures have high financial costs and suffer political instability in many regions of the world. Since the 1980s, many in situ networks have not be maintained, resulting in a sharp decline in the number of observation networks worldwide (Alsdorf and Lettenmaier 2003; Fekete et al. 2015; Shiklomanov and Rodda 2003). This affects both developed countries and the developing world. Regular funding is often missing to create open access of historical archives, thus relying on individual research teams. Furthermore, when such observational networks exist, access to the data is problematic, because information about water resources is a matter of national security. Finally, while in situ measurements remain essential for observing certain phenomena, they do not provide information on all the parameters that are needed, e.g., amount of water in flood plains (Alsdorf et al. 2007).

The same is true for lakes (several million involved Pekel et al. 2016; Sheng et al. 2016). It is physically impossible to ensure a perennial and global monitoring from in situ networks. A few national networks exist, i.e., in the USA, Canada, Russia, some South American and European countries, but these concern only a small number of lakes whose data are not always centralized or made available to the international scientific community. Moreover, only water level variations are measured, while information on the surface extent and water volume remains generally unknown.

In this context, space remote sensing techniques provide valuable information on the characterization of the water cycle, on a global or continental scale, as well as on the spatiotemporal variations of hydrological parameters (Alsdorf et al. 2007; Famiglietti et al. 2013, Cazenave et al. 2004; Smith 1997; Dorigo et al. 2021) This so-called hydrology from space has led to spectacular advances over the last few decades and is expected to gain momentum with the recent or upcoming launches of new satellite platforms dedicated to hydrology. With radar altimetry and satellite imagery, most of the variables (water levels of lakes, reservoirs, rivers, extent and volume of water in large flood plains, etc.) can now be measured with great accuracy, over periods that depend only on the mission lifetime and their renewal, with global coverage without distinction of borders. Some of these data are also freely available on databases created for this purpose: Hydroweb (<https://hydroweb.theia-land.fr/>), Dahiti (<https://dahiti.dgfi.tum.de/en/>), GRLM (https://ipad.fas.usda.gov/cropexplorer/global_reservoir/), Rivers&Lakes (<https://altimetry.esa.int/riverlake/shared/main.html/>), Altwater (<http://altwater.dtu.space/>), Hydrosat1 (<https://www.gis.uni-stuttgart.de/en/research/projects/hydrosat/>), generally supported by space agencies: NASA (National Aeronautics and Space Administration), CNES (Centre National d'Etudes Spatiales), ESA (European Space Agency), DLR (Deutsches Zentrum für Luft und Raumfahrt). These databases provide water level, area and volume changes on hundreds of lakes, and water level on thousands of virtual stations along rivers.

2 Space Techniques in Continental Surface Hydrology

We now describe advances made in recent years in monitoring the continental water cycle using current space techniques. The aim is to estimate variations in surface water stocks (soil waters are ignored here), i.e., in lakes and flood plains, and flows, i.e., river discharges. To achieve this, it is necessary to measure water heights and water areas for lakes and wetlands, while for river discharges it is necessary to estimate the slope and the cross-sectional area of the river. When these variables are combined or used in models, it is possible to deduce new variables such as stock variations and flows. Such variables are essential to analyze the role of continental surface waters in the water cycle, as well as their interactions with climate. Three main families of techniques are discussed here: radar altimetry (and incidentally laser); satellite imagery in different wavelengths, mainly visible, infrared and microwave; and finally, scatterometers and synthetic aperture radar (SARs).

2.1 Water Level Changes from Satellite Altimetry

Satellite altimeters are active instruments, designed to measure the distance from the satellite to the reflecting surface by measuring the round-trip time of short radar pulses. The shape of the reflected signal, called the "waveform," represents the time evolution of the reflected power when the radar pulse strikes the surface. The waveforms are acquired by

a tracking system onboard the satellite, called a "tracker." Almost all ocean waveforms have standard "oceanic" shapes, where the initial thermal noise is followed by a sharp rise called the rising front and then a gently sloping plateau. On the continents, the waveforms are quite diverse and can quickly deviate from those traditionally observed on the oceans, depending on the more or less important contamination produced by the backscattering of the water body environment in the case of rivers or small lakes, in particular when the topography changes rapidly. It is therefore no longer possible to find a single analytical expression that allows us to determine an accurate round trip time for all waveforms.

However, waveforms are still usable for continental hydrology (lakes, rivers, reservoirs), often with the help of reprocessing algorithms to identify the exact round trip travel time of the radar wave to deduce the satellite distance from the reflecting surface. This is called waveform retracking. This approach provides flexibility in data reprocessing with new and better suited algorithms, many of which are purely empirical or based on physical properties. Ocean-class waveforms can be encountered in the middle of very large lakes such as those in North America, Africa, or Eurasia (Crétaux and Birkett 2006; Yi et al. 2013). In the 1970s and 1980s, the first experimental radar altimeters were put into orbit but for very short periods and were only useful for studying the oceans. With the launch of the European Space Agency (ESA) ERS-1 satellite in 1991 and Topex/Poseidon, in 1992, a NASA-CNES mission, satellite altimetry started to be used over continental waters (Birkett 1995; 1998). The Topex/Poseidon mission, which lasted 13 years, really marked the take-off of hydrology from space. Subsequently, other missions were used, with instrumental and algorithmic improvements over the years: ERS-2 and Envisat from ESA, the successors of Topex/Poseidon, Jason-1, Jason-2 and Jason-3. During the 2010s, new instruments appeared: CryoSat-2 from ESA, which for the first time offers a synthetic aperture radar (SAR) mode, permitting an along-track increase of resolution thanks to the exploitation of the Doppler shift due to the speed of the satellite and with its two antennas (instrument SIRAL) spaced 1.1 m apart on the platform also allowed cross-track interferometry. It was followed by the Sentinel-3 missions of the European Copernicus program, which operate entirely in SAR mode. This mode has the major interest of a much better focus of the effective measurement, which no longer covers a circular ground footprint of several tens of km², as did the previous altimeters, but a 300 m (along-track) slice in the ground footprint. For the tracking of small targets (rivers, lakes and narrow reservoirs), this represents a breakthrough because the measurement is much less altered by surrounding reflective sources, especially when the target object is oriented perpendicular to the satellite ground track. Other innovations occurred during this decade with the French-Indian SARAL/AltiKa mission, whose radar wave frequency (Ka Band at 35.75 GHz) replaced the Ku Band at 13.6 GHz of the Topex/Poseidon and Jason missions, greatly reducing the ground footprint (Verron et al., 2018).

Since 1992, there have been a large number of altimeters in orbit, with revisit times of 10 days to 35 days depending on the satellite orbit, continuously and with notable technological advances. ESA, for the Copernicus program, recently launched the SAR mode and classical altimetry (interleaved) mission Sentinel-6 Michael Freilich to extend the Jason series. New space missions (SWOT, Sentinel-3NG and SMASH) will extend the constellation, allowing the development of operational space hydrology.

Some studies have estimated the accuracy of satellite altimetry for lakes and rivers. For example, Ričko et al. (2012), Crétaux et al. (2016) and Schwatke et al. (2015) have shown that, for large lakes, accuracy better than 10 cm is often reached, while it may be at decimeter to meter level for very small lakes or river sections. However, Boy et al. (2022) developed a method of altimetry data processing (call lake physical processing) allowing

to reach centimeter accuracy to be reached even for very small lake. This method is time-consuming, therefore not easily deployable on a wide range of applications, but it shows the potential of altimetry for the survey of very small (few hectares) water bodies.

The SWOT (Surface Water and Ocean Topography) mission developed jointly by NASA, CNES and the Canadian Space Agency, launched in December 2022, is the object of a new technological revolution from which researchers hope for great advances in the fields of oceanography and hydrology (Biancamaria et al. 2016). For previous altimeters, the measurements were made at the nadir of the satellite; hence depending on the orbital cycle, the ground coverage was uneven. Any targeted lake must be in the immediate vicinity of a satellite track. For a river, only a few point measurements at the intersection between the ground track and the river (sites called virtual stations) are measurable. For flooded areas, only part can be measured. With SWOT, which uses wide swath interferometry, the coverage is truly global, all lakes larger than 6 ha (around 2 million on Earth) and rivers wider than 100 m will be monitored by this satellite. Moreover, this instrument simultaneously measures not only water heights but also the contours of flooded areas (lake or river banks, floodplain boundaries). Thanks to the continuous coverage, the slope of the water line is also measured. Derived products can be developed: water stock variations in lakes and flood plains, exposed bathymetry and flow rates on continuous river sections (the flow velocity being related to the water line slope).

2.2 Water Extent from Satellite Imagery and Scatterometry

Without making an exhaustive list here, we will quickly recall the main techniques and sensors used to quantify the variations of the surface water extent by satellites. Different space remote sensing techniques, using observations made in a wide range of the electromagnetic spectrum (visible, infrared and microwave), allow us to obtain, with varying degrees of success, quantitative estimates of the extent and dynamics of surface waters in several environments (Alsdorf et al. 2007; Smith 1997; Prigent et al. 2007). Sahagian and Melack (1996) reviewed these different techniques that allow observations of surface waters over a wide range of spatial and temporal resolutions. Observations with low spatial resolution (e.g., 30 km) are generally limited to the detection of relatively large water surfaces, or regions where the cumulative area of small surfaces represents a fairly large portion of the satellite footprint. But they often have the advantage of frequent, long-term, continuous, temporal coverage (Papa et al. 2010; Parrens et al. 2017). High-resolution observations (e.g., > 100 m), on the other hand, provide fine spatial scale information but often suffer from low temporal repeatability, often limiting observations of large areas to a few data per season. Unlike microwave-based SAR and altimetry, optical and infrared observations (e.g., from LandSat, AVHRR, MODIS, etc.) provide good spatial and temporal resolution but are limited by their inability to penetrate clouds and dense vegetation (Verpoorter et al. 2014; Klein et al. 2015). This is particularly limiting in tropical regions during the wet season. However, they perform well in environments with less dense canopy cover, such as in the Okavango delta (McCarthy et al. 2005) and the Inner Niger delta (Aires et al. 2014; Bergé-Nguyen and Crétaux 2015). Although open water can be easily detected using infrared instruments, estimating the extent of water areas is more difficult in the presence of aquatic vegetation or trees. Indeed, most small water bodies are not permanent and many of them are covered by aquatic vegetation and/or trees which requires the development of specific algorithms to take them into account. Recently, several studies were published that demonstrated the power of artificial intelligence (AI) to determine water mask over the

continent in a robust and nearly automatic manner (Zhao et al., 2022; Mateo-Garcia et al. 2023). Huang et al. (2018) provide a very comprehensive review of surface water detection and monitoring from space using optical sensors. The bulk of the techniques used rely on contrast analysis (in optical or radar) of the surface reflectance of water compared to adjacent areas. To accomplish this, a number of indices have been defined, calculated from a combination of reflectance measured in different spectral bands. The detection of water is then made according to different approaches, which are generally defined into the supervised and unsupervised classes. For the former, reference areas in the image are predefined and then each pixel is analyzed according to a number of criteria built via a learning of the classification algorithm on the reference areas. In the case of unsupervised methods, the algorithm seeks to group pixels by class by optimizing a threshold value on a specific index, for example. The most commonly used index is the NDWI (normalized difference water index) which was proposed by McFeeters (1996). This index is expressed by the ratio:

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (1)$$

where Green is the frequency band in the green, NIR is the near infrared and MIR is the mid-infrared. Refinements have been suggested as with the MNDWI (modified normalized difference water index) proposed by Xu (2006) and expressed by the ratio:

$$MNDWI = \frac{Green - MIR}{Green + MIR} \quad (2)$$

Szabo et al. (2016) have performed a series of tests with several water indices and have shown that MNDWI is generally the most efficient index for water detection of water bodies located in different land configurations. AI methods that, from a set of test images, will allow the refinement of the threshold value that allows the visual separation of a water area from an emerged area are also commonly applied. This is the case of the unsupervised method developed by Otsu (1979) which determines the threshold value that minimizes the variances within a given class and maximizes the covariance between the two predefined classes. In this way, each pixel of a given image for which the index is greater than the threshold value can be considered as covered by water and conversely emerged if the index value is less than the threshold value. By summing the number of pixels contained in an area of the image identified as encompassing a given lake, we can therefore calculate the surface area of the lake on the date the image was taken by the satellite. The Canny Otsu algorithm is an operator widely used for edge detection in images: It is a method developed by Donchyts et al. (2016). It is introduced as a way to focus the OTSU calculation on regions with strongly defined interfaces. In the case of water surface detection, the interface between a water surface and the surrounding land acts as such a high-contrast region. This procedure has the benefit of reducing drastically the amount of data to be processed by the OTSU algorithm and focuses the statistics on water discrimination, especially when water is under-represented in the scene. Other AI methods exist that, in contrast to OTSU, are based on supervised approach. For example, in SVM (support vector machine) method, an a priori database can be used to train a machine learning algorithm exploiting both the image and the training dataset to perform a supervised classification of water (Martini et al. 2009). Since optical imagery (in the visible and infrared spectrum) is limited in the presence of clouds or dense vegetation, an alternative is to use radar remote sensing. Scatterometers and synthetic aperture radar (SAR) imaging radars are active microwave

instruments that measure the backscatter coefficient of the observed surface with an angle of incidence (off-nadir). The technique is based on the detection of high contrast between water and dry land, which generally provides good delineation of open surface water due to a low backscatter coefficient (Rosenqvist et al. 2002; Behnamian et al. 2017). SAR images have been used for the mapping of floods and their dynamics, using orbital sensors such as TerraSAR-X, Radarsat or Sentinel-1. This technique has the advantage of capturing images day and night without depending on cloud cover conditions. It has also capabilities, to some degree, to penetrate vegetation. The variety of SAR data processing approaches for flood detection is rather high in the literature (Bates et al. 2006; Matgen et al. 2007; Pulvirenti et al. 2011; Vassileva et al. 2016; Huang et al. 2020). Schuman and Moller (2015) and Shen et al. (2019) have reviewed principles of water detection and flood survey using SAR imagery. However, in the presence of vegetation, non-specular echoes (multiple scattering) contaminate the signal and water detection is then more difficult and environment-specific. Nevertheless, operating at lower frequencies (X-band 8–12 GHz, C-band 4–8 GHz and L-band 1–2 GHz) than scatterometers (Ku-band 12–18 GHz and C-band), they can penetrate clouds and vegetation, mainly in L-band, which makes SAR, with a typical spatial resolution of the order of 10–100 m, a preferred candidate for the observation of water surfaces and flooding, such as in the tropics (Hess et al. 2003) or boreal regions (Morrissey et al. 1996). The recent use of Sentinel-1 SAR (launched in 2014 and operating in C-band at a frequency of 5.405 GHz), which provides a global revisit time of 6–12 days, offers new opportunities for mapping spatio-temporal variations in surface water at fine scales (Pham-Duc 2017). Backscatter from radar altimeters can also be used to some extent to identify the presence of water in the sensor footprint, but the large inter-track distance of the orbit and lack of continuous spatial coverage of these instruments is a limiting factor for global scale exploitation (Frappart et al. 2021). Finally, passive microwave observations have long been shown to be useful for observing surface water and flooding (Giddings and Choudhury 1989; Choudhury 1991; Sippel et al. 1998; Mialon et al. 2005). Recently, the SMOS satellite operating in L-band and dedicated to measure soil moisture on land, has been used to characterize floods in the Amazon (Parrens et al. 2017, 2019) and Congo basins (Fratras et al. 2021). The emissivity is very sensitive to the presence of surface water and flooded areas, with a decrease in emissivity in both linear polarizations (horizontal and vertical) and an increase for the difference in polarization, especially at low frequencies, due to the different dielectric properties between water, soil and vegetation. However, the passive microwave signal can be contaminated by several factors, such as the atmosphere, clouds and rain. The signal can also be altered by absorption and scattering from vegetation and modulated by surface temperature (Frappart et al. 2020). Finally, due to their relatively low spatial resolution, available microwave observations (ground footprints of the order of 25–50 km) over regions with mixed scenes, i.e., surface water in the presence of other complex surfaces, provide ambiguous signals. Therefore, there is no indicator based on microwave information alone that can clearly identify and quantify the presence of surface water in mixed scenes. Thus, most techniques based only on the simple analysis of passive microwave observations have been limited to regional scales and have shown their limitations at the global scale (Sippel et al. 1998 for the Amazon or Mialon et al. 2005 for boreal regions). In these studies, the effects of vegetation, atmospheric (water vapor, clouds, precipitation) and surface temperature dynamics are generally assimilated to diffusion and simply treated in an empirical way, which limits a good restitution of the seasonal and interannual variability of the surface water extent dynamics.

2.3 Volume Change Calculation from Remote Sensing

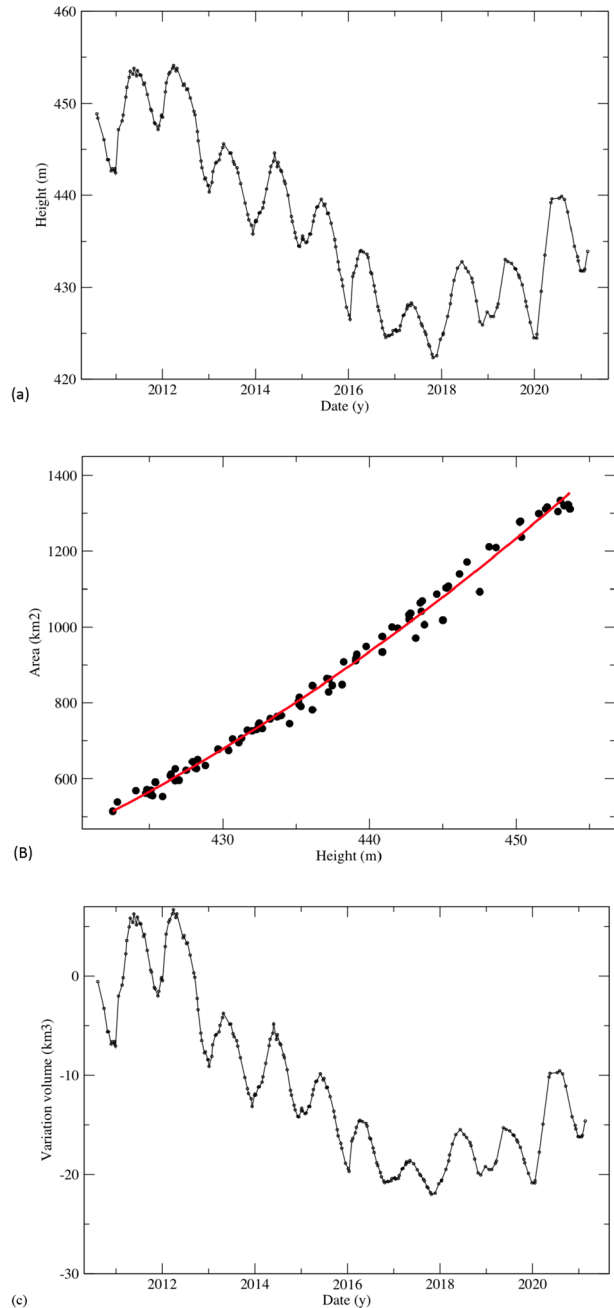
Volume changes of surface bodies are not directly measurable. Indeed, most studies on the effects of climate change on lakes rely on water volume variations, which are compared with other types of hydrological processes and variables (glacier mass balance, global variations in water stocks at the basin scale, precipitation, evapotranspiration, permafrost melting, etc.). Altimetry alone does not give access to lake (or reservoir) volume variations. To achieve this, satellite imagery must be used. Various approaches can complement each other. It is possible to use radar altimetry coupled with digital terrain models (DTMs) to infer extent and volume variations (Yao et al. 2018). However, this may be insufficient when DTMs are not accurate enough. Another approach consists of identifying on each of the lakes for which we are looking for volume variations, the dates (based on the altimetry series) for which the water heights are extreme, as well as some intermediate values, and to constitute a correspondence law between the heights and the extents. This law is also called hypsometry. This technique only allows calculation of volume change (not absolute volume of a lake) and requires simultaneous observation of height and extent. Once realized, it is enough for each value of water height measured by altimetry to deduce the area and then the volume variations by simple equations. To determine a volume variation between two dates t_i and t_{i-1} for which the heights are $H(t_i)$ and $H(t_{i-1})$ and the surface areas $S(t_i)$ and $S(t_{i-1})$, it is enough to apply the formula given by the following equation:

$$\delta V(t_i, t_{i-1}) = V(t_i) - V(t_{i-1}) = (H(t_i) - H(t_{i-1})) \frac{(S_i(t_i) + S_i(t_{i-1}) + \sqrt{S_i(t_i)S_i(t_{i-1})})}{3} \quad (3)$$

An example of this type of calculation is given in Figs. 1a, b and c.

This method is used by a large number of authors (Gao et al. 2012; Duan and Bastiaanssen 2013; Crétaux et al. 2016). It requires an a priori calculation of the hypsometry and its analytical modeling (usually in polynomial or exponential form (Peña-Luque et al. 2021) with, in both cases, coefficients that are calculated for each lake. Once this calculation is made, it is sufficient to measure the heights by altimetry and the areas and volume variations are deduced from these laws. Two approaches are used for monitoring multi-year variations of surface water stocks in large river basins. They are based on the fusion of water extensions provided by satellite imagery (passive microwave, visible and radar, or the fusion of several of these techniques) with another data source, either digital terrain models (DTMs) or time series of water heights from satellite altimetry at Virtual Station (VS). This approach is similar to the one used to measure water volume variations in lakes described in Sect. 3. However, there are some differences when one wants to measure water volume variations at the scale of large basins. Two approaches are considered for this purpose. The first is based on the use of hypsometric curves linking flooded area, height above a minimum value corresponding to the ground level or flood minimum, and volume (Hayashi et al. 2000). It was initially used, in large river basins, to represent the filling of floodplains following river overflow, in hydrological models (Yamazaki et al. 2011; Decharme et al. 2012; Paiva et al. 2013a). It has been applied to the Amazon and Ganges–Brahmaputra basins by filling DTM depressions observed by the Shuttle Radar Topography Mission (SRTM, 90 m) and Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM, 30 m) with Global Inundation Extent from Multi-Satellites (GIEMS) flooded extents (Prigent et al. 2007; Papa et al. 2010) over the period 1993–2007 (Papa et al. 2013; Salameh et al. 2017). The main limitation of this method comes from the accuracy of the DTM used. The second approach is to

Fig. 1 **a** Water height variations of the Sera Mesa reservoir in Argentina calculated from Cryosat-2 satellite altimetry data, **b** hypsometry calculated for reservoir height-area pairs, the areas having been measured by Landsat imagery, **c** volume variation resulting from the level and area data by applying Eq. (3)



combine inundation extension from satellite imagery and surface water levels to produce water level maps. This approach requires a network of elevation sensors dense enough to cover the main water areas within the studied basin. It was first applied on the Rio Negro, one of the main tributaries of the Amazon, and led to characterization of the amount of

water present in the floodplains during the 1995–1996 hydrological cycle (Frappart et al. 2012). It was then applied to several flood datasets and different altimetry missions. It has been used in conjunction with GIEMS in the largest river basins including the Amazon and Ganges–Brahmaputra. It has been used, for the first time, to characterize the effect of an extreme climatic drought on surface waters, with the example of the exceptional drought of 2005 in the Amazon basin (Frappart et al. 2012). It has also been used to estimate surface water volume variations at monthly time steps over the period 2003–2007 (Papa et al. 2015).

2.4 Methods of Discharge Calculation from Satellite Data

2.4.1 Current Situation with In Situ Network

The number of publicly and freely available water flux measurements in the main hydrological basins is critical. This is illustrated in Fig. 2. If the number of measurements deposited at the Global Runoff Data Center (GRDC) has grown steadily until the 80 s (red and blue curves), it has been decreasing since then, until it is close to zero for the monthly averages (blue curve). Part of the data are simply released to the GRDC with a long delay, but the number of stations not delivering their data anymore has also increased over the last years (U. Looser, personal communication). In the context of current global change, the current level of information is insufficient to allow accurate analyses of the evolution of regional hydrological regimes. Satellite altimetry discussed above does not directly provide river discharge, unlike the GRDC database, and future SWOT river products (including discharge) will not be as accurate as in situ measurements. However, the combination of

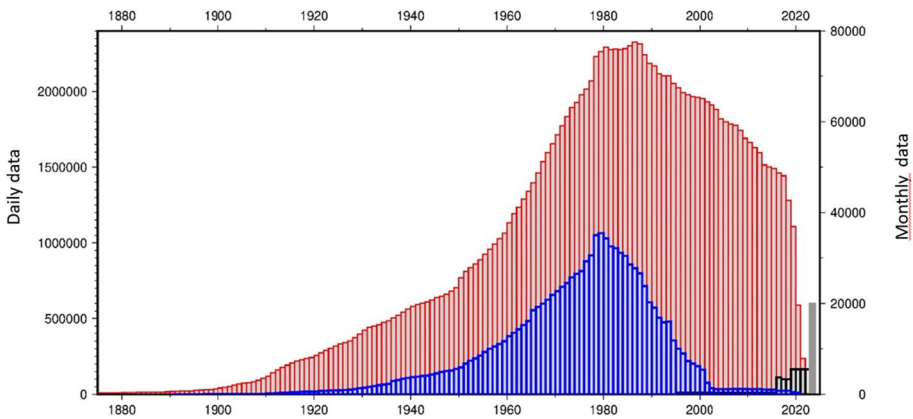


Fig. 2 Evolution over 150 years (from 1873 to 2023) of the number of publicly available measurements, at the GRDC for in situ measurements (extracted from table GRDC_station3.xls available on the GRDC website <https://www.bafg.de/GRDC>), and on the Hydroweb portal for satellite altimetry data. The red histogram corresponds to daily GRDC data (left Y axis), the blue histogram corresponds to monthly data (right Y axis). The amplitude of the axes is calculated so that the curves are comparable, with a factor of 30 between the amplitude for the daily data axis (left) and the monthly data axis (right). The black histogram corresponds to the data available on Hydroweb (reported on the left axis). The last bar, shaded, is an extrapolation that includes the SWOT measurements that will complete the series already constituted, starting in 2023 (but does not take into account all the other SWOT measurements)

both in situ and remote sensing data will be extremely useful for hydrologists in the coming years.

2.4.2 Satellite Altimetry Over Rivers

Although satellite altimetry was used over rivers since the launch of Topex / Poseidon (Koblinsky et al. 1993; Birkett et al., 1998), this was limited to large rivers such as the Amazon (Birkett 2002; Zakharova et al. 2006; Azarderakhsh et al. 2011, 2013; Paiva et al. 2013a,b; Paris et al. 2016; Silva et al. 2010, 2012, Tourian et al. 2016). With the improvement of retracking algorithms and the use of recent SAR altimetry, many more rivers are now monitored, e.g., the Congo (Lee et al. 2011; Becker et al. 2014), the Zambeze (Michailovski et al. 2012, 2014; Kittel et al. 2021), or numerous smaller rivers like the Danube and Po (Nielsen et al. 2022) or even the Garonne (Biancamaria et al. 2018). As explained above, it measures the height of the river surface with respect to a geodetic reference (commonly the WGS84 system also used for GNSS, GPS or Galileo positioning). Space altimetry thus has advantages and disadvantages when compared to in situ hydrometry.

The advantages are:

- Measurements are collected indifferently on any river of the globe that presents a minimum of observability (essentially a minimum width of about 50 m and a contrasting radiometric environment). Their availability is therefore independent of the context of terrestrial access to the site.
- Since all past and current altimeters were handled by space agencies, the raw data are made freely available and with very little delay (2–3 days).
- The measurements are located in an absolute geocentric reference frame; heights are therefore independent of the national levelling system (or national systems in the case of transboundary basins, which are not always compatible) and therefore give access to the slope of the water line (an essential hydrodynamic variable) and to its spatial and temporal variations.
- A quality control on the raw data is permanently performed, and there are no hidden errors in the data (such as instability of a ruler or reading errors by an operator).
- Water height can be measured even from very high (big flood) to the very low (big drought) level.

The disadvantages are:

- The location of the measurements is fixed by the geometry of the satellite orbit and not by hydrological considerations.
- The temporal sampling step is linked to the orbit configuration of the mission and is 10 days at best; this limits the use of satellite altimetry data in many applications that require more frequent data, ideally daily.
- Measurement uncertainty is still high, despite steady and rapid improvements. Over the last 20 years, uncertainty ranged from 80 to 50 cm with classical altimetry missions (Silva et al. 2010; 2012; Calmant et al. 2012) to 10–20 cm today with SAR missions (Halicki and Niedzielski 2021; Kittel et al. 2021).

With the SWOT mission, even better performance is expected, with uncertainties of only a few centimeters. SWOT will provide river discharges every 21 days along more than 120,000 reaches of 10 km along river worldwide, i.e., a larger number of measurements than released by GRDC.

2.4.3 Discharge Calculation

River water height is fundamental information in hydrology, but it does not quantify the water flow along the river. River flow is not yet measurable from space, but it can be deduced from height measurements. The flow rate is the volume of water that crosses a given river section per unit of time. It is expressed in m^3/s . Practically, it is calculated from the velocity of water particles through a section of river, via the following equation:

$$Q = \int_S v(ds)ds \quad (4)$$

where Q is the discharge, S is the cross-sectional area (in m^2) and v is the measured velocity (in m/s) at a point of elementary area ds . Nowadays, the distribution of v at any point of the river section at a point of water height measurement is measured by ADCP (acoustic Doppler current profiler) tools. Knowing height and river flow, we deduced a relation, called the rating curve. Once this curve is established, any height data can be converted into a flow estimate. In order to calculate river discharge using satellite data, one may assimilate altimetry and/or imagery data within the so-called rainfall/runoff models (Paiva et al. 2013b), or we can calculate rating curve, using height and discharge. The modeling approach consists of partitioning the water brought by rain to a basin into different reservoirs, the soil, the subsoil and its water tables, the vegetation, the atmosphere and the drainage network. There is a wide variety of models, which will not be described here. These models separate the fraction of precipitation that goes to vegetation or penetrate into the soil, with the one which evaporates, and the one which is transported downstream through the river. Such models have been developed for example over the Amazon (Guetirana et al. 2009; Guetirana and Peter-Lidars., 2012; Paris et al.; 2016). This type of model uses a lot of remote sensing information. First, the rainfall information itself may come from the GPM (global precipitation missions) constellation or from combination of satellite and in situ rain gauges data like GPCP (Adler et al. 2003), TRMM 3B42 (Huffman et al. 2007), or PERSIANN (Hsu and Sorooshian 2009). In the absence of a good quality local digital terrain model (DTM), the Space Shuttle SRTM product (glcf.umd.edu/data/srtm) and its MERIT variation (Yamazaki et al. 2017) are frequently used to describe the basin topography. Satellite imagery is also used for ancillary data such as land cover and vegetation cover maps (FAO/IIASA/ISRIC/ISS-CAS/JRC), soil nature, and of course the drainage network extracted from the flooded surface products described earlier (Yamazaki et al. 2015) (Fig. 3).

Satellite altimetry data can be assimilated into such models to improve their parametrization, in particular discharge computation. This has been done by Paiva et al. (2013b) over the Amazon basin. They assimilated height measurements from satellite altimeters into the MGB-IPH model (Collischonn et al. 2007). Initial conditions (rainfall forcing) and satellite-based water heights played a key role for accurately predicting discharge over the whole Amazon basin. Kittel et al (2018, 2020) used Sentinel-3A, Sentinel-3B and Cryosat-2 measurements to calibrate the parameters of a hydraulic models used over African

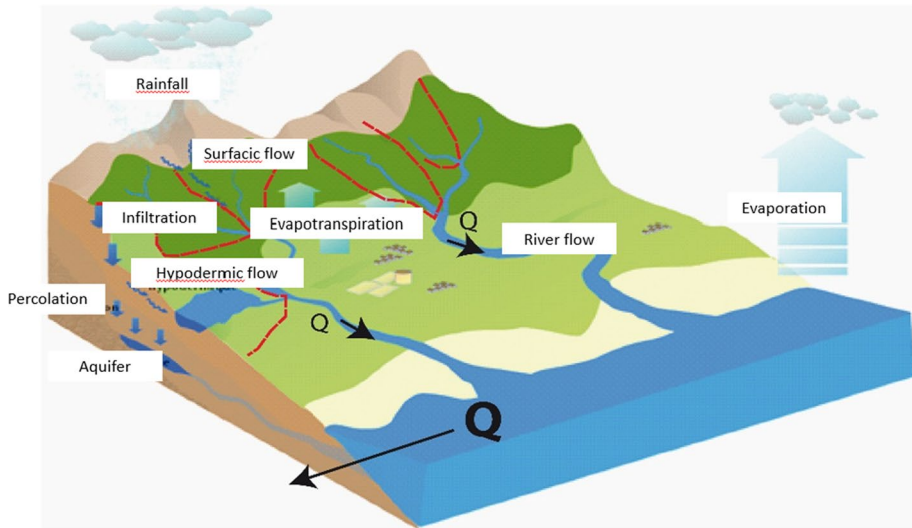


Fig. 3 Diagram of the hydrological modeling of a basin. The basin is partitioned into elementary sub-basins (red dashed lines) and, for each one, inflow and outflow exchanges (blue arrows) are calculated to propagate flows (Q) in the drainage network. Redrawn from (2015)

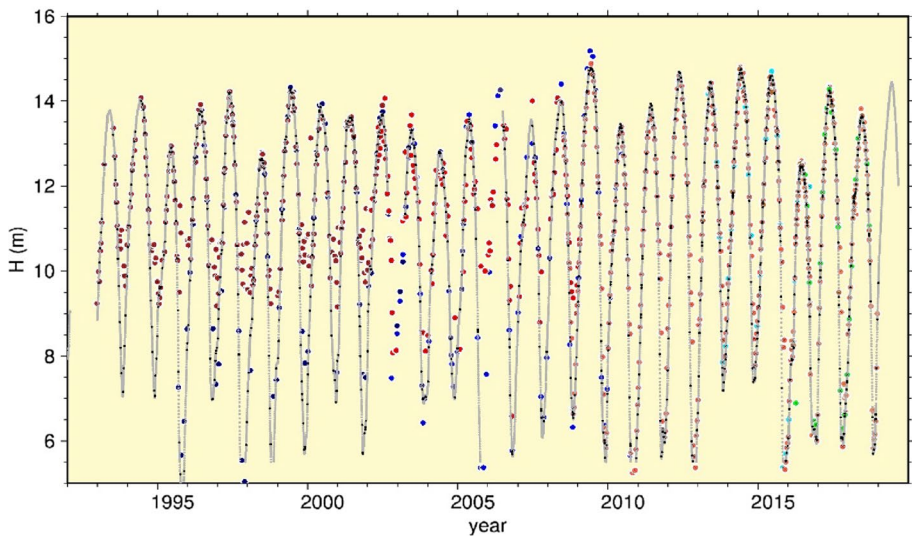


Fig. 4 Time series over the Amazon recomposed from all altimetry missions between 1992 and 2019. The grey line corresponds to the ruler measurements at Parintins port. Note that the in situ chronicle has long periods without data; satellite altimetry can partly fill these gaps

ungauged basins. The method based on rating curve does not imply the use of a model but may also rely on satellite altimetry. For some favorable sites, the low temporal resolution of satellite altimetry can be overcome by combining all nearby measurements acquired by

different missions crossing the river into a single time series. An example is given below (Fig. 4) at the Parintins site (Amazon basin) where measurements from Topex/Poseidon, Jason1, 2 and 3, ERS-2, ENVISAT, SARAL/AltiKa, ICESAT-1, Cryosat-2 and SENTINEL 3A are grouped into a single time series running from 1992 to 2019.

When using satellite altimetry to calculate rating curve, discharge cannot be obtained from in situ data since an Acoustic Doppler Current Profiler (ACDP) instrument cannot be deployed the day of the satellite flyby. In such a case, modeling has to be used to produce discharge from water heights, either for local studies (Leon et al. 2006), or on a basin-wide scale in the objective of constraining hydro-meteorological models (Emery et al. 2018; Parens et al. 2019). In some cases, altimetry-based rating curve is a much better fit to modern discharge measurements than in situ rating curves. Indeed, the altimetry-based curve could be established with a hundred pairs of altimeter height and modeled flow, distributed in a homogeneous way through a wide range of flow regimes (low water and floods included), while often, in extreme cases, the in situ rating curves may be poorly constrained for floods. That has been demonstrated by Paris et al. (2015) over the Amazon basin at Obidos station, where there were relatively few in-situ measurements used to establish the ‘official’ rating curves performed by ANA (Agencia Nacional de Agua, in Brazil) during flood events. However, calculating rating curves using satellite altimetry together with model may generate errors that depend on the model itself, particularly on its inputs (precipitation, DEM, parameters of the models). It is, however, a good alternative when in situ rating curves are not well distributed through different flow regimes, or when in situ rating curves are simply absent.

Some authors developed an original alternative method to calculate river discharge. They used altimetry in order to determine water level at a virtual station, and optical imagery with MODIS sensors, in order to measure the river flow through estimation of reflectance ratio (Tarpanelli et al. 2015, 2019, 2020, 2022; Sherer et al. 2020). They used the properties of the reflectance contrast between dry land and open water, and the variation of the signal which is linked to the river flow. Their method, moreover, allows forecasting river discharge, therefore making possible the development of operational flood forecast in ungauged basin.

3 Monitoring of Lakes and Reservoirs

Lakes and reservoirs are critical components of the hydrological and biogeochemical water cycles because of their fundamental ability to store, hold, clean and deliver water consistently. The general geographic distribution of the world’s lakes is also highly irregular, with most of them located in the Northern Hemisphere and in high latitude-glaciated areas (Downing et al. 2006; Sheng et al. 2016). The role of lakes in climate change studies has long been minimized, yet lakes are recognized as being important in several ways. According to Williamson et al. (2009), they are at the same time essential variables witnessing climate change, contributors and finally integrators of these changes. Through a large number of physical variables such as water level, surface temperature, ice thickness, presence of chlorophyll or water volumes, the monitoring of lake parameters over long periods helps to shed light on the impacts of climate change on the water resource contained in lakes, with multiple consequences. The presence of large numbers of lakes can also modify regional climate (Rouse et al. 2005), in particular through storage and re-emission of greenhouse gases (Williamson et al. 2009; Tranvik et al. 2009). In addition, lake sediments store large

amounts of greenhouse gases, accumulated over millennia, and are thus sources of continental information on past climate. Climate change is impacting lakes in several ways. For example, increased air temperature in mountainous areas accelerates the thawing of glaciers, leading to a dramatic increase in surface runoff, e.g., in the Tibetan Plateau (Wang et al. 2012; Gao et al. 2015) or in the Andes Mountains (Bliss et al. 2014; LópezMoreno et al. 2014). In tropical regions, water exchange between the ocean and atmosphere directly impacts continental waters on seasonal and interannual time scales. East African lakes are a good example. Many authors have studied these links, particularly between large lakes such as Victoria, Malawi or Tanganyika, and the Indian Ocean. They showed that the role of the Indian Ocean on lake water levels is significantly correlated with El-Niño (Nicholson and Yin 2002) or with the Indian Ocean Dipole (Tierney et al. 2013). In arid regions, the impact of climate change can also be very significant, although it may be masked by human use of water resources. This is the case in Central Asia, for example, where the Aral Sea began to shrink in the 1960s due to irrigation of the Central Asian steppes for agricultural development. This shrinkage has further been enhanced by global warming (Aus Der Beck et al. 2011; Crétaux et al. 2013). Lakes also play a major role in the water cycle processes of boreal regions (Siberia or Canada). These regions are characterized by the presence of large flooded areas and a very dense network of hundreds of lakes, composed of permanent and temporary lakes. This results in a high evaporation rate in summer, while in winter most of these lakes are covered by ice (Kouraev et al. 2007). Interannual changes in lake area in the Yukon Valley (Alaska) were quantified over the period 1954–2000 by Altmann et al. (2010) who found that 2300 lakes increased in area, 430 decreased in area, and only 200 remained unchanged. To illustrate the great interest of satellite altimetry for lakes, the example of Tibetan lakes is particularly convincing. The Tibetan Plateau (TP) is the highest and most extensive of the world's high plateaus and is often called the third pole. It is one of the most sensitive regions on Earth to climate change (Huang et al. 2011 and many others). The TP climate system is characterized by high spatiotemporal variability of precipitation with very dry conditions in the northwest (50 mm/year precipitation on average) to wetter conditions in the southeast (700 mm/year on average). Radar altimetry in such an isolated highland region is the only reliable and permanent source of information for water level measurements, especially to estimate temporal variations. Moreover, the lakes scattered by hundreds on the TP are almost all entirely natural, so their slow evolution can be correlated with regional or global climatic phenomena, as shown by many studies (Liu et al. 2009; Lei et al. 2014; Zhang et al. 2011; 2021; Wang et al. 2013; Song et al. 2014; Kleinherenbrink et al. 2015; Crétaux et al. 2016; Liguang et al. 2020). The main goal of these studies is to understand observed lake level changes in terms of glacier mass balance and precipitation changes over the TP. Over the past four decades, Zhang et al. (2021) showed that lake level rise was primarily observed over endoreic lakes, indistinguishable for glacier-fed and non-glacier-fed lakes. In order to determine lake level change over the TP, altimetry missions such as ICESat (1&2) or CryoSat-2 are very well suited because of their very dense coverage (see Table 1). In a recent paper, Liguang et al. (2020) highlighted the value of CryoSat-2. The water level changes of more than 260 lakes were measured over a 10-year period from 2010 to 2019. Among many other studies, this paper illustrates with great relevance the incomparable capacity of altimeters to meet this challenge. These authors showed that over the past decade, 76% of the lakes showed a positive trend in water level change, with greater amplitude in the northern TP than in the south. Studies performed to explain these observations concluded that the main driver is the increase in precipitation, while the loss of glacier mass represents an additional water input leading to increased lake expansion (Zhang et al. 2021).

Table 1 History of past and current satellite altimetry missions

Satellite (mode)	Agency	Frequency	Equatorial distance between orbits (km)	Period	Cycle (j)
T/P (LRM)	NASA/CNES	Ku	315	1992–2005	10
Jason-1 (LMR)	NASA/CNES	Ku	315	2002–2011	10
Jason-2 (LRM)	NASA/CNES/EUMETSAT/NOAA	Ku	315	2008	10
Jason-3 (LRM)	NASA/CNES/EUMETSAT/NOAA	Ku	315	2016	10
Sentinel-6-MF (SAR)	NASA/CNES/EUMETSAT/NOAA/ESA	Ku	315	2020	10
GFO (LRM)	NRL	Ku	165	2002–2008	17
ERS-1 (LRM)	ESA	Ku	80	1991–2000	35
ERS-2 (LRM)	ESA	Ku	80	1995–2002	35
Envisat (LRM)	ESA	Ku	80	2002–2011	35
SARAL (LRM)	CNES/ISRO	Ka	80	2013	35
Sentinel-3A (SAR)	ESA	Ku	104	2015	27
Sentinel-3B (SAR)	ESA	Ku	104	2016	27
CryoSat-2 (LRM/SAR/Sarin)	ESA	Ku	7.5	2010	369
ICESat-1 (Lidar)	NASA	Laser	28.8	2003–2010	91
ICESat-2 (Lidar)	NASA	Laser	28.8	2018	91
GEDI (Lidar)	NASA	Laser	25	2018	Non repetitive

Similar studies have been conducted on man-made reservoirs. The world has experienced a steady increase in reservoir construction over the past few decades. The resulting increase in water retention continues to affect the hydrological cycle and global mean sea level budget, necessitating an updated quantification of changes in global reservoir storage. However, to date, there is no in situ information on the temporal (seasonal to decadal) variations of water storage in reservoirs on the global scale. Moreover, the spatial distribution and the rate of impoundment of new reservoirs are very heterogeneous and only remote sensing currently offers the possibility of determining annual and seasonal variations. Frederikse et al. (2020) showed that, during the 1970s, the very massive water retention of continental reservoirs temporarily slowed the acceleration of sea level rise (although sea level rise subsequently accelerated because of accelerated thermal expansion and land ice mass loss). These authors demonstrated the significant role of reservoirs in understanding interannual changes in the global mean sea level. While some previous studies have analyzed the direct impact of new dam construction on sea level from years to decades, the effect of reservoir regulation on seasonal to decadal time scales has been little studied. Furthermore, Wada et al. (2017) showed that reservoir water storage change is strongly dependent on the time period involved. For example, they estimated that between 2002 and 2014, the total contribution from reservoirs to sea level was $-0.24 \text{ mm/yr} \pm 0.02$, while Chao et al. (2008) estimated this contribution to -0.55 mm/yr from 1950 to mid-2000s. Wada et al. (2017) considered that the construction of new reservoirs in the near future will decrease and thus the impact on the global mean sea level will become negligible. However, these studies rely on static reservoir data sets (total capacity, commissioning dates, average surface area), whereas temporal monitoring with altimetry data would be desirable to better quantify the impact of reservoirs on sea level. On a global scale, and given that there are now tens of thousands of reservoirs, using data from Cryosat-2 or ICESat-2 (laser altimeter launched by NASA in late 2018) would be essential. Cooley et al. (2021) used 1.5 year of ICESat-2 data coupled with a DTM to show the relevance of this approach. 1.5 year is obviously not long enough to establish decadal trends in water stock changes in reservoirs; however, this study showed that such a satellite mission could track several thousand of the largest reservoirs on Earth. More than 9000 reservoirs were measured, and a global mapping of seasonal water stock variations was provided, showing large variations. In some regions such as the Middle East and South American regions had the In some regions such as the Brahmaputra and Amazon basins, Cooley et al (2021) highlighted that the contribution of artificial reservoirs to surface water stock variations was much greater than that of natural lakes. On a global scale, 57% of the seasonal variability of volume changes is due to artificial reservoirs although they represent only a very small portion (4%) of all lakes and reservoirs on Earth. Recently Yao et al. (2023) calculated changes in volume of the 2000 largest lakes and reservoirs over the period 1992–2020, using a set of different satellite-based observations (including altimetry and imagery). More than 50% of these lakes have shrunk significantly with on average, a total loss of water of 21.5 Gt/year. In contrast, for the 900 reservoirs considered by this study, a net global increase at a rate of $4.87 \pm 1.98 \text{ Gt/year}$ was observed. Reservoir water storage even increased severely over the period 2010–2021, as shown on Fig. 5. A 10-year time series of 1750 reservoirs was established and showed that over this recent period, the trend of increasing water stocks was 20.55 Gt/year, i.e., around -0.06 mm/year of contribution to the global mean sea level. Moreover, a large proportion (60%) of this variation is due to new reservoirs built after 2010, while for those already in operation, the trends are much lower.

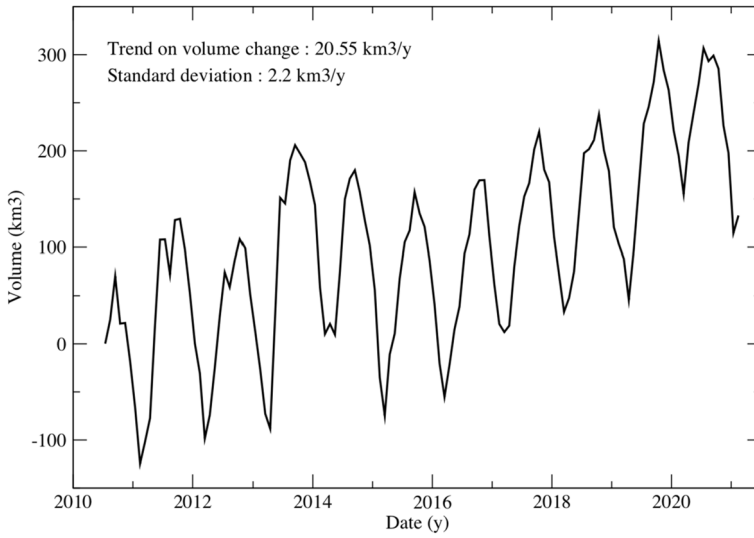


Fig. 5 Monthly variations in water stocks contained on the 1750 largest reservoirs currently in operation, as measured by Cryosat-2, and over the period 2010 to 2021

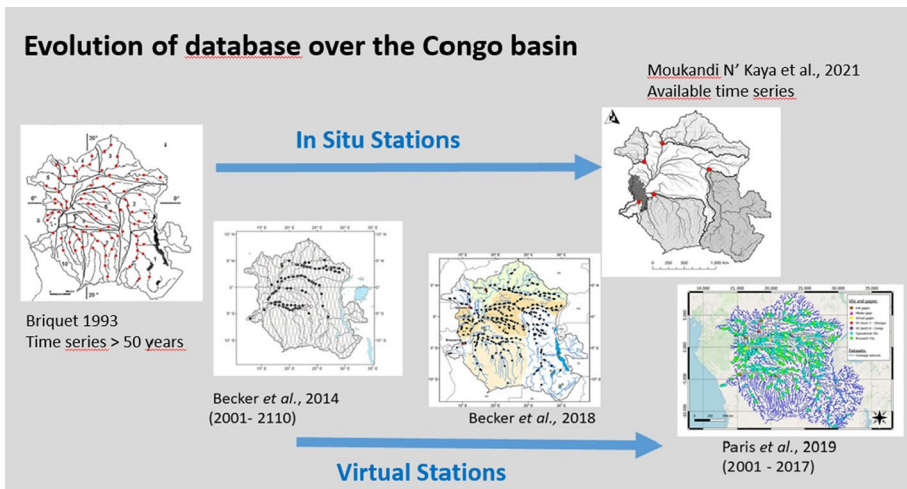


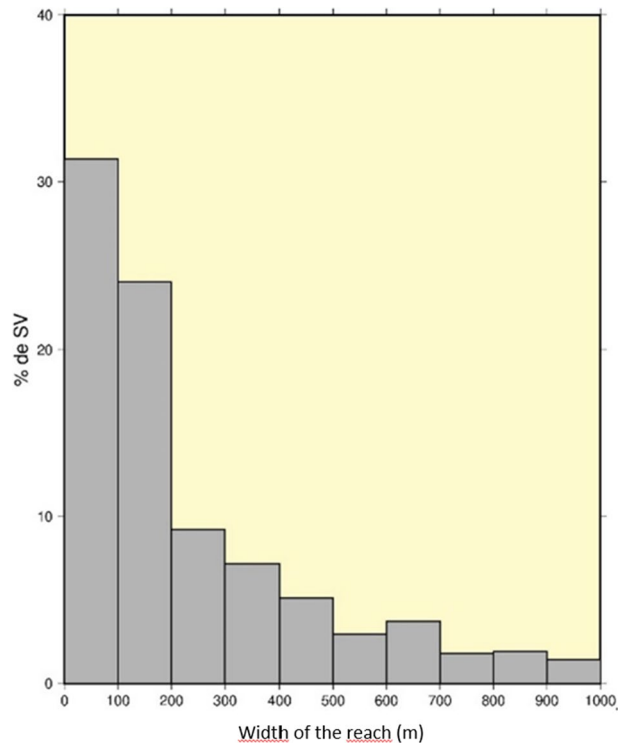
Fig. 6 Hydrological databases used in different studies in the Congo basin

4 River Monitoring: Example over the Congo Basin

The Congo Basin, the second largest hydrological basin by flow, is an example. Figure 6 illustrates the parallel evolution of in situ and altimetric data coverage over this basin, available for scientific studies.

Briquet (1995) used about 70 stations with up to 50 years of water level records. But in 2021, Moukandi et al. (2021) were only able to use 4 in situ time series. At the same

Fig. 7 Histogram of the width of the reaches at the level of the active virtual stations in Hydroweb for the Congo Basin. It can be seen on this figure that more than 30% of the reaches are less than 100 m wide, and more than half are less than 200 m wide. Satellite altimetry thus allows following water level variations on rivers of a basin in their most upstream part, where (potentially) water accumulation (or deficits) that will become extreme episodes such as floods or low water levels are initiated. Satellite altimetry can thus help to warn about these events, while they propagate downstream, to a region often more inhabited and presenting an increased risk for populations and infrastructures



time, Becker et al. (2014, 2018) were able to use about 100 series from satellite altimetry. Paris et al. (2021) produced an even richer database of several hundred sites. They used water level time series from the Hydroweb database (released in Near Real Time) and the MGB-IPH (Collischonn et al. 2007) model tuned to the Congo Basin to determine discharges. Today, more than a hundred rivers of all sizes (see Fig. 6) are sampled in the Congo Basin by more than 800 sites (virtual stations) observed by the Sentinel-3A, 3B and 6 missions (data available from Hydroweb) (Fig. 7).

5 Wetland Global Mapping and Their Role in the Water Cycle and Climate Change

Characterizing the distribution and quantifying seasonal and interannual variations in the global extent and volume of wetlands is a major challenge, given their great diversity and variability, from tropical to Arctic regions. For a long time, our knowledge of wetlands distribution from global to regional scales was based on so called "static" databases, which most often reflected the maximum extent of several components (floods and unflooded wetlands, lakes, rivers, and irrigated crops) (Matthews and Fung 1987; Matthews et al. 1991; Loveland et al. 2000). Until recently, the Global Lakes and Wetlands Database (Lehner and Doll 2004) has been an unprecedented inventory and source of information for resource management studies, ecology and hydrologic modeling. However, these datasets show some limitations as they do not provide information on temporal and spatial variations of

surface waters on seasonal or interannual scales. In this context, satellite observations have proven to be very important to study wetlands and their spatiotemporal variability (Schumann and Moller 2015). Recently, several studies based on LandSat observations have built global surface water detection databases (Feng et al. 2016; Yamazaki et al. 2015). Pekel et al. (2016) provides a detailed dataset (Global Surface Water Explorer) of open surface waters worldwide at 30 m resolution, which includes seasonal cycle characteristics and trends over the past 30 years. At the global scale, a multi-satellite approach must be considered, and in recent years many datasets have been developed. This includes, for example, the Surface Water Microwave Product Series (SWAMPS) (Schroeder et al. 2015) and the Global Inundation Extent from Multi-Satellites (GIEMS; Prigent et al. 2007; Papa et al. 2010) which quantify the variability of the surface water extent at ~ 25 km over long time periods (Prigent et al. 2012). The most recent version of GIEMS covers the period 1992 to 2015 on a monthly basis (GIEMS-2, Prigent et al. 2020), while SWAMPS now provides near real-time information (Jensen et al. 2018). These techniques use a complementary suite of satellite sensors including observations covering a wide frequency range of the electromagnetic spectrum from optical to active and passive microwave and offer a global mapping of surface water extent changes over a relatively long period of time. On a global scale, surface waters are characterized by strong seasonal and interannual variability. In conclusion, it is also worth mentioning the efforts developed to take advantage of the combination of the different observations described above. For example, low-resolution but long-term passive microwave estimates can be combined with optical data, such as those from MODIS, at higher spatial resolution but limited in time, via downscaling methodologies that combine the two estimates into long-term, high-resolution products, such as the proposed inundation extent product over the Inner Niger Delta (Aires et al. 2014). This was one of the starting points for several other studies using downscaling approaches based on topography and inundation index, which now provide global maps of surface water cover at high spatial resolution, such as GIEMS-D15 (Fluet-Chouinard et al. 2015; ~ 500 m spatial resolution) and GIEMS-D3 (Aires et al. 2017, 90 m). Figure 8 represents the 3 states of the global flood dataset called GIEMS-D15: the mean annual minimum (MAMin, with a total global area of 6.5×10^6 km²), the mean annual maximum (MAMax, 12.1×10^6 km²)

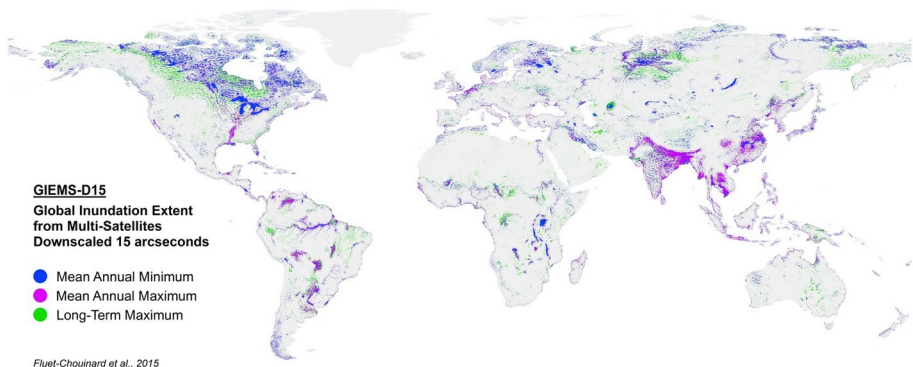


Fig. 8 The global map at 15 arc-second spatial resolution of the surface water extent from GIEMS-D15. MAMin and MAMax represent the average annual minimum and maximum estimates from the 12 years of GIEMS (0.25 degree resolution), respectively, which typically represent high/low seasonal states of global flood extent. LTMax represents a less frequent extensive flooding state obtained by combining the 3 maximum GIEMS years with the maximum Global Lakes and Wetlands Database (GLWD) wetland extent

and the long-term maximum (LTMax, $17.3 \times 10^6 \text{ km}^2$). The uncertainty associated with GIEMS-D15 results from the various sources of error introduced by the disaggregation method, those of the wetland map, and the GIEMS data. However, the evaluation over several regions in various environments showed good agreement with other independent estimates. GIEMS-D15 thus adequately represents the first distribution of surface water at fine spatial and global scales for different flood states, a datum that was not previously available for global water resource and ecosystem studies. Clearly, more investigations are needed to fully characterize the diversity and variability of the surface water extent at the global scale, especially with respect to the physical processes driving these dynamics. New opportunities are now available with the SWOT mission (Biancamaria et al. 2016) and the NASA/ISRO SAR L-band (NISAR), which will allow for improved monitoring of surface waters on a variety of time and space scales.

Monitoring the entire surface water reservoir requires knowledge of the water levels, the extent and the volume of all water bodies (Papa and Frappart 2021). SAR interferometry provides temporal water level variations from the interferometric phase difference (Alsdorf et al. 2001). This application, mainly based on successive passes of SAR sensors over the study area, is difficult to implement because of (i) the weak backscatter on open water surfaces and (ii) the loss of coherence from one pass to another due to changes in surface roughness related to variations in atmospheric conditions. On the other hand, it is quite widely used to track water level variations under vegetation due to the double bounce effect of electromagnetic waves corresponding to their reflection from vegetation before or after reflection from water (Richards et al. 1987). Most of these studies have either focused

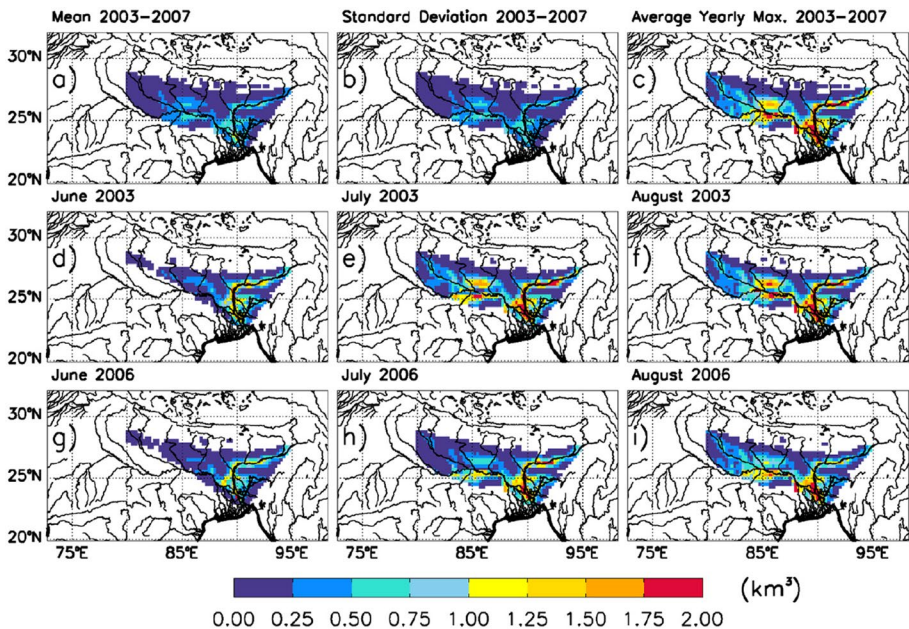


Fig. 9 Surface water stock changes in the Ganges–Brahmaputra from 2003 to 2007 and changes for two contrasting years. **a** and **b** Annual mean and standard deviation (STD) over 2003–2007 for each pixel of $0.25^\circ \times 0.25^\circ$. **c** Average annual maximum over 2003–2007. **d–f** Evolution of surface water volume during summer (JJA) 2003. **g–i** Evolution of surface water volume during summer (JJA) 2006. (Papa et al. 2015)

on small flooded areas, such as those in Louisiana or Florida (Lu et al. 2009; Hong and Wdowinski 2011), or on a portion of the flooded areas of a large basin such as the Amazon or Congo, but over short periods of time from a few acquisitions made over one or two years, sometimes in combination with radar altimetry (Lee et al. 2015; Cao et al. 2018). Figure 9 shows realistic structures with surface water volumes and changes observed along the main courses of both rivers. On average, the changes in surface water volume is less than $\sim 1 \text{ km}^3$ but can reach more than 2 km^3 during the rainy period. During the monsoon season (June–July–August, JJA), the evolution of surface water volume varies greatly between two very contrasting years, 2003 (Fig. 9d, e, f) and 2006 (Fig. 9g, h, i) with higher volumes of water in 2003 compared to 2006, revealing a rather strong interannual variability. In parallel, Fig. 10 shows the temporal variations over the period 2003–2007 and the average annual cycle of the aggregated surface water volume for the Ganges, Brahmaputra and the entire Ganges–Brahmaputra basin. In terms of temporal variations, Fig. 10 shows a strong seasonal signal for both rivers. The average annual amplitude of the surface water reservoir is $\sim 300 \text{ km}^3$ for the Ganges alone and 250 km^3 , for the Brahmaputra. Figure 10 also reveals for the first time that the annual variation of the surface reservoir accounts

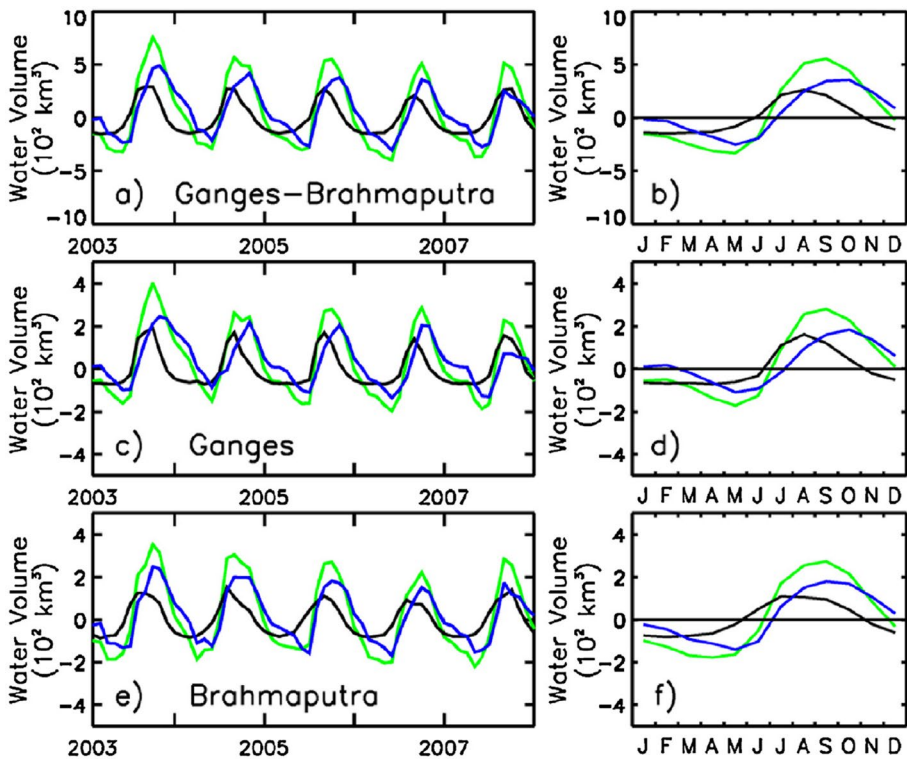


Fig. 10 Variations of total, surface and sub-surface (moisture + aquifers) water stocks in the Ganges–Brahmaputra (Papa et al. 2015). **a** For the entire Ganges–Brahmaputra basin: monthly variations of total water stock measured by GRACE (green), surface water stock (black) and resulting sub-surface water stock (blue). **b** Average seasonal cycle (2003–2007). **c** and **d** same as **a** and **b** but for the Ganges basin only. **e** and **f** same as **a** and **b** but for the Brahmaputra basin only

for ~45% of the total water stock variation on the G-B (~51% and ~41% for the Ganges and Brahmaputra alone).

6 Conclusions and Perspectives

After almost 30 years of using satellite altimetry in hydrology, the number of published studies has steadily increased. Based on several efforts to improve the data processing, satellite altimetry data are now assimilated in models describing hydrological processes at the basin scale (Paiva et al. 2013a, b). The production of papers related to the monitoring of natural lakes has grown exponentially over the years. Thus altimetry has been widely used to understand the impact of climate change at regional scales such as for example the Tibetan Plateau (Crétaux et al. 2016; Zhang et al. 2021) or many other regions (Great Lakes of the African Rift, Baikal, Andean lakes, Canadian Great Lakes, etc.). Cooley et al (2021) demonstrated that the use of Lidar data from the ICESat-2 mission allows the tracking of thousands of artificial reservoirs to quantify their role in total water storage change on seasonal to interannual scales. Meanwhile, lakes were identified by the Global Climate Observing System (GCOS) as sentinel of climate change. Lake water level, lake water extent, lake surface water reflectance, lake ice cover and lake surface temperature are considered by GCOS as essential climate variables (ECVs). The lake ECVs are produced in the context of the ESA Climate Change Initiative program dedicated to provide long-term accurate time series of 27 ECVs observable from space (Carrea et al. 2023). Used in synergy with the Global Database for Surface Water Extent Dynamics, space-based lake data have also been used to measure and interpret volume change at large basin scale such as the Amazon or Niger (Frappart et al. 2005, 2012; Papa et al. 2013). Concerning monitoring of rivers and their tributaries, altimetry has also been of great help for more than 30 years, whether on large rivers such as the Amazon or Congo rivers, but also now on smaller rivers. Altimetry-based water levels are complementary to field measurements whose availability is becoming scarce and even almost absent in many regions, especially in tropical basins (Getirana et al. 2009, Jiang et al. 2020; Kittel et al. 2021).

In large international conferences such as AGU (American Geophysical Union), EGU (European Geophysical Union), or ESA Living Planet, entire sessions are now devoted to the use of space-based measurements in water science. At the beginning of the satellite altimetry era, this technique was not designed for hydrology. Today, with SWOT and operational systems such as Sentinel-3, this technique has definitely entered a new era where observing continental waters is now considered as a main objective in Earth Observation. While early studies on the use of altimetry to monitor continental waters were very few, the situation has much evolved, with a rich literature coming from all countries worldwide. Recent studies have shown the high potential of satellite remote sensing as useful system of measurements to help in flood prediction or to perform global wetland mapping and monitor their dynamics. Satellite altimetry data are also now assimilated in hydrodynamical models allowing to compute river discharge and forecast flood events. Measuring water height and slope from satellite altimetry and reflectance of water using instruments like Modis is now also used to calculate river discharge. Several evolutions of the instrumentation on one hand (emergence of SAR altimetry mainly) and on the processing on the other hand (waveform retracking, Onboard DEM, full SAR processing, physical processing of waveforms) have taken place over the last 30 years, making altimetry a very useful tool not only for monitoring of water height in remote areas, but also for improving capacity

of flood predictions, or a system to measure the impact of climate change on continental water and their role in the global water cycle. Hydrology from space is now entering an era of operational monitoring. The optical and radar sensors (Radarsat, Sentinel-1/2/3, Landsat) play a key and central role to achieve the objective of making the Earth fresh water resources under continuous and accurate survey from satellite constellations. Some gaps were however identified over the years: temporal resolution of altimetry still not allows to perform survey of rapid changes of water height like those occurring during flash floods. For such applications, a daily sampling frequency is required. This is the purpose of a project initiated at LEGOS and now handled by CNES, consisting of developing a constellation of microsattelites with Ka-band altimeters onboard (the SMASH project), with a daily revisit time and covering hundreds of ri preliminary studies have shown that such a constellation would allow to have daily revisit over ~ 16,000 virtual stations worldwide. Meanwhile, the SWOT mission (Biancamaria et al. 2016) will fill the gap of classical altimetry missions in terms of spatial coverage and derived products (water level extent and volume changes of lakes, river height, slope width and discharge). Millions of lakes, thousands of rivers and floodplains over the continent will be seen by SWOT. ESA also plans to develop SWOT-like missions for the next generation the Sentinel-3 satellites (Sentinel-3NG). Although satellite techniques has proven their ability and efficiency to measure a high number of essential climate variables (ECVs) now feeding several global databases, development of new applications and investment from the private sector are still immature. In oceanography, after few years of development, satellite altimetry became a key tool for operational applications, in particular for decision-making purposes. Similarly, development of operational space hydrology is a major goal to pursue. Global databases exist, constellation of satellites is planned for the next decade, and the expertise in processing the space data and in modeling is also there. Considering the current challenges that human societies and ecosystems are facing today in terms of water resources and vulnerability due to extreme hydrometeorological events, as a consequence of global warming, operational space hydrology needs urgently to be implemented.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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