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On the use of satellite remote sensing to detect floods and droughts at large scales.

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Article Highlights

- Each components of the terrestrial water storage is a key hydrological variable to understand floods and drought periods.
- Their monitoring at river basin scale and over long period of time is facilitated by large scale sensors.
- The combination of Earth observations with other datasets can be an asset for the prediction of hydrological events and for monitoring.

Keywords:

Floods, droughts, large-scale, Terrestrial Water Storage, GRACE, SMOS, satellite altimetry, SWOT.

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Abstract

Hydrological extremes, in particular floods and droughts, impact all regions across planet Earth. They are mainly controlled by the temporal evolution of key hydrological variables like precipitation, evaporation, soil moisture, groundwater storage, surface water storage and discharge. Precise knowledge of the spatial and temporal evolution of these variables at the scale of river basins is essential to better understand and forecast floods and droughts. In this article we present recent advances on the capability of Earth Observation (EO) satellites to provide global monitoring of floods and droughts. The local scale monitoring of these events which is traditionally done using high resolution optical or SAR (Synthetic Aperture Radar) EO and in situ data will not be addressed. We discuss the applications of moderate to low spatial resolution space-based observations, e.g. satellite gravimetry (GRACE and GRACE-FO), passive microwaves (i.e. SMOS) and satellite altimetry (i.e. the JASON series and the Copernicus Sentinel missions) with supporting examples. We examine the benefits and drawbacks of integrating these EO datasets to better monitor and understand the processes at work and eventually to help in early warning and management of flood and drought events. Their main advantage is their large monitoring

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scale that provides a “big picture” or synoptic view of the event that cannot be achieved with often sparse in situ measurements. Finally, we present upcoming and future EO missions related to this topic including the SWOT mission.

1. Introduction

Hydro-meteorological extreme events count among the costliest natural disasters affecting human societies. They produce the largest cumulative total of life lost and socio-economical costs. In the context of global warming, these extreme events are intensifying and becoming more frequent in recent years (Stocker et al. 2013; Yamazaki et al. 2018 and references therein). This review paper focuses on floods and droughts and is part of a special issue on the benefits of integrating space-based or air-borne observations in order to better predict, monitor and help in post-disaster management of natural hazards in which several themes as storm surges (Melet et al. 2020), tsunamis (Hébert et al. 2020), landslides (Lissak et al. 2020) and fire (Pettinari and Chuvieco 2020) are investigated. Space-based or air-borne Earth Observations (EOs) have several benefits: 1) their instruments are not affected by the events, 2) they collect consistent data at different wavelengths and over different spatio-temporal scales and 3) they cover dangerous/inaccessible areas. Overall, EO data allow better understanding of the relationship between the hydrosphere, atmosphere, biosphere and solid Earth, and provide a global view of the phenomena and are complementary to in situ measurements (Tralli et al. 2005; Petiteville et al. 2015). Moreover, EO data can be used synergistically with demographic and socio-economic data to understand how hazards impact human societies, enhance our knowledge of the human influence on risks and thus elaborate mitigation, disaster and post-disaster management (Tralli et al. 2005).

In this article, the focus is put on recent advances on the monitoring of floods and droughts at the scale of large river basins through the observation of specific components of the hydrological cycle via space based EO. At the end of last century, droughts counted for one-fifth of the damage caused by natural hazards and has steadily increased in recent decades. On the other hand, the cost of floods is expected to increase by ten folds in 2030 (World Resources Institute 2019). It is important to note that this article does not address the local scale monitoring of these events which is traditionally done using high resolution optical or SAR (Synthetic Aperture Radar) EO (e.g. Domeneghetti et al. 2019) and in situ data. We review the innovative applications on the use of moderate to low spatial resolution missions to provide information facilitating the understanding and thus the forecasting of floods and droughts and discuss the future of these Earth Observation data.

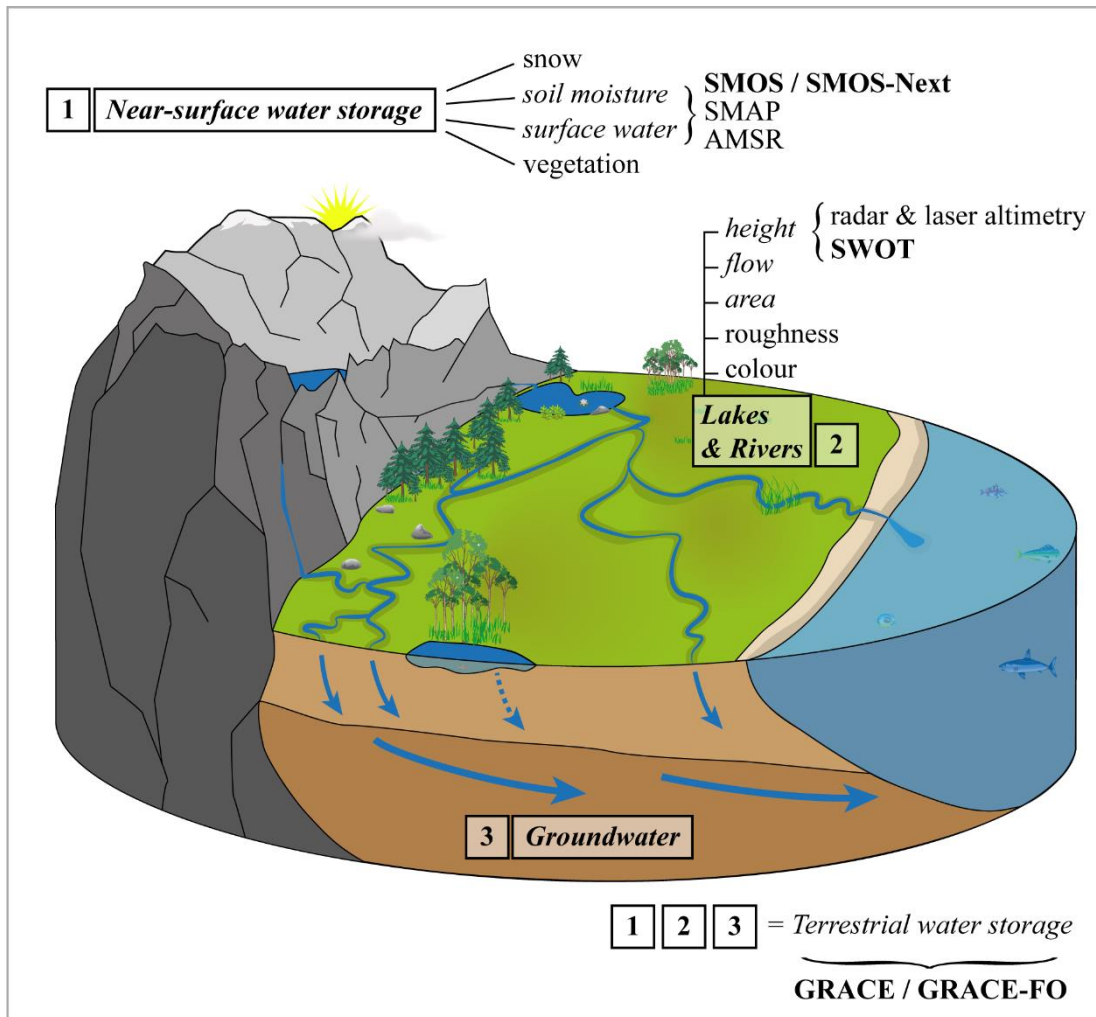


Fig 1 Sketch of the different water storage compartments investigated in this study. Terms in *italic* are state variables considered and **bold** terms are satellite missions presented in this article.

2. Water Storage on the Continents: General Remarks

Freshwater represents less than 3 % of the total amount of water on Earth. On land, freshwater is stored in various reservoirs such as ice caps, snow, glaciers, groundwater, soil moisture (in the unsaturated soil and root zone, i.e., in the upper few meters of the soil (e.g. Hillel 1998)) and in surface water bodies (rivers, lakes, man-made reservoirs, wetlands and inundated areas) (**Fig 1**). These different storage compartments are in direct interactions with the atmosphere. For example, in the tropical Pacific, long-term droughts and floods are under the influence of the El Niño-Southern Oscillation (ENSO) events (e.g. Ward et al. 2014; Fok et al. 2018 and references therein).

Short-time hydrological events such as droughts and floods (i.e., events of water surplus or deficit that deviate from the average conditions over days to several months) are controlled by natural phenomena and anthropogenic activities. Key hydrological variables that drive and characterize these events are precipitation, soil moisture, groundwater storage and river discharge (e.g. Niu et al. 2014). Precipitation is considered as the main variable for the assessment of meteorological droughts and it is the main driver of flood events and thus the main input for hydrological flood models. The World Meteorological Organization (WMO) recommends the use of the Standardized Precipitation Index (SPI) for the assessment of wet and dry conditions (Svoboda et al. 2012). While its importance is not debated, complementary indices have emerged in the recent decades for characterizing of droughts and floods at large-scale. Here we address the monitoring of flood and drought events in terms of soil moisture, inundated areas, groundwater, total water storage change and river discharge. Soil moisture is a key

variable of the water cycle that links subsurface and surface to atmospheric processes (e.g. Robinson et al. 2008; Niu et al. 2014; Grillakis et al. 2016; Babaeian et al. 2019). It is identified as an Essential Climate Variable (ECV) by the Global Climate Observing System (GCOS) (Bojinski et al. 2014) and is a major part of the so called “Green Water” (Hoekstra et al. 2011). As stated by Babaeian et al. (2019) “soil moisture is an effective indicator for drought conditions and flood risks and thus plays a unique role in their prediction”. In fact, soil moisture availability in the root zone is a direct indicator for agricultural droughts and can also inform on the wetness status in advance of strong rainfall events as an indicator of possible flood generation. Soil moisture accounts for about 0.79% of the available freshwater on Earth but it is the main interface for the atmosphere / biosphere / subsurface interactions.

Open water bodies include lakes, rivers, wetlands, peatland, floodplains and man-made reservoirs. Wetlands cover about 4% of the Earth’s land surface (Pekel et al. 2016) and are mostly present in tropical areas; for example, up to 20% of the Amazon Basin (Parrens et al. 2017). They play an important role in the hydrological regimes of large river basins as transition zones. Wetlands and floodplains are also the place of ecosystems with rich biodiversity (Costa et al. 2013) but they are very vulnerable to extreme changes.

Rivers account for 0.015% of the available freshwater globally, but like soil moisture they are the transfer medium for a large amount of the available freshwater. Since more than 50% of the world's population lives closer than 3 km to a surface freshwater body, and in majority near small to large rivers (74%) (Kummu et al. 2011), most of the world population is impacted by hydrological droughts and floods.

Groundwater is the main reservoir of available freshwater globally (96.7%) and accounts for 80% of the water extracted by humans. Groundwater is becoming an important supply of freshwater (~50 % of the drinking water) (Foster and Loucks 2006) in different regions of the world as the surface water is becoming less reliable (e.g. Richey et al. 2015). Arid and semi-arid regions represent ~30 % of the Earth’s surface and groundwater constitutes a significant resource of freshwater in these areas; poorly renewable as the water input is often very localised but exploitable (e.g. Margat and Van der Gun 2013). The importance of groundwater supply is known in drought conditions but only few EO-based studies have addressed its contribution to flood events. In karstic regions, groundwaters directly contribute to the generation of floods. However, they remain less common than river flooding and generate less damages (e.g. Yu et al. 2019). Runoff from groundwater storage tends to be delayed relative to the faster reacting near-surface storage compartments (Yu et al. 2019 and references therein) and can thus have a major contribution to the later stages of a flood event (Huntingford et al. 2014).

Precise knowledge of the spatial and temporal evolution of the aforementioned storage variables and of their sum as an integrative measure of the water storage in a river basin, i.e., total terrestrial water storage (TWS) change which is one of the four fundamental components of the terrestrial water balance besides precipitation, evapotranspiration and runoff, are important to better understand and forecast flood and drought events at the scale of river basins.

3. Space-Based Observations of the Water Cycle Components

3.1. Monitoring of Soil Moisture

The observation of surface soil moisture can be obtained using active or passive microwaves (Njoku et al. 2003; Kerr et al. 2012; Tomer et al. 2015). Optical remote sensing on the other hand will provide a proxy information of the impact of soil moisture on soil emissivity and is more applied for soil texture characterisation (Gomez et al. 2019). The retrieval of soil moisture from active microwave is generally applied using SAR data from ASCAT (Wagner et al. 2013), RadarSat (Tomer et al. 2015) or Sentinel-1 (Paloscia et al. 2013). The retrieval of soil moisture from passive microwave has been applied to C-Band (Njoku et al. 2003) and L-Band (Entekhabi et al. 2010; Kerr et al. 2012). The more recent L-band data from the SMOS (ESA) and SMAP (NASA) missions are considered as the most adapted for soil moisture retrieval considering radiative transfer physics (Ulaby 1981), but they can be hampered by

their coarse resolution (~50 km and 36 km, respectively). Downscaling algorithms combining the microwave to optical or radar have been applied to enhance the resolution (Merlin et al. 2010; Tomer et al. 2016). The computation of root zone soil moisture from surface soil moisture can be provided through parsimonious models (Albergel et al. 2008; Al Bitar et al. 2013) or assimilation into land surface models (LSM) (Reichle 2018). The advantage of the parsimonious models is their ability to reduce the number of inputs mainly due to their independence from precipitation data. This is a major advantage in large irrigated areas. The advantage of data assimilation (DA) systems is their coherent retrieval or prediction of the ensemble of state variables (e.g. root zone soil moisture, surface and/or vegetation temperatures), still one must keep in mind that errors on one variable will impact the other ones. Nevertheless, SMOS and SMAP missions provide a high temporal revisit (3 days for ascending and descending orbits). They give access to consistent information over the globe as the acquisition configuration are similar across ecosystems. Yet several drawbacks can be mentioned as 1) the sensitivity of L-Band acquisition to radio frequency interference from illegal emissions in the observation bandwidth from civil and military applications, 2) the retrieval using parsimonious models requires one to take into consideration the transpiration of the vegetation that is ill characterised and, in many cases, bypassed and 3) the resolution of the original data often needs to be enhanced using error-prone disaggregation approaches.

3.2. Monitoring Inundated Areas Using Passive Microwaves

Flooded areas are commonly monitored using high resolution thermal, visible or radar observations, as they can provide information at local scale. For example, Pekel et al. (2016) provided a 30 years database of surface water changes from LANDSAT (NASA) dataset. Mueller et al. (2016) presented a similar analysis over the Australian continent while providing the details for an operational continental water detection suite. These three techniques present major drawbacks in specific conditions. For optical (thermal and visible) remote sensing the cloud cover can be a major issue during flood events and over tropical areas. Moreover, thermal remote sensing is highly sensible to the presence of water vapor in the atmosphere while relative humidity over 80% are frequent in tropical regions and during wet weather. SAR is widely used to monitor the flood extents (Bonn and Dixon 2005; Matgen et al. 2011; Twele et al. 2016) and is an essential data source used during the activation of the International Disasters Charter. The main drawbacks of the SAR data are the impact of dense vegetation and soil roughness in dry conditions. In this paper we are addressing the monitoring of inundated areas at the scale of river basins. In these conditions the use of passive microwaves has been demonstrated in several studies (Prigent et al. 2007; Schroeder et al. 2015; Al Bitar et al. 2016).

Recently, the multi-angular full-polarizations brightness temperatures from SMOS (Al Bitar et al. 2017) were used in a contextual approach to retrieve the flooded water fractions at 25 km resolution (Parrens et al. 2017). The application to the Amazonian basin shows that flood and drought events related to water surface changes can be monitored at 10 days temporal resolution. To reduce the inconvenience of coarse resolution, disaggregation algorithms to sub-kilometric resolutions have been applied to such datasets using auxiliary data related to flood probabilities, Digital Elevation Models (DEM), and basin hydro-morphological information (Aires et al. 2017; Parrens et al. 2019). At these resolutions the dataset is highly dependent on the input auxiliary data quality, mainly the DEM. The main advantage of microwave-based datasets is their ability to provide large-scale information. For example, the SMOS swath is about 1400 km. Another advantage related to the large scale is the ability though the frequent revisits (3 days global coverage for ascending and descending orbits) to provide coherent and consistent information at global scale. Finally, the use of low-frequency passive acquisition (e.g. L-Band at 1.4 GHz) is less prone to screening effect from the vegetation compared to passive C-Band (AMSR-E). Low-frequency passive sensors are also less sensitive to vegetation structure and surface roughness than in active microwaves (ASCAT). Still the data have several drawbacks, e.g. 1) the low-resolution of the acquisition and 2) their strong vulnerability to Radio Frequency Interference (RFI) (Soldo et al. 2016) because of the swath width and the low measured surface emissions (10^{-4} W m^{-2}).

3.3. River Elevation and Discharge

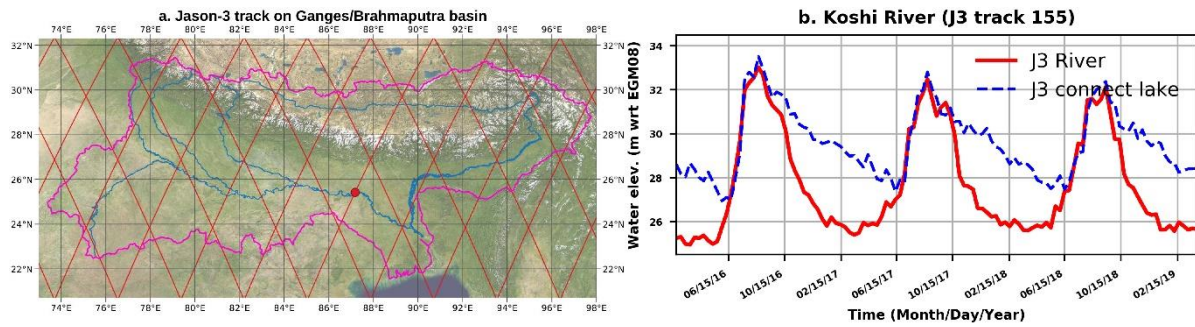


Fig 2 *a* Jason-3 satellite tracks (red lines) over the Ganges/Brahmaputra basin (magenta boundaries, which come from GRDC Major River Basins database). The background image comes from the NASA MODIS “Blue Marble Next Generation” image (Stöckli et al. 2005). Blue lines represent the Ganges river and its major tributaries, and the Brahmaputra river. *b* Jason-3 water elevation time series on the Koshi river (red dot on panel *a*.) and on a nearby lake connected to the river during seasonal floods (red and blue lines, respectively).

Nadir radar and SAR altimeters (e.g., Jason-1,2,3, Envisat, Saral/AltiKa and Sentinel-3A/B) provide measurement of water elevations (i.e. the distance between water body surface and a reference surface, ellipsoid or geoid). However, they cannot provide water depth, nor any information on water body bathymetry below the lowest water level observed. Initially conceived to measure ocean surface topography, they have been used since the 1990s to also measure inland waters elevations with an accuracy of few decimetres to a metre over continents (Santos da Silva et al. 2010), depending on the observation configuration, previous measurements and instrument characteristics. The main limitations of such instruments are their spatial and temporal sampling. They only provide measurements along the satellite track, missing all water bodies that are not overflowed beneath by the satellite. Current missions on a repetitive orbit (the satellite passes over the same point at a constant time step) have an intertrack distance (i.e. the distance between two adjacent ascending or descending tracks) at the equator between 315 km (the Jason series) to 52 km (when considering the two satellites of the Sentinel-3 series). The lower the intertrack distance, the higher the repeat period. For example, the Jason satellites have a 10 days revisit time, whereas it is 27 days for the Sentinel-3 satellites. In contrast, in situ gauges provide daily or better time sampling. These characteristics restrict nadir altimeter observation capacity to large scale floods (Coe and Birkett 2004; Frappart et al. 2005; Biancamaria et al. 2011; Boergens et al. 2019). Nevertheless, satellite altimetry provides free measurements over multiple points of the river network (see **Fig 2a** for an example of Jason-3 space sampling over the Ganges/Brahmaputra basin). They have thus been quite useful for large and poorly gauged basins, especially in a context of transboundary basins, to provide measurements both on the river and on the floodplain (**Fig 2b**).

To overcome the space and time sampling issue, many studies have combined observations from the same mission at different location along the river network or even multiple observations from different altimetry missions, in order to increase water level time series to observe as many events as possible (Hossain et al. 2014; Tourian et al. 2016; Boergens et al. 2019). For example, Tourian et al. (2017) has been able to compute daily water level and discharge on the Niger River mainstream using Envisat, SARAL/AltiKa and Jason-2 data and the few in situ data available for this basin.

Combining altimetry observations with measurements from other space sensors is also a promising perspective. Combination of altimetry data with optical sensors, especially the MODerate resolution Imaging Spectroradiometer (MODIS), has been the most investigated (Tarpanelli et al. 2015, 2017, 2019; Ovando et al. 2018; Pham et al. 2018). In these studies, relationships between MODIS images for different wavebands and altimetry-based water elevations are computed to complement altimetry time series with the high temporal resolution of optical sensors enabled by their large swaths.

3.4. Monitoring of Terrestrial Water Storage Including Groundwater

In spite of its fundamental role for the global water cycle, for a long time there was no technique available that allowed for monitoring variations in total terrestrial water storage in an integrative way, including all relevant storage compartments on and below the Earth surface. Also, the lack of in situ data with the ability to measure long-term changes in the groundwater storage explains why the groundwater variability was poorly constrained (e.g. Famiglietti et al. 2011; Famiglietti 2014; Chen et al. 2016; Bonsor et al. 2018) before the launch of new types of sensors. Indeed, since the beginning of the century, a new generation of Low Earth Orbiter (LEO) satellites has been operated to precisely determine the Earth's static gravity field, such as the GOCE (Gravity field and steady-state Ocean Circulation Explorer) mission (Drinkwater et al. 2006). The most important one for hydrological applications is the Gravity Recovery and Climate Experiment (GRACE) mission (Tapley et al. 2004) and its successor GRACE-FO (Landerer et al. 2020), which is dedicated to map the static gravity field and its time variations. Since its launch in March 2002, with the co-orbiting twin vehicles, it has measured the time variations of the Earth's gravity field for 15 years and with unprecedented precision. These two satellites are in the same orbit at 450-500 km altitude with a separation of about 200 km. The high-precision measurements of the inter-satellite distance change were enabled by the on-board K-Band Range Rate (KBRR at a precision of 0.1 m s^{-1}) system (Tapley et al. 2004). Together with Global Positioning System (GPS) observations and on-board accelerometer and star camera observations the estimation of the gravity variations is indirectly obtained by inverting the ultra-precise KBRR observations between the two vehicles (Houborg et al. 2012). GRACE and GRACE-FO yield crucial information on the temporal and spatial variations of TWS for the period 2002 to today, with a gap between GRACE and GRACE-FO from June 2017 to June 2018. TWS is a unique integrative observation that notably includes, e.g., groundwater storage variations down to any aquifer depth and the mass loss of ice caps and glaciers, typically with a temporal resolution of one month and spatial resolution of $\sim 300 \text{ km}$. From the TWS variations, water storage variations in individual storage compartments such as groundwater can be singled out by the subtraction of water mass variations in other components if available from complementary observations and models or in a model-based data assimilation framework (see, e.g. Frappart and Ramillien 2018). Both approaches are at the expense of additional errors introduced in the final product by the uncertainties of the separation approaches themselves.

4. Progress in Flood Applications

Flood is defined by the World Meteorological Organization International Glossary of Hydrology (WMO 2012) as: “(1) Rise, usually brief, in the water level of a stream or water body to a peak from which the water level recedes at a slower rate. (2) Relatively high flow as measured by stage height or discharge.” In this review study, we focus on long-lasting floods with large coverage in space which can be captured by moderate- to low- spatial resolution space-based observations. We do not consider flash floods (defined as “flood of short duration with a relatively high peak discharge” in WMO, (2012)) which can last a few hours and be very intense locally and cannot be observed with such satellite instruments. The following sections present how the space-based observations presented in section 3 can observe and provide meaningful measurements for these large-scale floods.

4.1. Added Value of Satellite Altimetry

Daily discharge has been computed using DA techniques by updating hydraulic/hydrological model state variables with altimetry-derived observations (Schumann et al. 2010; Hirpa et al. 2013; Michailovsky et al. 2013; Finsen et al. 2014; Emery et al. 2018). These improved time series help to get better estimates of the dynamics and the magnitude of flood events at the river basin scale. A particular advantage compared to classical approaches based on often scarce in situ data is that the altimetry-based reanalyses may allow for a spatially distributed discharge estimation for large basins. In a few studies, the calibration of hydraulic model parameters with altimetry time series has been investigated (e.g.

Schneider et al. 2017; Jiang et al. 2019). As highlighted by Jiang et al. (2019), for parameter estimation, contrarily to water elevation/discharge time series densification by higher temporal resolution, a better spatial coverage is more important than re-visit times with high frequency. The benefit of a better calibrated model is the possibility to simulate more accurately past events and to eventually forecast them with lower uncertainty in future. Bates et al. (2014) provides a more in-depth review of satellite data used to observe floods and how they have been combined with models.

However, very few studies implemented a proof-of-concept of flood forecasting system using altimetry observations. Based on the work from Biancamaria et al. (2011), Hossain et al. (2014) implemented a real flood forecasting system of daily water levels with a 5-day lead time over Bangladesh (Ganges/Brahmaputra/Meghna basin) using Jason-2 data and a hydraulic model. This system has then been used operationally by Bangladesh Institute of Water Modeling as a decision-making tool (Hossain et al. 2014b). Tarpanelli et al. (2017) also developed two proof-of-concept systems to forecast discharge with a 4-day lead time over the Niger basin, using either MODIS images, or altimetry data. They found that altimetry data provide more accurate forecasts but lack sufficiently frequent re-visit times. On the contrary, the MODIS-based forecast system is somewhat less accurate but enables daily forecasts which are more suitable for operational agencies. However, to the authors' knowledge, this system has not yet been used operationally.

One must keep in mind that nadir radar altimeters due to the vertical accuracy, and time and space samplings cannot bring as much information as in situ data. However, due to their large spatial coverage, especially for big transboundary basins and where there are few gauges or where the gauge data are not shared with downstream countries, altimetry measurements could help to provide more knowledge on large floods.

4.2. Monitoring and Predicting Flood Events With Satellite Gravimetry

The mass changes observed by GRACE and GRACE-FO encompass water storage changes associated with the evolution of hydrological events. Satellite gravimetry thus can be used to assess the magnitude of large-scale flood events in terms of their storage amplitude, duration and frequency in river basins worldwide. Furthermore, monitoring catchment wetness conditions opens up the opportunity to use GRACE / GRACE-FO in a predictive mode for early warning applications, i.e., for indicating river basin states that favour the generation of flood events. Added value for flood monitoring and forecasting relative to other observation data can be expected as gravimetry is the only comprehensive observation technique that delivers the wetness state in an integrated form for all TWS compartments.

4.2.1. Monitoring Flood Events With GRACE / GRACE-FO

Monthly GRACE products from various processing centres and with different solution strategies (see, e.g. Jean et al. 2018 for an overview of available solutions) have frequently been used to describe flood events. For example, Seitz et al. (2008) reported evidence of observed extreme weather fluctuations in Central Europe for the period 2003-2008 including the associated flood events by performing a regional analysis of GRACE data over Europe based on spherical wavelet / B-spline and global spherical harmonic solutions. Chen et al. (2010) studied the exceptional 2009 Amazon flood and inter-annual terrestrial water storage change observed by GRACE and concluded that the TWS increase in the lower Amazon basin in the first half of 2009 were clearly associated with the exceptional flood season in that region.

Abelen et al. (2015) related soil moisture from the WaterGAP Global Hydrology Model (WGHM) (Döll et al. 2003) and from the satellite sensors Advanced Microwave Scanning Radiometer—Earth Observing System (AMSR-E) and Advanced Scatterometer (ASCAT) to GRACE-based total water storage variations. For the La Plata basin in South America, they found that GRACE water storage dynamics represented the ENSO-dependent sequence of drought and flood events with a temporal delay of few months compared to near-surface soil moisture. Furthermore, Boening et al. (2012) and Fasullo et al. (2013) reported heavy precipitation over the Australian continent during the 2010-2011 La Niña. Based on GRACE observations, they highlighted regional spots of much higher wetness than normal,

particularly in northern Australia. This is illustrated in **Fig 3** showing GRACE-based water storage anomalies in Australia over a period of 8 months from June 2010 to February 2011. This information can be associated to the anomaly in total water storage including surface water and groundwater with respect to long term average. While **Fig 4** shows the excess and deficit information from the SMOS-based root zone soil moisture during February 2011 compared to the seasonal averages. The maps in Fig 3 and Fig 4 show similar patterns in several regions but also discrepancies that can be explained by the associated representative time period for each observed component by the two satellites that are complementary.

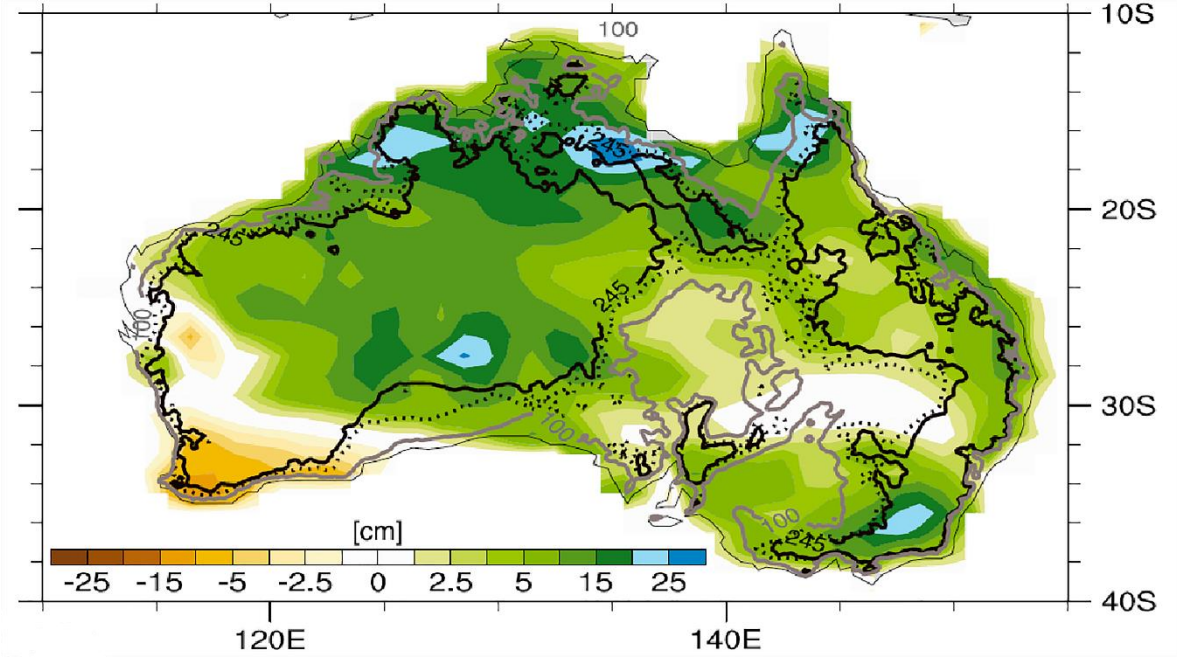


Fig 3 Water storage anomaly (expressed in cm of equivalent water height) for Australia based on GRACE for the period June 2010 to February 2011 (modified from Fasullo et al. 2013).

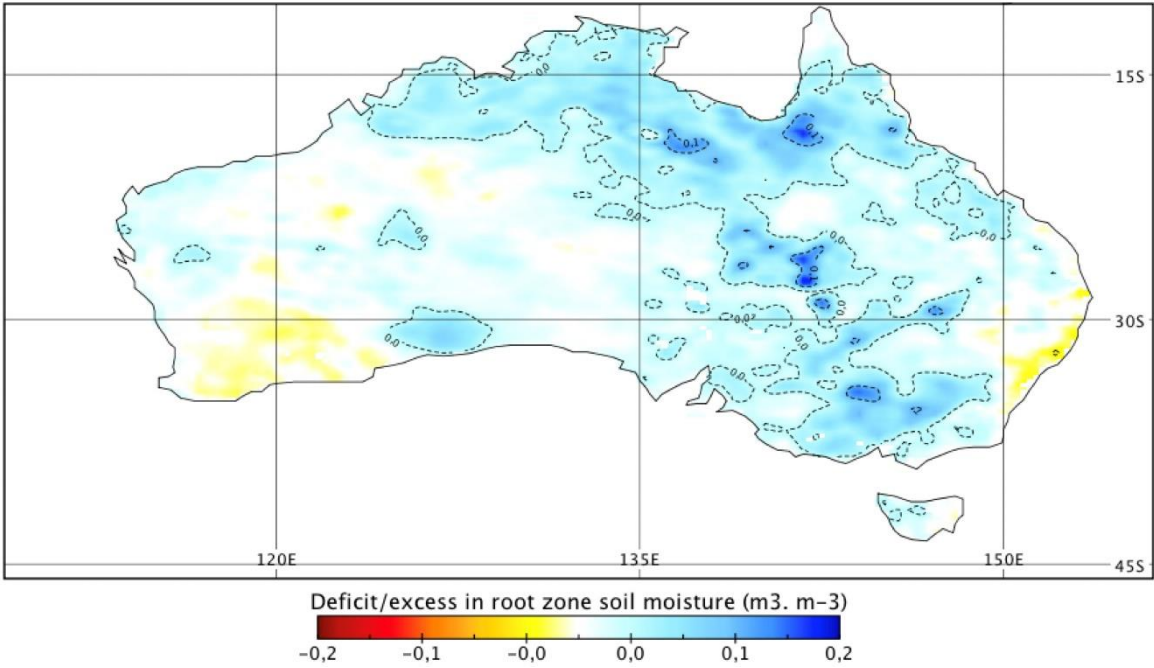


Fig 4 Root zone soil moisture deficit and excess over Australia in $m^3 m^{-3}$ for February 2011 based on SMOS root zone soil moisture.

Zhou et al. (2017) exploited TWS observations from the temporal gravity field model HUST-Grace2016, which was developed by a new low-frequency noise processing strategy, for identifying flood events in the Yangtze river basin and its sub-basins. ‘Universal’ floods were found in 2010, 2012 and 2016, while a ‘regional’ flood was observed in 2003. Similarly, Sun et al. (2017) showed for the Yangtze river basin that GRACE water storage anomalies and a GRACE-based flood potential index could effectively monitor large-scale flood events.

Following a probabilistic approach of the occurrence frequency and the expected return levels of hydrological extremes (i.e. the expected anomalous flux or storage values once in N years), Kusche et al. (2016) mapped these statistics on a global scale. They identified hot spots of anomalously high-water storage that can be related to flood events with good statistical significance despite a quite short time period of 144 months of GRACE data. Moreover, they predicted that with the continuation of the GRACE mission by GRACE-FO, it would be possible by around the year 2020 to detect changes in the frequency of total fluxes for at least 10–20% of the continental area.

While all flood analyses mentioned before used standard monthly GRACE products, Gouweleeuw et al. (2018) were the first to assess daily GRACE data for flood monitoring. They analysed two daily gravity field solutions based on GRACE observations and evaluated them against daily river runoff data for major flood events in the Ganges-Brahmaputra Delta (GBD) in 2004 and 2007. They found that variations over periods of a few days of the daily GRACE data reflect temporal variations in daily river runoff during major flood events. This confirmed in particular the potential of daily GRACE gravity field solutions based on a Kalman filter approach for gravity-based large-scale flood monitoring. They concluded that the release of daily GRACE gravity field solutions in near-real time may enable flood monitoring for large events. Gruber and Gouweleeuw (2019) further detailed how GRACE dynamic measurements and empirical external covariance information can be combined in the Kalman filter approach for the daily, short-latency mass changes products and reported on an evaluation of the product for describing flood dynamics in the Mekong delta.

Instead of using GRACE data after conversion to a data set of surface mass variations, Han et al. (2009) studied the terrestrial water storage in the Amazon basin and its surrounding areas by exploring directly the instantaneous measurements of distance changes between two satellites from the GRACE mission. These measurements are directly influenced by large water masses in the river network and adjacent floodplains and are thus potentially sensitive to flood dynamics. Han et al. (2009) anticipated that the assimilation of GRACE inter-satellite range-rate data will improve the surface water models by tuning the effective flow velocities within the large basins. Following a similar concept, Ghobadi-Far et al. (2018) developed a transfer function to determine the in situ line-of-sight gravity difference (LGD) directly from GRACE range-acceleration measurements. They demonstrated the use of LGD data based on forward computation of the gravity effects from hydrological models and comparison with the GRACE LGD data and concluded that the approach could serve as a tool suitable to study mass changes at high temporal resolution, including near real-time monitoring of floods.

4.2.2. GRACE-based Flood Indicators and Flood Potential Assessment

In the studies mentioned above, GRACE provided information on water storage anomalies in flood-affected regions for the event period itself. This is a valuable contribution for assessing the impact of the hydrological event on the water cycle in terms of magnitude and duration. Several studies, however, also explored the potential of GRACE information in a predictive way for forecasting flood events. The fundamental concept behind this is that the GRACE mass anomalies describe the wetness state of a river basin, which in turn is a key factor for flood generation. Wet pre-conditions in the sense of high, i.e. near-surface groundwater levels, close to saturated soils or filled surface water bodies indicate a reduced ability of the river basin to store additional water that comes with the next rainfall event. Thus, the probability that much of this rainfall becomes runoff and eventually generates a flood is increased. On this basis, Reager and Famiglietti (2009) estimated the flood potential of a region by inferring its storage capacity from the repeated maxima of the monthly time series of GRACE water storage anomalies. The flood potential is then defined as the actual water storage anomaly relative to the storage capacity.

Molodtsova et al. (2016) evaluated this flood potential index for a large number of floods in the US and demonstrated its skill in particular for predicting large-area, long-duration floods in the summer season that are rainfall driven. Idowu and Zhou (2019) confirmed the value of the flood potential index for indicating flood events in the Niger basin. Eventually Jäggi et al. (2019) presented a wetness index based on daily GRACE water storage data. They showed for the example for the Danube basin that the index exceeded threshold values several weeks before the flood peak, making it a potentially useful candidate for early flood warning.

Reager et al. (2014) further developed the flood potential concept towards predicting flood discharge by an autoregressive model, driven with water storage anomalies. They showed that the GRACE-based information on elevated total water storage could improve the prediction with lead times of several months for the example of the Mississippi flood in 2011. With a similar approach for a Ganges sub-basin, Chinnasamy (2017) confirmed that adding GRACE-based water storage anomalies improved flood discharge prediction with long lead times in comparison to a model that relies on precipitation only. Also, Chao and Wang (2017), for the Yangtze river basin, showed with a time-lagged autoregressive model that TWS changes from GRACE were effective for characterizing flood potential and for flood early warning with lead times of several months.

Beyond statistical forecast models as used in the studies mentioned before, integration of GRACE-based water storage anomalies into physically based hydrological and flood forecasting models may allow for additional early warning applications. As a first example, Reager et al. (2015) assimilated GRACE water storage anomalies into a hydrological model. For the 2011 Missouri flood, flood generation understanding, and modelling could be improved by resulting in wetter pre-event conditions and by providing more detailed information on the contributions of different storage compartments to the pre-event flood potential.

5. Progress in Drought Applications

Droughts are the costliest hydrological events in terms of economic, environmental and human life losses and they impact a broad variety of regions in the world (e.g. Zhang and Jia 2013; Bayissa et al. 2017 and references therein). They are generally controlled by a deficit of groundwater, water available in the unsaturated zone, or in surface water bodies. They can be classified (e.g. Wilhite 2000; Zhang and Jia 2013; Du et al. 2019 and references therein) as meteorological droughts that are mainly associated to a deficit of precipitation and/or an increase of potential evapotranspiration. They can also be caused by sea surface temperature anomalies that lead to persistent continental drought while a warm temperature with low precipitation over a short period of time generates flash drought. Agricultural droughts are driven by a deficit of soil moisture associated or not with a deficiency of surface/subsurface water supply, i.e., hydrological droughts. The latter can also be described as socio-economic droughts where the available water is insufficient to cover the demand of some socio-economic goods and/or habits. This may induce a slower-progressing drought along with a deficiency of TWS and more particularly of groundwater availability. These different types of drought can occur alone but most of the time, a meteorological drought triggers the other ones.

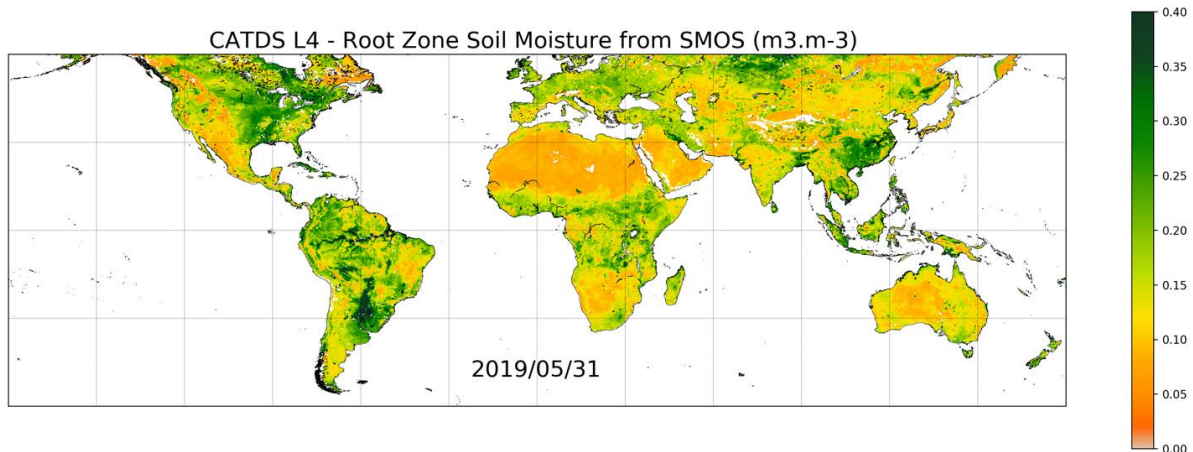
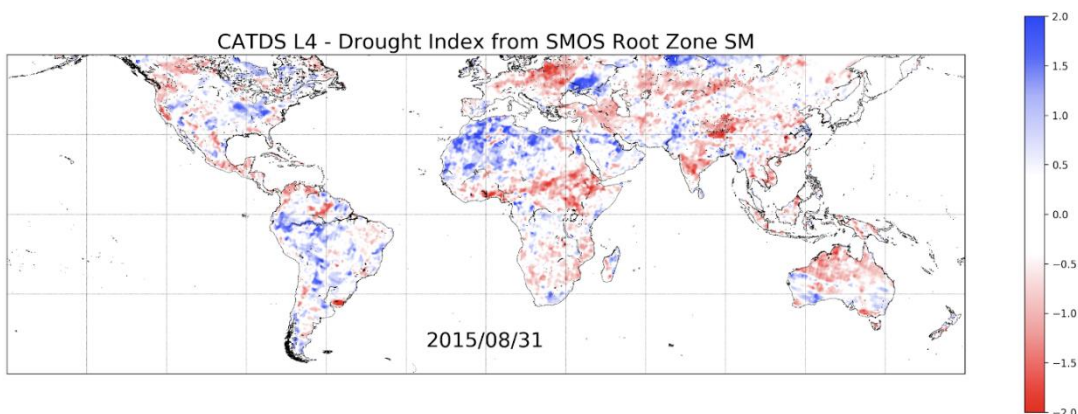


Fig 5 Global root-zone soil moisture in $m^3 m^{-3}$ obtained from SMOS surface soil moisture at 25km resolution using a parsimonious model for 31 May 2019.

5.1. Agricultural Droughts of 2019 from L-Band Radiometers

One major information related to agricultural drought assessment is the water availability in the root zone. The definition of the water availability and root zone depth depends on the observed cropping type, phase of development and irrigation practices, but it is generally admitted that the root zone definition of crops at large scale is related to the first meter of soil and the water availability is defined as percentage of available water between the wilting point and the field capacity associated to the soil texture. The root zone soil moisture is not directly accessible currently by remote sensing technologies. Some studies addressed through local radiometers the capacity of future P-Band mission from active or passive remote sensing to measure root zone soil moisture (Garrison et al. 2018), but there is currently no operational satellite in this bandwidth. Still, root zone soil moisture can be indirectly quantified from remote sensing through vegetation stress condition (Swain et al. 2013), TWS, or the link between precipitation, surface and root zone soil moisture. The vegetation stress condition can be monitored using thermal remote sensing (Anderson et al. 2007) which provides an a-posteriori information about drought as the vegetation starts to show water stress after available water depletes. As mentioned in previous sections, TWS information can be acquired using gravimetric data at a coarse spatial resolution and root zone soil moisture may be singled out by removing the contributions from other water storage compartments if available, or by modelling via TWS data assimilation. The link between surface soil moisture and root zone soil moisture is more direct. **Fig. 5** shows the root zone soil moisture obtained from the surface soil moisture SMOS data used in a parsimonious model. The model is based on two steps. First an exponential function is used to update the rootzone soil moisture based on the observed one. Second a soil model is used to compute the infiltration and vegetation extraction through computation of transpiration. In this case the MODIS NDVI data is used to compute the FAO56 crop index KC (Er-Raki et al. 2009).



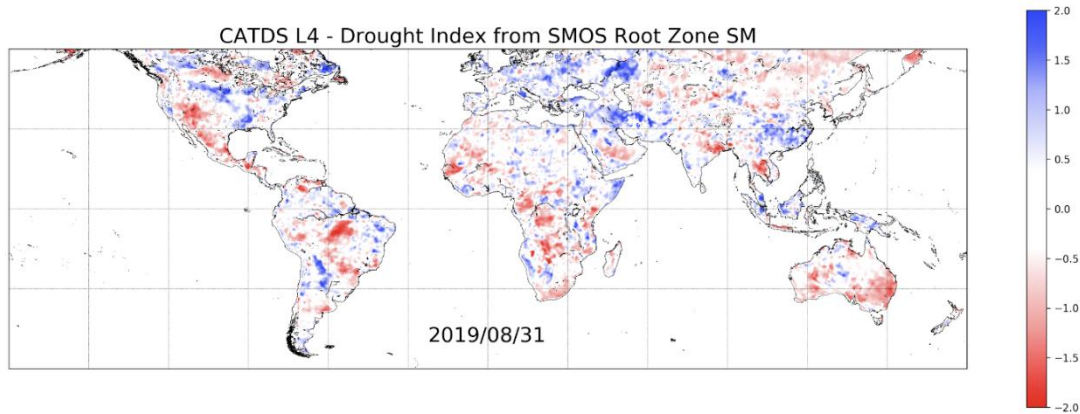


Fig 6 Global drought index obtained from the SMOS root zone soil moisture for August 2015 (upper panel) and August 2019 (lower panel).

Once a rootzone soil moisture is obtained, agricultural drought indicators can be determined. Al Bitar et al. (2013) and Kerr et al. (2016) defined the drought based on the standard anomaly index where an empirical cumulative density function is fitted to the timeseries statistics at each node and the drought is defined on probability thresholds. **Fig 6** shows the drought index defined as root zone soil moisture anomalies for August 2015 and August 2019. The figure clearly shows the increase of the increase of droughts in 2019 to an already dry condition in 2015 leading to the massive forest fires in Australia. The figure also shows the dramatic conditions in large parts of Amazonia and in South Africa in 2019.

The main advantage of the use of passive L-Band remote sensing for agricultural drought monitoring is that, when combined with a parsimonious depth-scaling model, it provides the closest information to the state variable of interest, i.e. the root zone soil moisture.

5.2 Droughts of Amazon Basin of 2010 observed by SMOS Water Fractions

Anomalies of the extent of water surfaces may represent droughts that have an impact on wetlands and floodplains and can thus be classified as indicators of hydrological drought. **Fig 7** shows two complementary information layers on meteorological and hydrological drought conditions over the Amazonian basin for the 2010 drought event. **Fig 7a** shows the anomalies obtained from rainfall data (adapted from Lewis et al. 2011) while **Fig 7b** shows the anomalies of water surface extent during the drought event. These water surface anomalies, expressed as anomalies of the surface water areal fraction (SWAF) in 25 km grid cells have been derived from SMOS by Parrens et al. (2017). They show two facets of this drought event that impacted the rainforest and the floodplains. The two components of this drought event had dramatic consequences on the ecosystem. While the meteorological drought had a direct impact on biomass and thus the carbon budget, the hydrological drought had an impact on the Amazon river floodplains and Bolivian wetlands ecosystem in the south of the basin.

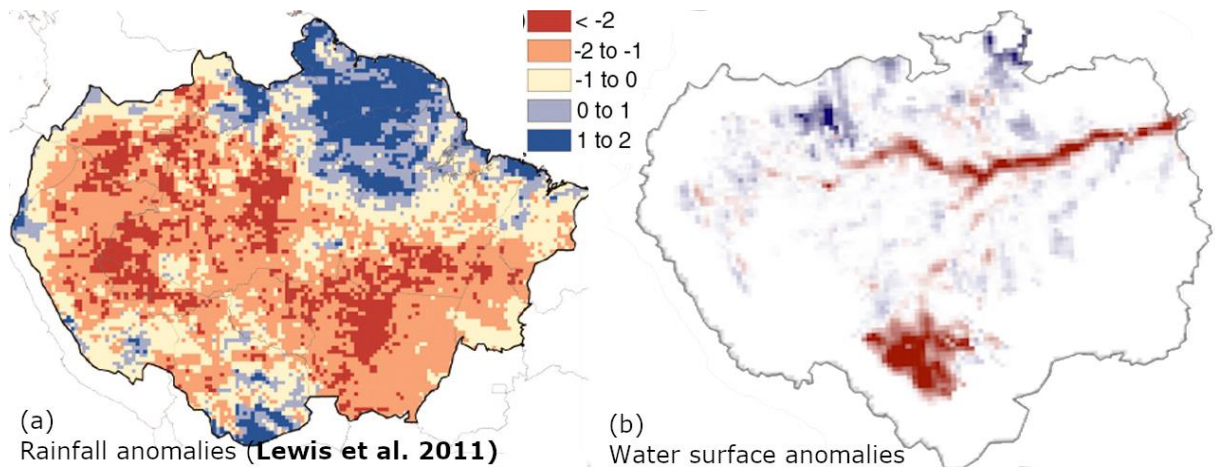


Fig 1 Standardized anomalies of **a** rainfall (adapted from Lewis et al. 2011) and **b** water surfaces based on the surface water areal fraction (SWAF) (Parrens et al. 2017) over the Amazon river basin during the 2010 drought event.

5.3 Monitoring and Predicting Drought Events With GRACE-Based Gravimetry

TWS estimations from GRACE give useful information about the water content variations through all the compartments at large spatial scale and over more than a decade. In order to better characterise droughts, information concerning water variations of all compartments are crucial and thus justifies the use of GRACE TWS estimations for droughts monitoring (e.g. Rodell 2012). Moreover, the drought event that impacted Texas in 2011 demonstrated that the depletion of water observed by GRACE is dominated by changes in soil moisture storage (Long et al. 2013). Since its launch, in different regions of the world, droughts have been observed directly with GRACE TWS data as for example in the Amazon river basin (Chen et al. 2009) and in Texas (Long et al. 2013). It has also demonstrated its ability to monitor droughts that affected several tropical basins during an El Niño event. For example, the 2015-2016 El Niño led to one of the most intense droughts ever recorded over southern Africa (e.g. Siderius et al. 2018). This event prevented groundwater recharge, hence produced groundwater decline over two consecutive years as reported from an analysis of GRACE data (Kolusu et al. 2019).

Some methods have been proposed to better characterise droughts by detecting anomalies in the TWS series (Thomas et al. 2014) and with the Normalized GRACE-derived groundwater storage deviation that permit quantification of the groundwater storage deficit (Thomas et al. 2017). Meanwhile, various drought indices obtained from GRACE have been used, e.g. the Drought Severity Index (DSI) and the Total Storage Deficit Index (Cao et al. 2015; Zhao et al. 2017; Nie et al. 2018). These partial examples demonstrate the interest and the ability of GRACE to allows globally consistent and effective drought monitoring. Two disadvantages of GRACE data for the monitoring of droughts are 1) the short period of time acquisition regarding the monitoring of drought events over several decades and 2) the spatial resolution. Concerning the short-time period of acquisitions, Long et al. (2014) and Zhang et al. (2016) developed a method based on artificial neural network approach to reconstruct longer TWS series from which it is possible to observe past drought events. In order to compensate the low spatial resolution of GRACE, some studies have demonstrated the benefits of GRACE data assimilation into land surface models, allowing spatial and temporal downscaling and providing information about groundwater and soil moisture by vertical decomposition (Houborg et al. 2012; Li et al. 2012). Despite their limitations, GRACE TWS estimations are the only information that permit the monitoring of droughts in regions where in situ data are sparse or inexistent. On the contrary, complementing in situ measurements and modelling, these estimations are extremely useful for groundwater resource management, especially during ENSO-driven events. Moreover, assimilation of GRACE and other data into regional/global hydrological models may be of great value to forecast floods and droughts events affecting river basins.

6. Future of Earth Observations for Large-Scale Flood and Drought Surveys

6.1. Future Altimetry Missions

Jason-3 (launched in 2016), Sentinel-3A (launched in 2016) and Sentinel-3B (launched in 2018) are the nadir radar altimetry missions currently in operation at the time of writing. A new nadir altimetry mission (Sentinel-6A) will be launched in 2020 on the same nominal orbit as the Jason series. However, to alleviate nadir altimetry important observation gaps, the Surface Water and Ocean Topography (SWOT) mission will be launched in early 2022. SWOT will provide 2-D images of water surface topography, which should enhance hydrological hazards observation at least spatially. SWOT will observe all rivers wider than 100 m (with a goal to go down to 50 m) and all water bodies with an area above 250 m x 250 m, i.e. 62,500 m² (with a goal to go down to 100 m x 100 m) (Desai 2018). The main payload will measure water topography over two 50 km wide swaths. It will observe 96.5% of continents between 78°S and 78°N (Biancamaria et al. 2016), providing an almost global coverage of all water bodies on continental surfaces (see **Fig 8** for SWOT coverage over the Ganges/Brahmaputra basin). If the repeat period of the orbit is 21 days, thanks to swaths overlaps, it will observe many regions multiple times during one repeat period (**Fig 8**). Compared to nadir or even SAR altimeters, SWOT will provide unprecedented spatial observations of water elevation, along with water area and river surface slope. From these measurements, global estimates of water storage change and river discharge will be derived (Durand et al. 2016; Desai 2018), which are essential for water management.

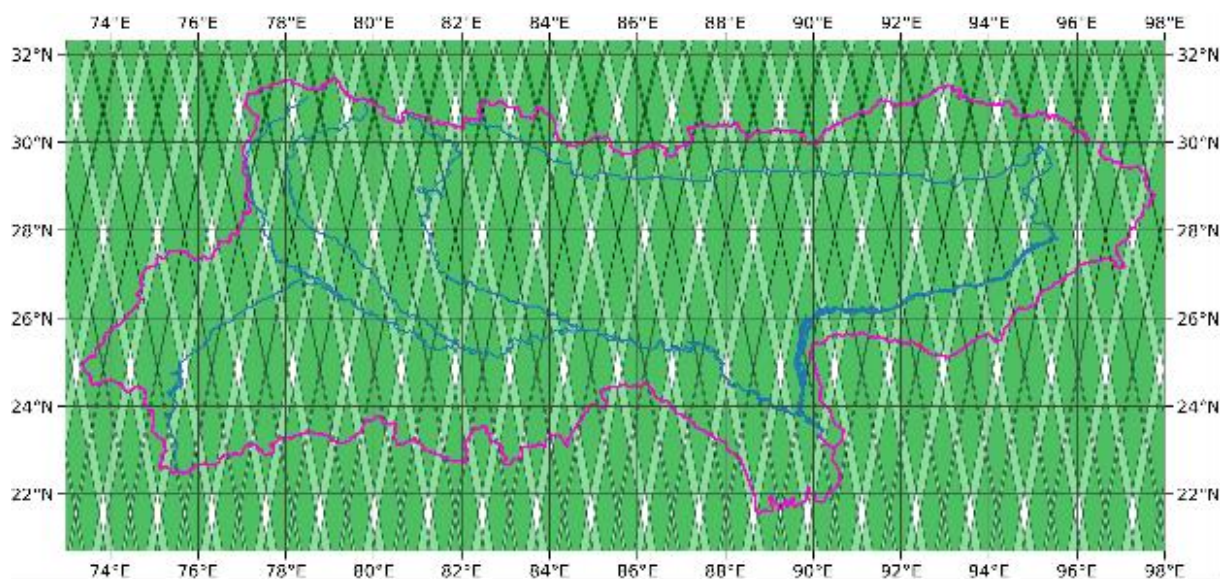


Fig 8 SWOT coverage (green polygons) over the Ganges/Brahmaputra basins (magenta boundaries). Light green corresponds to regions with one SWOT observation during a satellite repeat period (21 days), green regions correspond to two observations during a repeat period, whereas white regions will never be observed by SWOT. Blue lines represent the Ganges river and its major tributaries, and the Brahmaputra river

Despite its almost global coverage, SWOT will not be able to observe floods lasting only a few days or less, because of its still coarse time sampling. Frasson et al. (2019) investigated specifically the question of flood observability with SWOT. Comparing the 4,664 past flood events reported in the Dartmouth Flood Observatory database with SWOT orbit, they concluded that “SWOT would have seen 55% of these, with higher probabilities associated with more extreme events and with those that displaced more than 10,000 people”. More specifically over the Cumberland River basin within continental US, Yoon et al. (2016) estimated that SWOT has “only a 5% chance of direct observations of the 2-day flash flood event”. Nonetheless, even if such new observations could help to forecast floods, SWOT uneven time sampling might be an issue. Therefore, SWOT will definitely improve large scale flood observation, but not smaller scale flood events. This issue could be somewhat alleviated using some DA techniques,

currently under development, to derive enhanced space and time sampling discharge time series by taking advantages of the unprecedented SWOT spatial coverage over large to medium river basins (Brisset et al. 2018; Oubanas et al. 2018; Yang et al. 2019).

It is also expected that SWOT will be better suited than nadir altimeter to calibrate/correct model parameters thanks to its spatial coverage (Yoon et al. 2012; Pedinotti et al. 2014; Boergens et al. 2019), which then could provide better forecasts.

Benefits of SWOT DA into hydraulic or hydrological models have also been investigated to optimize reservoir control for flood mitigation in the Cumberland River basin (Yoon et al. 2016), to guarantee minimum flow within the upper Niger River basin (Munier et al. 2015) and to forecast some flood events within the Ohio River basin (Andreadis and Schumann 2014). Especially, this latter study estimated that assimilating SWOT data into a hydraulic model should help to forecast water height up to lead times of 11 days. However, it is still unclear how SWOT data will be effectively used into operational forecast systems, as SWOT wide swath products might not be delivered in real time (the time latency should be less than 45 days, according to SWOT Product Description Documents for hydrology surfaces) and its required nominal lifetime is only 3 years, with a goal to go up to 5 years (Desai 2018).

Space and time samplings of nadir altimetry missions limit the use of these sensors to observe and even more to forecast floods that last few days or less. In comparison, SWOT wide swath altimetry will provide global coverage, but its time sampling also restricts flood observation to major floods (Frasson et al. 2019). To improve samplings, a constellation of satellites seems to be a good option, as no single orbit will allow both frequent time and space samplings. The Centre National d'Etudes Spatiales (CNES) in France is currently proposing a constellation of two satellites with a wide swath altimeter, as potential candidate to the Copernicus – Next Generation Sentinel-3 Topography program (after 2030). It should observe similar water bodies as SWOT, but with a better time sampling (~10 days) and a longer lifetime more suitable for operational use (Cheymol et al. 2019). To increase temporal sampling, CNES is also studying the feasibility of a constellation of nadir altimeters optimized for inland water bodies, called Small Altimetry Satellites for Hydrology (SMASH) (Blumstein et al. 2019). It should provide daily measurements of water elevation with 10 cm accuracy, a data latency of less than 6 hours, and a long mission lifetime (> 10 years), particularly well-suited for operational applications.

6.2. Future of L-Band Microwave EO

L-Band EO data for flood and drought applications currently are provided by the SMOS and SMAP missions which are active since 2010 and 2015, respectively, with both missions beyond their nominal lifetime of 3 years. The continuity of L-Band observation is under study in the context of the ESA future Copernicus Imaging Microwave Radiometer (CIMR). If L-Band observation is confirmed aboard, this will ensure the continuity of the L-Band acquisitions but will not meet the needs expressed by the scientific community (Escorihuela and Kerr 2018) with respect to the spatial resolution. Actually, the L-Band radiometer on board CIMR is foreseen to have a coarser resolution than SMOS due to the mesh antenna size. Other initiatives for high resolution like SMOS-HR are under investigation at CNES (Rodríguez-Fernández et al. 2019). It is worth mentioning that the future NISAR (NASA/ISRO) mission which will include an S-Band and L-Band SAR will provide interesting opportunities for soil moisture and groundwater subsidence monitoring.

6.3. Future of Gravimetry Missions

Space-based TWS estimates by gravity data currently rely only on GRACE-FO mission launched in 2018 (Flechtner et al. 2014), thus extending the 15-year long record of GRACE, in spite of a close to 1-year gap (GRACE ended in October 2017). But only by ensuring continuous and further improved TWS measurements from space, numerous questions regarding the changes and dynamic processes in land hydrology, cryosphere, ocean, atmosphere and solid Earth can be addressed (Pail et al. 2015). The NASA Earth Science Decadal Survey Report (National Academies of Sciences, Engineering, and

Medecine 2018) thus highlighted monitoring spaced-based TWS as one of five top priorities in Earth Observation for the next decade (National Academies of Sciences, Engineering, and Medecine 2018). Based on this prioritization, NASA is currently running various studies how a Next Generation Gravity Mission (NGGM) should be realized, e.g. in terms of the number of satellites (or satellite pairs), orbit configuration, and instrumentation. Also, ESA launched a feasibility study on NGGM with the use of Laser interferometer for ranging measurements (Dionisio et al. 2018). A NGGM based on the innovative observational concept of a high-low tracking formation with micrometre ranging accuracy (Pail et al. 2019) is currently being studied by CNES. Eventually also, the reversing of GNSS-based kinematic trajectories of Low Earth Orbiter constellations might be able to monitor groundwater evolution (e.g. Bezděk et al. 2016 and references therein).

7. Conclusions

This article presents a review on the major scientific and technical developments made since over more than 20 years with low and moderate resolution satellite-based datasets in order to promote their use for flood and drought prediction and monitoring. Satellite gravimetry, L-Band passive microwave Earth Observation and nadir altimetry provide unique opportunities to monitor total terrestrial water storage and its individual compartments, soil moisture, surface water level and extent and river discharge, i.e. key hydrological variables to understand, predict and monitor flood and drought events. In fact, GRACE / GRACE-FO, SMOS and nadir altimeters missions have considerably improved our knowledge on the evolution at large spatial and long temporal scale of these variables. New methods developed along with the use of these sensors offer a better estimation of the dynamics and magnitudes of flood events, as well as a better spatially distributed discharge estimation in river basins with sparse in-situ observations. Furthermore, a better estimation of the long-term evolution of groundwater storage and of the total wetness state of river basins as represented by gravity based TWS have been an asset to study the storage amplitude, duration and frequency of large-scale floods and to highlight important groundwater withdrawals or severe droughts. The most important benefit of using moderate to low spatial resolution sensors is their ability to provide a synoptic view of these events from the river basin to the global scale. Very often, this synoptic view cannot be achieved with often sparse in situ measurements or with remote sensing techniques of high resolution but low spatial coverage. Finally, the most promising perspective to increase the understanding, forecasting and mitigation of hydrological events will be to assimilate the moderate to low resolution satellite data into LSMs, combine them with higher spatial resolution data, either space- or UAV- based (Antoine et al. 2020) and to use new methodologies, involving Artificial Intelligence, for instance.

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