



The Potential of EO Data for Enhanced Flood Monitoring and Forecasting: A Consortium Assessment

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Abstract

The monitoring and modeling of riverine floods have been covered extensively in the scientific literature with a substantial number of scientific contributions related to calibration/validation of hydraulic and hydrological models and assimilation of Earth Observation (EO) data into them. These models, when used for flood forecasting purposes, rely heavily on ground-based hydrological networks along with numerical weather models which, particularly in data-scarce regions, are often challenged by data sparsity. In these situations, EO data offer a viable solution to enhance the skill of these flood forecasting systems by providing global-scale observations of key hydrological variables such as precipitation, soil moisture, river discharge, water levels, and flood extent. This manuscript reviews and discusses the capability of these EO data in enhancing flood forecasting systems, by analyzing their accuracy, lead time, and reliability, while at the same time highlighting key challenges such as data latency, spatial–temporal resolution trade-offs, and model assimilation constraints. By leveraging recent advancements in remote sensing, data assimilation techniques, and artificial intelligence, EO-based flood forecasting has the potential to bridge existing observational gaps, particularly in vulnerable regions. The paper also outlines future research directions and technological developments needed to maximize the impact of satellite data in operational flood forecasting systems.

Keywords Earth Observation · Flood forecasting · Satellite hydrology · Remote sensing

Article Highlights

- Earth Observation (EO) data improve flood forecasting by providing global hydrological variables like precipitation, soil moisture, and river discharge
- Satellite data assimilation enhances model accuracy, especially in data-scarce regions
- Challenges include data latency, spatial-temporal resolution trade-offs, and integration into operational systems
- Future advancements in remote sensing and AI can enhance lead time and reliability of flood forecasting

1 Introduction

Floods rank among the most devastating natural hazards, causing significant loss of life, infrastructure damage, and environmental degradation (IFRC 2020). In the period 2000–2024, floods accounted for the highest number of internally displaced persons compared the other major natural disasters, with nearly 1.8 billion people affected in nearly 180 countries with a total of 135'000 deaths and 338'000 injured. From an economic point of view, the losses from flooding events amounted to 973 billion US dollars (EM-DAT 2025, <https://public.emdat.be/data>). As global temperatures rise due to climate change, floods are projected to become more frequent and severe (AghaKouchak et al. 2020). A warmer atmosphere holds more moisture, resulting in heavier downpours and disruptions to snowmelt patterns. Between 2000 and 2015, the proportion of the global population exposed to floods increased by 20–24%. With ongoing climate and demographic changes, this trend is expected to continue, driven by the growing number of people living in flood-prone areas (Tellman et al. 2021; Rentschler et al. 2022). These statistics reveal that, although forecasting tools have improved, flood events continue to cause widespread impact, underscoring the gap between scientific progress and its operational uptake. In view of this, more effective strategies are required to anticipate flood events, reduce vulnerability, and mitigate their impacts, addressing the combined roles of hazard, exposure, and vulnerability. While risk assessment and land-use planning play a key role in long-term flood mitigation (Acuña-Alonso et al. 2022; Kumar et al. 2023; Wu et al. 2023), real-time flood forecasting is critical for reducing immediate impacts and enhancing emergency response. Traditional flood forecasting relies on ground-based hydrological networks, but these systems often suffer from data gaps, particularly in vulnerable and data-scarce regions. Earth Observation (EO) data, particularly those from remote sensing, offer a transformative opportunity to complement and enhance existing forecasting systems, providing near-global coverage of key hydrological variables such as precipitation, soil moisture, river discharge, and flood extent (Tedla et al. 2024; Adams et al. 2024). Indeed, while EO missions provide valuable observations of both atmospheric and terrestrial water, they are particularly well suited to monitor surface water dynamics, which are the primary drivers of riverine flood events. The integration of satellite observations with hydrometeorological networks, numerical weather models, and advanced data assimilation techniques can significantly enhance the accuracy and lead time of flood forecasts (Schumann 2024; Esposito et al. 2022). Additionally, recent advancements in artificial intelligence, AI, and big data analytics are further refining predictive models, enabling more precise and actionable forecasting products. However, accurate forecasts alone are not sufficient: Effective early warning dissemination, risk communication, and international cooperation are essential to ensure that these forecasts translate into timely and effective flood response actions (Zabini et al. 2021; Perera et al. 2020; Driessen et al. 2018). Indeed, accurate flood forecasting systems are essential for minimizing

the devastating impacts of flooding, supporting timely evacuation and rescue operations, and enabling efficient water resources management. The potential monetary benefits of early flood warnings were calculated on the order of 400 Euro for every 1 Euro invested (Pappenberger et al 2015). Traditionally, flood forecasting has relied heavily on ground-based data for calibration and validation of hydrological models used for operational flood forecasting and key hydrological variables such as precipitation and river discharge (or water level) to estimate flood evolution timing and flooded areas extent. However, significant limitations persist in current systems, particularly regarding data availability, spatial coverage and forecasting accuracy. Many regions, especially in the Global South, which are often those most vulnerable to disasters, either lack real-time monitoring network, have challenges for acquiring, maintaining and adequately storing the data, or have experienced a decline in the number of active river and rain gauges. Even in countries with a well-established monitoring network, large portions remain poorly monitored. These gaps hinder the effectiveness of forecasting, as does the uncertainty inherent in precipitation predictions generated by numerical weather models, due to limitations in data quality, and model parametrization and calibration.

This manuscript investigates the role of EO data for improving riverine flood forecasting, particularly for short- to medium-term predictions, which are crucial for early warning systems, emphasizing their integration into existing models to improve the accuracy of flood forecasting systems, particularly in data-scarce regions. It highlights the potential of EO data, such as precipitation, snow, total water storage, river discharge, soil moisture, and water levels, to enhance flood predictions while addressing challenges like data latency, assimilation, and uncertainty. With the proliferation of commercial satellite missions as well as the recent technological advances contributing also to new public missions (e.g., HydroGNSS, Sentinel-3A/B, Sentinel-6 Michael Freilich, SWOT), the study emphasizes the potential of EO for flood forecasting, especially in vulnerable regions. This article also examines the limitations of current missions and opportunities for the future ones, offering a comprehensive outlook for both the scientific community and stakeholders aiming to integrate EO into their flood forecasting systems.

2 Relevant Satellite Technologies

Rather than providing a statistical and revision analysis of existing studies, this article presents a consortium assessment, reflecting an expert-driven evaluation and discussion. Specifically, this article focuses on the strengths and limitations of current and future EO missions and methodologies, aiming to identify pathways for improved flood forecasting capabilities through collaborative expert analysis. Satellite remote sensing technologies have become pivotal in advancing hydrological research (McCabe et al. 2017) and applications, such as integration with flood forecasting or early warning systems (Schumann, et al 2023). The last two decades have seen a proliferation of available remotely sensed data (Famiglietti et al. 2015; De Lannoy et al. 2022). At the same time, advances in numerical modeling, data processing algorithms, and the Internet of Things have driven the scientific community to develop methods, products, and services that use such remote sensing data to estimate surface flows, which are still highly uncertain (Tarpanelli et al. 2019; Gleason and Durand 2020). The following provides an overview of studies utilizing EO data to estimate key hydrological variables relevant to flood forecasting systems, encompassing surface water dynamics, precipitation, and terrestrial water storage. The EO variables discussed in this section (e.g., precipitation, soil moisture, snow cover, surface water extent, river discharge, total water storage) represent the core inputs commonly required in flood

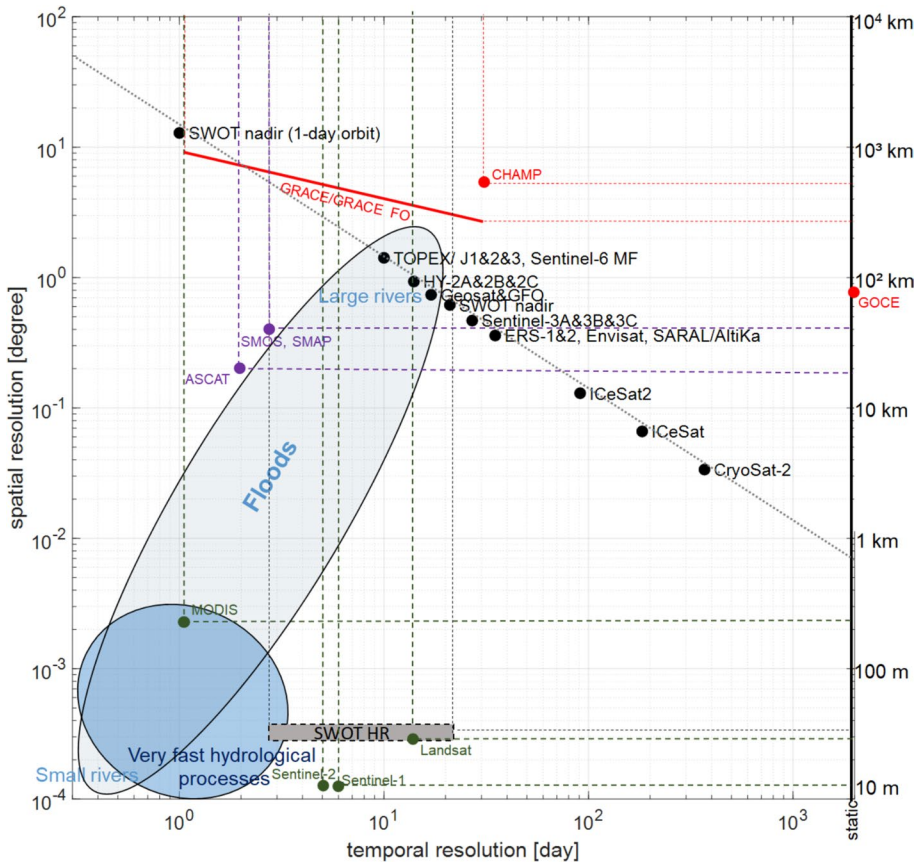


Fig. 1 Adapted from Tourian (2025): Satellite spatiotemporal resolution for flood monitoring. This diagram shows the spatial (y-axis, in degree) and temporal (x-axis, day) resolution of satellite missions typically used for flood monitoring (blue-shaded area). The dashed line represents altimetry trade-offs. Satellite positions illustrate the balance between large-scale, long-term (e.g., gravity) and high-resolution, short-term (e.g., optical/radar) observations. *Note:* The included technologies (e.g., SWOT, Sentinel series, Landsat, MODIS, Sentinel-1&2, CryoSat-2, ICESat-2, GRACE/GRACE-FO, GOCE, SMOS, SMAP, ASCAT) represent the main satellite observation techniques—radar and laser altimetry, gravimetry, optical and SAR sensors as well as soil moisture sensors—that contribute to flood detection, extent mapping, and hydrological context analysis. Gravity missions (e.g., GRACE, GRACE-FO, GOCE) capture large-scale, low-temporal-resolution hydrological variations, while optical and radar sensors (e.g., Sentinel-1&2, Landsat, MODIS, SWOT) provide finer spatial and higher temporal detail. Passive microwave missions (SMOS, SMAP, ASCAT) contribute soil moisture observations at intermediate spatial and temporal scales, supporting the assessment of surface wetness and flood susceptibility

forecasting systems, as highlighted in recent reviews (e.g., Schumann et al. 2023; Deste-fanis et al. 2025).

Figure 1 illustrates the spatiotemporal resolution of various satellite remote sensing missions relevant to flood monitoring, i.e., missions capable of observing river reach characteristics and floodplain dynamics. It is important to note that the figure focuses on flood monitoring, not flood forecasting. The x-axis represents temporal resolution on a logarithmic scale (from sub-daily to decadal), while the y-axis represents spatial resolution in

degrees on a logarithmic scale (from 10^{-4° to 10^{2°). For reference, one degree corresponds to roughly 110 km at the equator. The blue-shaded bubble represents the spatiotemporal characteristics of flood events, highlighting the scales at which floods in small and large rivers evolve and can be observed. The black dashed line indicates the spatiotemporal resolution of satellite altimetry missions in terms of ground track resolution, illustrating the trade-off between spatial and temporal resolution, where higher spatial resolution is generally associated with lower temporal resolution and vice versa. Individual satellite missions are positioned according to their observational capabilities. Gravity missions (e.g., GRACE, GRACE-FO, GOCE) provide coarse spatial but temporally consistent observations of large-scale hydrological variations. While their standard products are monthly gravity fields, daily to sub-weekly variations can be resolved at very coarse spatial scales (i.e., several thousand kilometers) when spatial resolution is reduced. In contrast, optical and radar sensors (e.g., Sentinel-1&2, Landsat, MODIS, SWOT) deliver finer spatial resolution with higher revisit frequencies, enabling the monitoring of flood extent and short-term dynamics. Passive microwave missions such as SMOS and SMAP provide global soil moisture observations with spatial resolutions of about 35–50 km and 25–40 km, respectively, and revisit times of approximately three and two to three days. ASCAT offers complementary surface soil moisture measurements at 12.5–25 km resolution and a 1–2-day revisit cycle, providing valuable information on antecedent soil wetness and flood susceptibility. The figure highlights a key challenge in remote sensing: While some missions capture large-scale, long-term hydrological changes, others are better suited for high-resolution, short-term events, underscoring the need for data fusion and complementary observations to achieve appropriate flood monitoring especially over smaller rivers. Moreover, different sensors observe distinct hydrological quantities; for example, optical and radar sensors primarily capture flood extent, altimetry provides water height, and gravimetry observes mass or storage changes. Therefore, data fusion is required not only to bridge spatial and temporal scales but also to integrate these complementary observables, enabling a more comprehensive and physically consistent monitoring of floods across regions and river sizes. This underscores the importance of multi-sensor integration and data fusion to enable effective flood monitoring across spatial and temporal scales.

2.1 Precipitation

As the primary driver of floods, accurate spatial and temporal precipitation estimates are critical for reliable flood monitoring, predictions, and forecasting. Satellite observations provide spatially extensive and temporally consistent precipitation estimates, although their accuracy can vary substantially across regions and time periods. This capability is particularly valuable in poorly gauged or ungauged regions, where ground observations are sparse or unavailable. While satellite precipitation data have a latency of at least several hours, they remain valuable for large-scale flood events in relatively large catchments characterized by multi-day response times. However, it has less value for smaller-scale flash flood events.

Satellite precipitation products (SPPs), available since 1981, are freely accessible and come in various resolutions and coverage options (Maggioni et al. 2016). They commonly utilize active and passive microwave sensors to quantify precipitation intensity and distribution. As a complementary tool, geostationary satellites, such as Meteosat, with 30 min of intervals observations each day, provide high temporal resolution estimates based on cloud-top properties (Wardah et al. 2008; Maggioni and Massari 2018). Nowadays, a plethora of

SPPs is available with characteristics and qualities that can be used to forecast and monitor river flood events. They can be divided based on input data and the approach used to estimate precipitation. We can therefore define three main categories of SPPs:

- (1) Products that integrate microwave (MW) and infrared (IR) estimates, possibly supplemented and corrected with ground estimates;
- (2) Products based on a single type of data, such as IR or microwave estimates;
- (3) Products that use a bottom-up approach and estimate rainfall through variations in soil water content.

In the following, we will be briefly described one product for each category, as a way of example.

Among the precipitation SPPs that use and integrate MW and IR available on a global scale and characterized by high spatial–temporal resolution the integrated multi-satellite retrievals for GPM, (IMERG, Huffman et al. 2015; <https://gpm.nasa.gov/data/directory>) is probably one of the most known and used dataset. It is obtained by merging and integrating MW and IR data obtained through a constellation of satellites. The IMERG algorithm is run at $0.1^\circ \times 0.1^\circ$ spatial and half-hourly temporal resolutions in two low latency modes, i.e., early run (ER, latency of 4–6 h after observation) and late run (LR, 12–18 h), and in one high latency mode, i.e., final run (FR, about 3 months). The main difference between the ER and LR is that ER only has forward propagation (which basically amounts to extrapolation) due to the short latency, while LR has both forward and backward propagation (allowing interpolation). The ER and the FR are differentiated by their calibration scheme and the fact that ER has a climatological rain gauge adjustment, whereas the FR uses a month-to-month adjustment based on Global Precipitation Climatology Centre (GPCC) data.

In contrast, the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS, Funk et al. 2015; <https://data.chc.ucsb.edu/products/CHIRPS-2.0/>) combines satellite-based precipitation estimates with in-situ observations. The algorithm calibrates satellite precipitation estimates (obtained through TMPA) with Thermal InfraRed (TIR) Cloud Cold Duration (CCD) statistics monthly over a pixel of $0.25^\circ \times 0.25^\circ$ of spatial resolution. The obtained data are then integrated with stations' daily precipitation estimates. The CHIRPS dataset is available in the period 1981 to near-present at 0.05° of spatial resolution for the $\pm 50^\circ$ latitude band. Due to the ingestion of rain gauges data, the product is available with three weeks of latency, although in some areas the timeliness is reduced to 7 days (availability to be checked over the test sites: <https://data.chc.ucsb.edu/products/CHIRP/daily/2025/>), limiting the product usage in the forecasting phase. Alternative products based on a totally different approach are available, like Soil Moisture-to-Rain-ASCAT (SM2RAIN_ASCAT) dataset that come from the SM2RAIN algorithm (Brocca et al. 2019) applied to soil moisture (SM) data from the Advanced SCATterometer (ASCAT, Wagner et al. 2013). The algorithm estimates the amount of rainfall fallen into the soil by knowing the variation of the soil saturation conditions in time. The dataset is available starting in 2007 until 2024 daily over a fixed grid of 0.1° at the global scale. The availability of SM data with a short latency (about 1.5 h) allow to provide rainfall in NRT, also by integrating SM-derived estimates with MW observations. To this end, the Satellite Application Facility on Support to Operation Hydrology and Water Management of EUMETSAT (H SAF, <https://hsaf.meteoam.it/>) has begun the provision of several SM2RAIN-derived products with different characteristics to match multiple hydrological needs. H49 (SM-derived

only NRT product), H64 (SM-derived estimates plus MW observations) and H87 (long-term rainfall data record based only on SM observations) are operationally released in the framework of H SAF.

This list is far from exhaustive in terms of SPPs useful for river flood forecasting and monitoring, but it provides the main features and algorithms that define the current state of the art of this application.

2.2 Snow

Understanding snow cover dynamics is crucial for flood forecasting, as snowmelt significantly contributes to river runoff. Snow cover and snow water equivalent (SWE) represent slowly varying components of the hydrological system that provide valuable information on catchment pre-storm conditions. Their persistence makes them leading indicators of flood potential, allowing for extended forecast lead times compared to precipitation-based predictors, particularly in regions where snowmelt substantially contributes to runoff generation (Massari et al. 2023). Accurate monitoring of snow extent and snow water equivalent improves the prediction of both the timing and volume of meltwater input to river systems. Satellite-derived snow cover data have increasingly been used to enhance runoff estimates (Shrestha et al. 2014; Riboust et al. 2019; Musuuza et al. 2020; 2023). In Europe, the Copernicus Land Monitoring Service provides high-resolution snow cover products from 2016 to present. These include the Fractional Snow Cover dataset at high (20 m and 60 m) and low resolution (1 km) offering daily information on the percentage of snow both on the ground and on the top of the canopy. The products are derived mainly from Sentinel-2 data (with 5-day revisit) and are available in near real time. Each release includes Fractional Snow Cover, Wet/Dry Snow and SAR Wet Snow datasets. More details are available at: <https://land.copernicus.eu/en/products/snow/fractional-snow-cover> and <https://land.copernicus.eu/en/products/snow/high-resolution-gap-filled-fractional-snow-cover>. Although snow cover does not directly provide the water volume stored in the snowpack, it is widely used indirectly to constrain snowmelt timing and dynamics, for example by calibrating hydrological/nival models through snow depletion curves (SDC) or melt-factor parameters. In addition, fractional snow cover observations are increasingly assimilated into land surface and hydrological models using an observation operator that relates SCF to SWE or snow depth (HS) (either empirically or with a parameterized SDC), which improves the spatiotemporal evolution of the snowpack and the timing of melt contributions to runoff (e.g., Margulis et al. 2015; Giroto et al. 2014; Alonso-González et al. 2021; Aalstad et al. 2018; Arsenault and Houser 2018).

These high-resolution datasets are complemented by global, lower resolution products provided by Copernicus Land Monitoring Services and the ESA Climate Change Initiative programme. One example is the Snow Cover Extent dataset (1 km resolution), available from 2018 to the present, which provides daily maps of snow cover fraction across the Northern Hemisphere ($> 35^{\circ}$ N) including forested areas. These data are also available in near real time (<https://land.copernicus.eu/en/products/snow/snow-cover-extent-northern-hemisphere-v1-0-1km>).

Another key dataset from the Copernicus Land Monitoring Service is the Snow Water Equivalent product for the Northern Hemisphere ($> 35^{\circ}$ N), which provides daily updates on the amount of equivalent liquid water stored in the snowpack. These data are available in near real time at a spatial resolution of 5 km, covering the period from January 2006 to the present (<https://land.copernicus.eu/en/products/snow/snow-water-equivalent-v1-0-5km>).

Looking ahead, the snow science community is actively investigating future satellite missions to retrieve snow mass, either via snow depth or snow water equivalent. Promising results have emerged from L-band interferometry and Ku-/X-band radars technologies, although these are not yet operational. In the meantime, Sentinel-1's C-band radar has shown potential for snow depth estimation at high spatial and temporal resolution. Despite earlier concerns about its limited sensitivity, particularly in co-polarized backscatter, recent findings by Lievens et al. (2019) have demonstrated improved performance using a cross-polarized approach. This method proved especially effective for deep, dry snow, though challenges remain in areas with shallow snow or dense forests.

2.3 Soil Moisture

Soil moisture represents slowly varying components of the hydrological system that provide valuable information on catchment initial conditions. Its persistence is a leading indicator of flood potential, often offering longer lead times for forecasting than precipitation-based predictors (Massari et al. 2023), particularly in regions where soil saturation processes dominate flood generation. Indeed, the runoff response to precipitation is significantly influenced by soil moisture, which is the determinant of flood severity (Tramblay et al. 2022; Massari et al. 2023; Ortenzi et al. 2025). Monitoring soil moisture helps maintain accurate flood model predictions via data assimilation, therefore contributing to improvements in flood forecasting (Crow and Ryu 2009; Brocca et al. 2010; Azimi et al. 2020). Current quasi-operational L-band passive satellite products providing soil moisture data include the Soil Moisture and Ocean Salinity (SMOS) mission (Kerr et al. 2010) and the Soil Moisture Active Passive (SMAP) mission (Entekhabi et al. 2010). In addition to these missions, other sensors operating in C-band, such as the Advanced Microwave Scanning Radiometer 2 (AMSR2) onboard the GCOM-W satellite and the Advanced SCATterometer (ASCAT) onboard the METOP satellites, have been extensively used to retrieve soil moisture with spatial resolutions and revisit times suitable for flood forecasting.

The SMAP soil moisture products have been available since March 2015, providing global coverage at a spatial resolution of approximately 36 km and a temporal resolution of 2 days (Entekhabi et al. 2010). The mission offers multiple soil moisture data products, including Level 2 (L2) radiometer- and radar-derived soil moisture estimates, Level 3 (L3) gridded soil moisture maps, and Level 4 (L4) model-assimilated soil moisture data, which integrate satellite observations with land surface models. These products support various hydrological applications, including flood forecasting although only the Level 2 and Level 3 are available within 12 h after sensing. In addition to standard-resolution products, NASA also provides an enhanced-resolution SMAP soil moisture product (~9 km), which has been available globally since March 2015. This product is generated using Backus-Gilbert optimal interpolation to enhance spatial resolution and is available with a latency of approximately 50 h (NSIDC, SMAP Data) (Chan et al. 2018).

The ESA Soil Moisture and Ocean Salinity (SMOS) mission was the first dedicated satellite mission for soil moisture monitoring. The Microwave Imaging Radiometer using Aperture Synthesis (MIRAS) sensor onboard SMOS provides global-scale SM observations with a spatial resolution of 36–50 km and a revisit time of 1–3 days (Kerr et al. 2012). The dataset has been available since January 2010 and can be accessed via the ESA dedicated FTP server (<https://smos-diss.eo.esa.int/oads/access/>). In addition, a NRT SMOS soil moisture product is available, which is based on a neural network approach designed to enhance the timeliness of SM retrievals (Rodriguez-Fernandez et al. 2017). This dataset

has been available since May 2015 and can also be accessed through the Centre Aval de Traitement des Données SMOS (CATDS) website (<https://www.catds.fr/>).

Another key soil moisture dataset comes from the Advanced SCATterometer (ASCAT) onboard the Metop-A, Metop-B, and Metop-C satellites. The soil moisture retrieval is based on a change detection algorithm developed by the Vienna University of Technology, which rescales backscattered signals between dry and wet reference values, applying a vegetation correction to improve accuracy (Wagner et al. 2013). The data are provided operationally by the EUMETSAT Satellite Application Facility on Support to Operational Hydrology and Water Management (H SAF, hsaf.meteo.am.it).

Unlike SMOS and SMAP, which provide absolute soil moisture values, ASCAT soil moisture data are expressed as the degree of saturation. The dataset has been available since January 2007, covering the global scale with a spatial sampling of 12.5 km and a daily temporal resolution. Both the long-term data record and the NRT soil moisture product (available approximately 1.5 h after sensing) are released by H SAF and can be freely accessed through their dedicated FTP server upon registration on the <https://hsaf.meteoam.it/>.

Despite their importance, these quasi-near real-time products are characterized by coarse-scale spatial resolution and revisit time of 1–3 days so they might be not suitable for flash flood forecasting activities (Azimi et al. 2020).

2.4 Total Water Storage

Total water storage (TWS) represents the sum of all water stored on and beneath the Earth's surface, including surface water (rivers, lakes, wetlands and reservoirs), soil moisture, groundwater, snow, and ice. Understanding TWS is crucial for hydrological studies, as it provides a comprehensive picture of regional water availability and plays a central role in water resource management, drought assessment, and flood forecasting (Hosseini-Moghari et al. 2019; Tapley et al. 2019; Saemian et al. 2024). Conventional measurements of TWS components, such as variations in surface water storage (SWS), soil moisture storage (SMS), and groundwater storage (GWS), are typically conducted at localized points. While land surface models (LSMs) and hydrological models can simulate changes in these components, they often fail to capture certain critical processes, particularly those related to deep soil moisture and groundwater storage variations (Long et al. 2015; Scanlon et al. 2018).

The launch of the Gravity Recovery and Climate Experiment (GRACE) satellite mission in 2002, followed by its successor GRACE Follow-On (GRACE-FO) in 2018, revolutionized our capability to monitor large-scale changes in TWS from space (Tapley et al. 2019). These missions detect variations in the Earth's gravity field caused by mass redistribution, including changes in terrestrial water storage. GRACE and GRACE-FO have enabled the observations of TWS anomalies at basin to continental scales (e.g., Saemian et al. 2022; Behling et al. 2022; Chen et al. 2022).

TWS data from GRACE have been widely used to assess and anticipate flood potential. One approach involves combining TWS anomalies (TWSA) with precipitation and other hydrological indicators to evaluate flood susceptibility (Reager et al. 2014; Jiang et al. 2023a, b; Khorrami et al. 2023). Elevated TWS values can indicate saturated catchments, where additional rainfall may easily trigger flooding. Another strategy derives river discharge from TWS changes using the runoff–storage relationship, which links water storage dynamics to flow generation (Riegger and Tourian 2014; Tourian et al. 2018; Yi

et al. 2023). This method provides valuable insights, particularly in regions with sparse in situ discharge measurements. Additionally, GRACE-based TWSA can be assimilated into hydrological models to improve discharge estimates and floodplain mapping, helping correct model biases by integrating large-scale water storage observations. TWS data also contribute to runoff estimation using water balance equation that combine precipitation, evapotranspiration, and TWS changes or via the atmospheric water balance, incorporating precipitation and moisture flux divergence (Lorenz et al. 2014; Sneeuw et al. 2014).

Despite these advantages, there are inherent limitations in using GRACE and GRACE-FO for flood forecasting. The primary challenges include the relatively coarse spatial resolution (~300 km) (Houborg et al. 2012) and the monthly temporal resolution and the data latency (typically two months due to processing time). An important conceptual point is that the gravimetric resolution of GRACE is not fixed: It varies with the signal amplitude of the hydrological signal. As Lorenz et al. (2014) note, the detectability of a change in terrestrial water storage depends not only on its spatial scale but also on its intensity. This means that basins exhibiting large water storage variations can still produce meaningful signals, provided that the known limitations are carefully considered. For example, GRACE effectively captures only a portion of the seasonal to long-term patterns of drought, while short-term flood signals are detectable only when they involve very large volumes of water and occur over extensive areas. These characteristics underscore the limited suitability of GRACE for monitoring extreme hydrological events and for forecasting rapid-onset floods.

The above-mentioned constraints limit the direct applicability of GRACE observations for real-time flood prediction. To overcome these limitations, researchers have explored various downscaling techniques to improve the spatial resolution of GRACE-derived TWS, allowing for more localized hydrological assessments (e.g., Vishwakarma et al. 2021; Tourian et al. 2023; Gou and Soja 2024). Efforts have also been made to predict TWS changes a few months ahead using statistical and machine learning, ML, approaches, effectively addressing the data latency issue (e.g., Ahmed et al. 2019; Li et al. 2024). Furthermore, methods such as the Kalman filter have been applied to refine the temporal resolution of GRACE TWS, generating daily or sub-monthly estimates to better align with hydrological model requirements (e.g., Gouweleeuw et al. 2018; Eicker et al. 2020; Rateb et al. 2024). More recently, studies have explored the fusion of GRACE data with other remote sensing and geodetic observations, such as GNSS station displacements and Interferometric Synthetic Aperture Radar (InSAR), to enhance the estimation of TWS changes and improve spatial and temporal resolution (Agarwal et al. 2020; Li et al. 2023; Carlson et al. 2024).

Looking forward, the next generation of gravity missions, such as MAGIC, MAGIC-NGGM, and similar concepts, promise to significantly enhance the spatial and temporal resolution of gravity-based water storage monitoring. These future missions are expected to greatly improve the performance of variable gravity estimates, offering finer-scale observations and reduced latency. However, their improvements, while notable, are still unlikely to support real-time flood forecasting applications due to the intrinsic constraints of gravimetric methods.

2.5 Surface Water Height

Surface water height over rivers, lakes, and reservoirs is a crucial variable in hydrology, particularly for flood forecasting and water resource management (García-Pintado et al. 2015; Alsdorf et al., 2007; Sanyal et al. 2005). Satellite radar altimetry has played a transformative role by providing systematic, global, and long-term observations of water levels,

particularly in ungauged or sparsely gauged regions where in situ measurements are lacking (Falck et al. 2021; Saemian et al. 2020; International Altimetry Team 2021). Since the early 1990s, various missions have provided valuable datasets for hydrology. TOPEX/Poseidon, launched in 1992, pioneered high-precision satellite altimetry, followed by the Jason series missions (Jason-1, Jason-2, Jason-3, and Sentinel-6MF), which continued its legacy with improved accuracy and spatial coverage (Tourian 2012). These missions operate in the Ku- and C-bands, providing measurements every 10 days with an inter-track distance of 315 km at the equator. In parallel, altimeters on ERS-1 and ERS-2 (Ku-band), ENVISAT (Ku- and S-bands), and SARAL/AltiKa (Ka-band) expanded altimetric measurements to inland water bodies, offering a 35-day repeat cycle and an inter-track distance of 80 km at the equator. CryoSat-2, launched in 2010, further extended observations to polar regions with its very long repeat cycle orbit, achieving a high spatial sampling resolution of 7 km, but with a lower temporal resolution of 369 days, albeit with a pseudo-repeat cycle of 30 days. More recent missions, such as the Sentinel-3 constellation (Sentinel-3A in 2016 and Sentinel-3B in 2018), operating in Ku- and C-bands, offer a 27-day repeat cycle and an inter-track distance of 52 km when both satellites are considered. Sentinel-6A Michael Freilich continues the legacy of the Jason series with enhanced accuracy and global coverage. These advancements, with revisit times ranging from 10 to 35 days depending on the mission, have significantly improved water level monitoring in rivers, lakes, and floodplains (Tourian et al. 2022; Kitambo et al. 2022).

Recent missions such as SWOT are expected to revolutionize the monitoring of surface water (see Sect. 5.1 for details).

The ability of satellite altimetry to measure water surface elevation across large and remote areas enables the detection of abnormal water level rises, which serve as an early indicator of potential flood events. Furthermore, these altimetric water levels can be used to calibrate hydraulic models, enhancing their representation of river dynamics and floodplain inundation processes (Domeneghetti et al. 2021; Birkinshaw et al. 2010; Michailovsky et al. 2013). Assimilating altimetric observations into hydrological models enhances the accuracy of flood forecasts, as these models depend on realistic water level conditions to simulate flow propagation and flood extent.

Several publicly available databases provide altimetry-based time series of water levels over rivers and lakes, offering valuable datasets for hydrological research and applications: Hydroweb.Next (formerly Hydroweb, <https://hydroweb.next.theia-land.fr/>), the Copernicus Global Land Monitoring Service (<https://land.copernicus.eu/global/products/wl>), the Database for Hydrological Time Series of Inland Waters (DAHITI; Schwatke et al. 2015; <https://dahiti.dgfi.tum.de/en/>), HydroSat, (<https://hydrosat.gis.uni-stuttgart.de>), and finally the Global River Radar Altimeter Time Series (GRRATS, Coss et al. 2020; <https://podaac.jpl.nasa.gov/dataset/>).

Despite the availability of the aforementioned databases and altimetry data for almost 30 years (International Altimetry Team 2021), for flood monitoring the available water surface height observations remain inadequate in terms of spatiotemporal distribution and near real-time availability. While satellite altimetry provides valuable long-term records, its spatial coverage is limited, with observations constrained to specific orbital tracks, leaving significant gaps in river networks (Dettmering et al. 2020; Cerbelaud et al. 2025). The temporal resolution is similarly insufficient, as revisit times often fail to capture rapid hydrodynamic changes associated with flood events, particularly in medium to small rivers. Moreover, the performance of altimetry reaches its limits when monitoring smaller rivers, where complex surrounding topography complicates signal retrieval, leading to noisy waveforms for which specialized retracking approaches are required to extract reliable water level time

series (Passaro et al. 2018; Tourian et al. 2025). The latency of current satellite-derived hydrological products further restricts their usability for real-time flood forecasting. Even with advancements in data processing, delays in data availability, ranging from several days to weeks, severely limit their integration into operational flood prediction systems. This challenge is especially critical for extreme hydrological events, where high-frequency, near-real-time observations are essential for accurate forecasting and early warning.

2.6 Surface Water Extent

Although inland water bodies, such as rivers, lakes, and reservoirs, cover only a small portion of the Earth's surface, they play a vital role in climate regulation and flood mitigation. Accurate, timely information on their spatial and temporal dynamics is essential for flood forecasting and hydrological modeling. Satellite remote sensing, with its global reach and frequent revisits, enables consistent monitoring of surface water extent and river width across river basins worldwide.

Surface water extent time series are crucial for calibrating and validating flood models. Similarly, river width time series can be used to estimate discharge (see Sect. 2.7), an essential variable in flood forecasting. Numerous efforts have focused on generating dynamic water masks from satellite data. MODIS, for instance, offers high temporal resolution, but its coarse spatial resolution (250–500 m) limits detection of smaller water bodies (e.g., Klein et al. 2017; Zhang and Gao 2016). Higher-resolution imagery from Landsat and Sentinel-2 (30 m and 10 m, respectively) offers improved spatial detail, albeit with sparser temporal coverage (Tourian et al. 2016; Yao et al. 2019; Schwatke et al. 2020). Commercial platforms like PlanetScope offer even finer resolution, though they are often restricted in terms of accessibility (Scherer et al. 2024).

Beyond optical sensors, synthetic aperture radar (SAR) imagery has been widely used for monitoring the dynamics of water bodies, particularly under cloud-covered or flood-prone conditions. SAR's all-weather capability makes it an ideal complement to optical data, though its processing is more complex (Chen et al. 2020; Tsai et al. 2020). Most techniques rely on spectral thresholding, leveraging water's low reflectance in the NIR or radar backscatter properties. However, pixel-based approaches can suffer from inaccuracies, as they ignore spatial and temporal dependencies. To improve robustness, region-based algorithms that incorporate both spatial and temporal context have been proposed (e.g., Elmi et al. 2016; Elmi 2019).

Global datasets such as the SRTM Water Body Data (SWBD, NASA Jpl 2013), the Global Inundation Extent from Multiple Satellites (GIEMS, Papa et al. 2010), the Global Surface Water Dataset (GSW, Pekel et al. 2016), and the Global WaterPack (Klein et al. 2024) provide pre-processed maps of surface water. These datasets are valuable for large-scale analysis but are often constrained by the spatial and temporal resolution of their respective source datasets. Recent efforts, like the region-based restoration algorithm of Elmi and Tourian (2023), address these limitations by refining existing water masks through the use of spatiotemporal relationships among neighboring pixel labels. The method enforces consistency between adjacent pixels in space and time, allowing misclassified areas to be corrected based on the behavior of surrounding regions.

Online databases further enhance access to inland water body time series. Hydroweb (<https://www.theia-land.fr/en/hydroweb/>) was among the first to provide lake surface area records (Crétaux et al. 2011), followed by DAHITI (<https://dahiti.dgfi.tum.de/en/>), Schwatke et al. 2019). More recently, HydroSat (<https://hydrosat.gis.uni-stuttgart.de/php/>)

maps.php?d_content=1&source=1) has introduced time series of river reach widths, a key step forward. The Bluedot Observatory (<https://lep.landseuse.eu/Explore/11#about>) also delivers near-real-time lake and reservoir area data using Sentinel-2 imagery.

Despite these advances, existing datasets still fall short for operational flood forecasting. Most cover only a subset of water bodies and lack real-time updates. To address this, tools like Water Area Tracking from Satellite imagery (WaTSat, Elmi and Ahrari 2025) have emerged, enabling users to generate custom time series from MODIS via Google Earth Engine.

Nonetheless, current global surface water datasets remain limited in spatial and temporal resolution, often missing rapid changes during extreme events or small water bodies that influence flood dynamics. There is a pressing need for next-generation tools that integrate high-resolution imagery, hydrological modeling, and real-time data processing to support more reliable and actionable flood forecasting.

2.7 River Discharge

River discharge is a key variable for flood forecasting and hydrological analysis. Traditionally estimated from in situ measurements of water level, flow velocity, and cross-sectional geometry, it can now be increasingly derived from satellite observations, especially in regions where ground-based data are sparse or unavailable. Among satellite-based methods, radar altimetry is one of the most mature and widely adopted. By measuring water surface elevation (see Sect. 2.5), altimetry enables the derivation of river discharge through rating curves or integration within hydrodynamic models (Tourian et al. 2013; Paris et al. 2016; Elmi et al. 2021). The use of satellite altimetry for river monitoring has significantly advanced over the past three decades, with missions such as CryoSat-2, Sentinel-3, and Sentinel-6MF and more recently launched SWOT and planned Sentinel-3 Next Generation Topography and CRISTAL, offering improved accuracy and spatial resolution (see Sect. 2.5). These missions have facilitated the reconstruction of long-term time series of river discharge (Tourian et al. 2016; Belloni et al. 2021; Schumann et al. 2023), supporting both climatological studies and water resource assessments.

Nevertheless, the limited revisit time of individual altimeters can hinder their applicability in operational flood forecasting, which requires higher temporal resolution. To address this, researchers have explored multi-mission merging techniques and along-river correlation approaches to densify water level observations (Boergens et al. 2017; Zakharova et al. 2020; Nielsen et al. 2022). Nielsen et al. (2022) demonstrate how spatial correlation of water levels along river reaches can be leveraged to interpolate temporally consistent water surface elevations and slopes, thereby enabling more continuous discharge estimation. The emergence of wide-swath altimetry, especially with the SWOT mission, further enhances these capabilities, because it allows the derivation of water surface slope (WSS) and river geometry simultaneously over large areas, offering new perspectives for discharge estimation at regional to global scales (Scherer et al. 2022; Scherer et al. 2023; Ke et al., 2025).

In parallel, optical remote sensing provides a robust and complementary pathways for discharge estimation by exploiting surface reflectance in near-infrared (NIR) band. Methods based on NIR reflectance indices, pioneered by Brakenridge et al. (2005) and further developed by Tarpanelli et al. (2013, 2019, 2020), leverage the temporal dynamics of the wetted area to quantitatively infer river discharge. This approach is particularly effective in hydrologically variable environments, where sharp wet–dry transitions enhance spectral contrasts. More recently, Filippucci et al. (2022) strengthened the method’s versatility by

integrating land cover classification (e.g., permanent water, vegetation) with high-resolution imagery, thereby extending its effectiveness to smaller river and morphologically complex floodplains.

The integration of these diverse satellite observations has led to the development of dedicated platforms that provide value-added discharge products. HydroSat (Tourian et al. 2022) and DAHITI (Schwatke et al. 2015) are two prominent examples that combine altimetry, imagery, and ancillary data to estimate water level, extent, discharge, and volume anomalies globally. While these systems have significantly improved our ability to monitor rivers from space, many remain limited in terms of NRT availability and temporal continuity, which are crucial for flood response (Elmi et al. 2024).

An important limitation of EO-based flood forecasting models is the scarcity of ground truth data for calibration and validation. To address this challenge, researchers have also developed statistical approaches that bypass the need for temporally synchronous in situ observations. One common technique is quantile mapping, which matches the distribution of historical in situ discharge with that of satellite-derived proxies (Tourian et al. 2013). Elmi et al. (2021) enhanced this method by introducing a stochastic Monte Carlo framework that propagates uncertainties and improves robustness. Looking ahead, the next frontier in satellite-based discharge estimation lies in developing fully remote approaches that operate without any in situ calibration. Scherer et al. (2020) demonstrate that, under specific assumptions, discharge can be estimated solely from satellite-derived variables such as slope and width, even in ungauged catchments. Ke et al. (2025) take this further by using a Kalman-filtering framework to assimilate SWOT-derived and synthetic discharge observations into a spatiotemporal process model, enabling daily discharge estimates at the basin scale. These innovations mark a significant step toward global, scalable, and autonomous discharge monitoring systems.

2.8 Flood Extent

Flood extent observations are vital for the assessment of the magnitude of the floods. These are normally obtained from field data, aerial photography, and satellite remote sensing. Synthetic aperture radar (SAR) sensors are particularly effective for detecting flooded areas under all weather conditions. High-resolution SAR images, such as those from the commercial TerraSAR-X and COSMO-SkyMed satellites, can provide critical information for flood detection and emergency management and are occasionally tasked in emergency context (e.g., through the Copernicus Emergency Management Service). However, their use is limited due to the data coverage and availability at the critical time required for operational flood mapping. In contrast, Copernicus Sentinel-1 mission, with its two polar-orbiting satellites, systematic acquisitions, and free and open-data policy, provides consistent and timely coverage with a revisit time of 6–12 days on the same orbital track (shorter at high latitudes), making it the primary operational resource for large-scale flood monitoring. While offering less frequent revisits, other SAR missions, such as JAXA's ALOS-PALSAR, provide valuable L-band data, which is particularly useful for penetrating dense vegetation and therefore advancing scientific understanding of flood dynamics in forested areas. Flood frequency analysis can be based on images acquired in interferometric wide-swath scanning (IW, 10-m resolution), considering all images acquired from both ascending and descending orbital tracks. Data acquired before this period have been considered pre-operational due to the lower number of images. The loss of Sentinel-1B in December 2021 impacted revisit time, which was reduced to a global coverage every 12 days on

average, until Sentinel-1C release of data in 2025, after its launch in December 2024. The SAR monitoring requires expertise in image processing, understanding sensor-specific limitations, and integrating satellite data with topographic and hydrologic models to achieve accurate flood mapping and prediction.

Optical sensors, from medium to high resolution, are often used to detect flood extent during or after inundation events (Sakamoto et al. 2007; Ogilvie et al. 2015). Sentinel-2 mission benefits from a constellation of now three satellites (Sentinel-2A, Sentinel-2B, and Sentinel-2C) to take over the service of the now 9-year-old Sentinel-2A) which provide multispectral imagery of the Earth with a maximum resolution of 10 m. With two satellites working together, the revisit time is 5 days at the equator. In contrast to SAR sensors, which work in all weather conditions, optical sensors are compromised by the presence of clouds. Regarding the VIIRS sensor, it is mounted on 5 platforms of the NOAA Joint Polar Satellite System and provides daily images with 375 or 750 m spatial resolution, depending on the band. In this case, the analysis is based on the 5-day VIIRS products (375 m resolution) provided by the Cooperative Institute for Meteorological Satellite Studies (CIMSS). Besides the flood masks, the VIIRS products also contain the flooded fraction, that is, the percentage of the pixel covered by water. This information can be used with the in combination with a DEM to downscale flood extent to the resolution of the DEM. This process is based on the height above nearest drainage (HAND). For each “parent” VIIRS pixel, the corresponding “children” pixels are ordered by HAND value, marking the n lowest as flooded, where n is a threshold value determined by the flood fraction and the children pixel count.

For the calculation of flood extent from optical images, FloodSENS (Gaffinet et al. 2023), a “living” ML model, has been developed to map floods with consistent accuracy in the biomes it was trained for, combining optical imagery with auxiliary data such as topography to improve delineation under challenging conditions.

Figure 2 illustrates the feasibility of flood monitoring using current satellite sensors as a function of event duration and flooded area. It is important to clarify that the plot refers to flood extent rather than elevation, since all listed sensors are imaging satellites. Each point corresponds to an observed flood event from the dataset available from the Dartmouth Flood Observatory, which combines satellite data with information from institutional and media sources to identify, delineate, and classify flood events on a global scale from 1985 onwards. The shaded areas define the regions of spatiotemporal conditions under which three satellite systems, Sentinel-1, Sentinel-2, and VIIRS, can provide adequate temporal sampling and spatial resolution to detect and monitor flood dynamics.

Sentinel-1, with a revisit time of approximately 5–6 days and a spatial resolution of 10 m, ensures consistent observations even under cloudy conditions due to its radar capability. This ability to penetrate clouds gives Sentinel-1 a clear advantage, especially because cloud cover is highly probable during flood events. Sentinel-2, offering 10–20 m optical imagery with a nominal 5-day revisit, provides higher spectral richness but its effective temporal resolution is often reduced by cloud contamination. VIIRS, on the other hand, delivers near-daily observations at a coarser spatial resolution (~375 m), allowing frequent detection of large flood events and complementing the higher-resolution Sentinel data. The special role of Sentinel-1 SAR imagery is therefore crucial: While the spatiotemporal resolution of Sentinel-2 and VIIRS is relevant for flood monitoring, their utility in real situations is strongly limited by cloud cover, whereas Sentinel-1 remains fully operational.

Overall, the distribution of events in the figure demonstrates that most floods fall within the observable domain of at least one of the three sensors. This indicates that, with the current constellation of Earth observation satellites, it is already feasible to achieve near-global

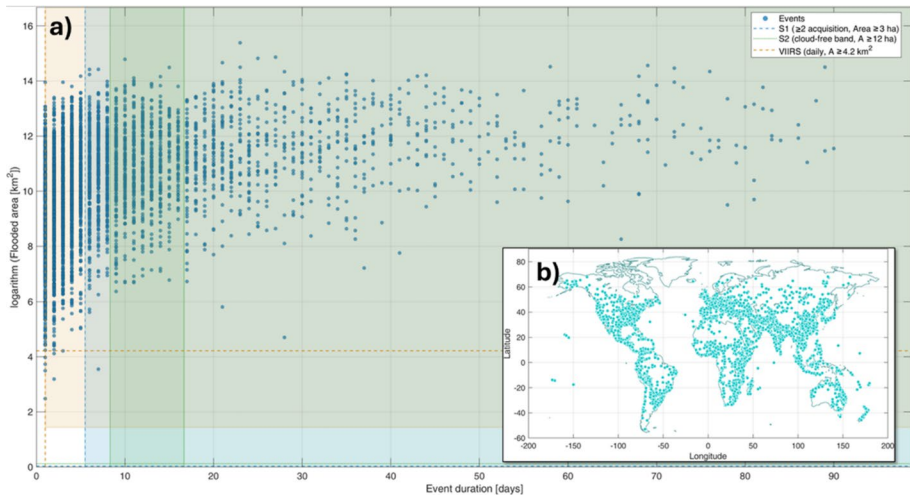


Fig. 2 Feasibility of flood monitoring using satellite data. The scatter points **a** represent flood events (duration vs flooded area) observed by DFO (Dartmouth Flood Observatory). Colored shaded regions indicate combinations of spatial and temporal scales that can be effectively monitored by Sentinel-1, Sentinel-2, and VIIRS sensors, given their revisit time and spatial resolution. **b** Location of the events across the globe

flood monitoring at relevant spatial and temporal scales, especially through the synergistic use of radar and optical data.

3 Applications of Satellite Data in Flood Forecasting Systems

An effective flood forecasting system for at-risk communities requires integrating data, forecasting tools and skilled personnel. Such a system must provide sufficient lead time for communities to respond effectively, as longer lead times can significantly reduce damage and save lives. However, the forecasts need to be accurate enough to inspire trust; without confidence in a decision support system, decision makers are less likely to trigger warnings and communities are less likely to act on warnings. For maximum effectiveness, the system must remain reliable during extreme flood events, particularly when these are sudden and widespread, and communities must be prepared to mitigate their impact. A flood-forecasting system relies on interconnected components among data sources, forecasts, communication channels, decision support, notification, coordination, and responses that work seamlessly together, as even one weak link can render the whole process ineffective. For example, if critical data are unavailable or if warnings fail to reach those at risk or fail to provide clear guidance, the system cannot fulfill its purpose. Because, in addition to the forecasting processing chain and skill, even when these are accurate, failures during any of the last processing steps, such as timely notification to the public and adequate responses from the authorities, can have huge consequences on the impact of a flood event.

For example, in the July 2021 floods in Germany and Belgium (Rhein and Kreibich 2025) where 190 fatalities were reported, evaluations highlighted shortcomings in the warning chain and crisis communications, which contributed to many people being caught on ground floor (37%) or outside on the street (18%). Similarly, in the October 2024 Valencia floods in Spain, where 2023 fatalities occurred, several victims were trapped in

underground garages, ground floors, or on the streets, raising concerns about the effectiveness and clarity of warning messages. These cases illustrate that early warning systems must not only be technically sound, but also deliver valid, timely and actionable alerts that prioritize saving human lives.

Regarding the flood forecasting data and modeling, the scientific literature recently emphasized on four elements that are fundamental for such a system: (1) forcing input data, (2) the model, (3) the lead time, and the (4) forecast uncertainty.

The first element relates to the forcing input data necessary for the application of flood forecasting models, such as precipitation, soil moisture, snow, water level, and river discharge. A forecasting system requires these data to be available in real time, and it is important to operate a data acquisition and transmission system that allows for the real-time storage of accurate values of hydrometeorological quantities in a central station. Generally, these systems are difficult to find in countries of the Global South, while even if available in economically advanced nations, many areas often remain unserved by these systems. Satellite data can overcome this limitation in spatial and temporal coverage, but their use in current flood forecasting systems is yet hugely under-exploited. An efficient way to use the satellite data is in the pre-processing of the system to calibrate the flood forecasting model in a direct manner, or to consider the hydrological parameters calculated starting from satellite data such as hydrometric water level or river discharge which could feed the forecasting models. Other novel studies are exploring the assimilation of satellite observation to directly reduce the predictive uncertainties of flood forecasting models (Nguyen et al. 2024a, b).

The second element refers to the numerical models to simulate river flows; in some cases, they predict river stage levels and therefore potential flooding. Flood forecasting models can range from simple statistical models to complex rainfall–runoff and hydrodynamic models that simulate the behavior of water in rivers and floodplains. Models can be classified into two main groups: data-driven models (Tarpanelli et al. 2017; Schumann et al. 2017; 2019) and physical process-driven models (Alfieri et al. 2024; Arheimer et al. 2020; Cea et al. 2025). Data-driven models are calibrated (fitted) using historical observations, such as river discharge records, meteorological variables and other relevant environmental data, and the trained models are then applied to near-real-time situations (including statistical, ML, and deep learning approaches better discussed in Sect. 5.2). High interest was raised around the innovative approach adopted by Google to develop a ML-based global hydrological model for flood forecasting (Kratzert et al. 2018; Nearing et al. 2024). While the model does not explicitly represent physical processes, it utilizes a long short-term memory (LSTM) network in conjunction with an encoderdecoder to implicitly represent hydrological storages. LSTMs are particularly useful for modeling hydrological systems as their model architecture allows for the learning of long-term interactions between various cell states. When trained on enough data, the cell states have been shown to mimic storages traditionally modeled in process-based models (Lees et al 2022). The physical process-driven models, ranging from lumped-conceptual to fully distributed physically based models, simulate the rainfall–runoff process forced by weather forecasts from numerical weather prediction (NWP). One potential advantage of such approaches is that they can explicitly capture complex catchment dynamics that predictors used in statistical models may not fully or clearly represent, thus offering more interpretability of results and insights into catchment hydrology (Guse et al 2021; Herath et al 2021). While newer data-driven models are offering improvements in the forecasting of extreme events, it has previously been understood that physically based models offer more reliability when presented with extreme events not seen during training or calibration (De La Fuente et al 2024; Frame

et al 2022a, b). However, they typically require daily precipitation and evaporation data as inputs, whereas statistical models are generally not based on a limited set of input information, but rather they are able to take advantage of whatever relevant data are available. Under these premises, a third group is configured as the hybrid solution that integrates dynamical and statistical streamflow forecasting models (Robertson et al. 2013).

Among this variety of models, researchers and organizations collaborate to provide streamflow forecasting systems at the global (GloFAS—Dottori et al. 2017; Alfieri et al. 2013; C3S 2020; WWH—Arheimer et al. 2020—<https://hypeweb.smhi.se/>; Global run-off—Pappenberger et al. 2010), continental (EFAS—Alfieri et al. 2014; SMHI Hypeweb, <https://hypeweb.smhi.se/>); national (Brown et al. 2014; Thirel et al. 2010; Liu 2016), regional (Demuth and Redamacher 2016), and basin (Amarnath et al. 2016; Shi et al. 2015; Yuan et al. 2016) scale. However, global and continental scale systems provide highly uncertain estimates of river discharge in sparsely gauged areas (e.g., lower- and middle-income countries in the Global South), and satellite data are still lacking in these systems.

In addition, the European Union Copernicus Emergency Management Service (CEMS, <https://emergency.copernicus.eu/>) provides a comprehensive operational framework for flood preparedness and response. CEMS is organized around two main components. The first focuses on Early Warning and Monitoring and includes the European Flood Awareness System (EFAS), which provides flood forecasts for continental Europe, and the Global Flood Awareness System (GloFAS), which delivers global-scale flood forecasts using hydrometeorological models. It also encompasses the Global Flood Monitoring (GFM) system, which delivers near-real-time flood extent maps derived from satellite data, using systematic acquisitions from Sentinel-1.

The second component is the on-demand mapping service (covering Rapid Mapping and Risk & Recovery), which can be activated by authorized users worldwide to produce, among others, very high-resolution flood extent maps, as well as damage assessment products caused by natural or human-made disasters. Together, these services provide both systematic monitoring and rapid emergency response capabilities.

Another interesting initiative worth mentioning is EOTEC DevNet (<https://eotec-dev.ceos.org/tools/>), the Earth Observation, Training, Education and Capacity Development Network. This initiative, a joint effort of CEOS, GEO, WMO, UNOOSA and CGMS, seeks to bring the power of satellite-derived Earth information of flooding to more users around the globe by improving coordination and collaboration among capacity-building providers.

Despite the scientific literature demonstrated that hydrological models using EO products (river discharge, precipitation, soil moisture, reservoir water level, snow, flood extent and total water storage) as forcing and in data assimilation frameworks provide improved performances (Alfieri et al. 2022; Revilla-Romero et al. 2016; Garcia-Alen et al. 2024) and extend the applicability even in ungauged or poorly gauged basins (Jiang and Wang 2019), a crucial point emerging from this review is that the use of satellite data in operational flood forecasting systems is nearly absent. This evidence, which reflects both technical and institutional barriers to the uptake of EO by the hydrological community, is further elaborated in the following Sect. 4, where we discuss in detail the weakness of current satellite technologies and the prospects for their integration into operational forecasting chains.

The third element relates to the possibility of extending the lead time of the forecast using nowcasting techniques (0–3 h) or quantitative precipitation forecasts provided by NWP models (1–4 days). If the basin response time (i.e., the time needed for water to flow from the most remote point in a basin to its outlet) is too short for warning activities, it is necessary to extend the forecast horizon that can be used for precipitation forecasts. For this purpose, an estimate of the amount of rain that will fall on an area of interest in the

following hours\days should be used as an additional input to the rainfall-runoff model. Precipitation forecasts can be estimated using meteorological models limited to the area or, if the forecast horizon is of the order of 6 h or less, using meteorological extrapolation techniques. For this purpose, the following techniques can be conveniently employed: (1) 'nowcasting' techniques, typically based on radar and/or satellite imagery, which provide short-term forecasts (0–6 h) of rainfall fields by extrapolating their motion, (2) empirical extrapolation methods using rainfall network and/or radar measurements, which extend point or local observations in space and time but are generally less sophisticated than radar/satellite nowcasting, and (3) quantitative ground precipitation forecasts provided by NWP, capable of capturing the triggering and subsequent evolution of the precipitation systems generating forecasts up to 4–10 days in advance.

The fourth element consists of the forecast uncertainty that can become much larger due to errors in the input forcing as well as in the rainfall–runoff process. Regardless of the model used to develop future flood predictions, many sources of error influence the forecast, making uncertainty a fundamental aspect in properly supporting decision-making activities (Montanari and Grossi 2008; Coccia and Todini 2011). Uncertainty in flood forecasting depends on five main elements: (1) errors in the measurement of hydrometeorological quantities; (2) errors in the data used to calibrate forecast models; (3) approximations in the structure of the forecast models; (4) errors in the values attributed to model parameters; and (5) forecast uncertainty of rainfall fields when there are used as input data for modeling. In general, a forecast does not eliminate uncertainty about a future event but only reduces it. Therefore, it is extremely important to quantify the residual uncertainty, to make the forecast useful for practical purposes, in other words, valid. A deterministic forecast provides a single predicted value without explicitly accounting for uncertainty often leading to an overconfident representation of future conditions. In contrast, a probabilistic forecasting quantifies forecast uncertainty by providing a range of possible outcomes along with their associated probabilities. This probabilistic approach enables end users to make informed decisions by considering different risk scenarios and uncertainty levels.

Incorporating uncertainty estimation into the flood forecasting method can be useful for the decision maker to improve the reliability of both the forecasting model and the warning system in real-time flood management. Quantifying the uncertainty within a forecasting system provides information to make rational decisions (Todini 2017; Barbetta et al. 2017). Neglecting uncertainty may induce a misleading illusion of certainty for decision makers and end users. In fact, when such a forecast turned out to be wrong, the consequences would probably be worse with respect to a situation where no forecast was available. Especially, recurring false positives drastically reduce the trust of the end user toward the forecasting system. To demonstrate the value of a forecasting system, it is crucial to compare its performance with simple benchmark forecasts, such as flow climatology and persistence, which provide a baseline for evaluating forecast improvements. Additionally, archiving historical forecasts or conducting re-forecasting experiments is essential for systematically assessing forecast skill as a function of lead time. This evaluation should be carried out both with and without satellite EO data to quantify the added value of satellite-based information in improving forecast accuracy. Further insights on this approach can be found in Charoensuk et al. (2024).

Based on the above premises, flood forecasting systems are already operational even at a global level, but they are driven by only ground data and their uncertainty is still high. The assimilation of satellite data would provide a tangible advancement for the benefit of the community, especially in the Global South countries. Some examples are available in the literature and in the following they are described to highlight the field of application.



Fig. 3 Contributions of the remote sensing satellite data in the flood forecasting systems

To better illustrate the potential contribution of satellite observations, Fig. 3 shows the role they can play at different stages of a flood forecasting chain: from the pre-processing phase (e.g., calibration and definition of initial conditions), through real-time data assimilation during the event, up to post-event validation. This conceptual scheme underscores how satellite-derived information can enhance both the input variables and the predictive skill of the models, thereby reducing uncertainty and improving flood preparedness and response.

3.1 The Critical Aspect of the Initial Conditions

One of the critical aspects affecting hydrological modeling is the correct estimation of the initial conditions, which strongly influences the flood response to precipitation events. In this context, inherent uncertainty in the model structure and errors in parameters and forcing may cause an incorrect estimation of basin antecedent conditions thus providing an erroneous response to precipitation events (Brocca et al. 2008). Numerous studies have shown the benefit of using satellite products to improve pre-event initial states. For example, assimilating satellite-derived soil moisture can better characterize the antecedent wetness conditions before a storm, leading to improved flood simulations (Massari et al. 2014; Azimi et al. 2020; Setti et al. 2020). Alternatively, proxies such as river discharge records or antecedent precipitation indices (API, Ponce and Hawkins 1996), can provide information on catchment wetness and are used in many operational applications.

Initial conditions are also crucial for hydraulic structures. Dams and reservoirs generate disconnections within a catchment and accurate knowledge of their initial conditions would improve the representation of the processes involved in modeling. The knowledge of the initial water level of the reservoirs can help simulate the availability and possible discharge of stored volumes during flood events. Therefore, initial conditions of soil moisture and reservoir water level can be considered an important discriminator for reliable prediction. Similarly, accurate knowledge of snow cover on the ground, particularly snow water equivalent, is crucial as it dictates potential meltwater contributions to river systems. In addition, if river discharge is available on a global scale, it can represent a substantial improvement in modeling and thus in eventual prediction (Schumann et al. 2023).

3.2 Improved Model Calibration: Use of Satellite Data to Validate Forecasts and Update Parameters

Model calibration is the process of selecting suitable values of model parameters such that the hydrological behavior of the catchment can be simulated closely. Generally, this procedure is automatic due to: (1) the need to speed up in terms of computational efficiency the process of calibration and (2) the elimination of the subjective human judgment involved in the manual approach. Traditionally, hydrological models are calibrated against ground measured discharge. However, studies in literature demonstrated the advantage to use remote sensing data for calibrating the rainfall/runoff model and the hydrodynamic model including: river discharge (Hossain et al. 2014; Tarpanelli et al. 2017; Biancamaria et al. 2016; Falck et al. 2021), actual evapotranspiration (Sun et al. 2021), snow-covered area (Schneider et al. 2022), land surface temperature (Zink et al. 2018), and soil moisture (Sutanudjaja et al. 2014; Eini et al. 2023). Additionally, satellite estimation of water level shows promising applications in the calibration of hydraulic models. These models are mainly devoted to the simulation of the flow routing within the main channel through physical laws of fluid motion at different degrees of complexity including one- and two-dimensional models (abbreviated as 1D or 2D models). Studies in the Amazon (Getirana et al. 2009; Paiva et al. 2013), Brahmaputra (Michailovsky et al. 2013), and Zambezi (Michailovsky et al. 2012), and Po (Domeneghetti et al. 2014; 2021) rivers provide different examples of the improvement that can be obtained by integrating satellite data with flood models. Additionally, the use of flood extent maps from EO would be highly useful to evaluate and improve the forecast of flooded areas (Revilla-Romero 2015).

3.3 Data Assimilation and Post-processing

To partially reduce the uncertainty coming from the input data, the model scheme and the meteorological forecast, two techniques can be performed: data assimilation and post-processing.

Data assimilation is the process of adjusting model states and parameters over time to bring simulations closer to available observations as the simulation progresses. While different approaches exist (e.g., sequential filtering and smoothing), sequential methods are particularly suited for near-real-time and forecasting applications. In addition, post-processing techniques are required to compensate for errors in model structure or initial conditions and to correct biases of the forecasts. The data assimilation technique computes model corrections based on the assumption that the uncertainties in model output and observations are known. Data assimilation techniques have been widely applied in hydrological studies (Pulvirenti et al. 2011; Revilla-Romero et al. 2016; De Lanoy et al. 2024) to also update the state variables and model parameters. Beside soil moisture (Crow et al. 2005; Massari et al. 2015; Betschold et al. 2023) and water level (Michailowsky et al. 2012) recent literature showed the use of SAR data for flood maps into hydrological-hydraulic forecasting models (Di Mauro et al. 2021; Mason, et al. 2021). Assimilation of long-repeat orbit satellite altimetry data was demonstrated in several studies involving drifting orbit altimeters from Cryosat-2 and ICESat-2 (Schneider et al. 2018; Bauer-Gottwein et al. 2023; Coppo Frias et al. 2023).

One major challenge in assimilating EO data into hydrological models is the issue of representativity, meaning that the observed variables do not always directly correspond

to the variables simulated by the model. This discrepancy complicates the definition of the observation operator required for data assimilation (Cooper et al. 2019; Tourian et al. 2017). A clear example of this is water surface height measurements from satellite altimetry, which are referenced to an ellipsoid, whereas hydrological models typically represent water levels relative to riverbed depth. This fundamental difference means that there is no direct comparison between the two variables, and their magnitudes can differ significantly. While algorithms exist to convert altimetric height into discharge, they introduce additional uncertainty and often require in situ discharge data for calibration. This reliance on in situ measurements can be a limiting factor, especially in regions with sparse or unavailable ground-based observations, ultimately affecting the reliability of EO data assimilation in flood forecasting and hydrological modeling.

The spatiotemporal coverage of EO data can be a major limitation for data assimilation systems. A low spatiotemporal resolution reduces the amount of information available to constrain models, limiting their ability to represent dynamic processes at fine scales. While techniques such as localization algorithms and smoothers can partially compensate for these gaps by propagating observed information to unobserved regions and times, these approaches introduce additional uncertainties. This issue is particularly critical for operational forecasting, which requires near-real-time observations at specific locations of interest. Moreover, satellite revisit times may be insufficient to capture fast-evolving hydrological events, such as flash floods, while spatial resolution constraints hinder the accurate representation of complex river systems or urban flooding. Finally, the effective availability of data can be further constrained by processing delays or access restrictions, preventing optimal use for applications requiring frequent model updates (Lahoz and Schneider 2014).

4 Challenges and Limitations

While the paper provides an overview of current opportunities and challenges in flood forecasting and monitoring, there are several critical points to be considered. Recent advancements in AI, particularly ML, and EO data have the potential to transform the capabilities of flood prediction models (see, for example, the recent landmark paper by Nearing et al. 2024). While AI and EO data have shown promises, they are not without limitations, including data quality issues, resolution constraints, and operational latency. These limitations could significantly impact the efficacy of the proposed forecasting systems. In the following, such a concept is analyzed in detail.

4.1 Acquisition Times: Delay in Data Availability

Latency refers to the time between satellite data acquisition and its availability for analysis. In flood forecasting, minimizing latency is critical, as delays reduce the lead time available for preparedness and response. Satellite latency varies depending on orbital characteristics, data transmission infrastructure, and processing requirements. For example, geostationary platform can deliver near-real-time products, due to their constant position relative to Earth, while polar-orbiting missions often experience longer delays. High-resolution or multispectral data, valuable for mapping flood extents and water levels, also require more complex processing, which can increase latency.

Recent advances, including onboard processing real-time data relay, and NASA NRT hubs such as MODIS Rapid Response and LANCE, have substantially shortened delays

and improved the timeliness of flood forecasts. For example, Sentinel-3 provides NRT altimetry product within 2–5 h, with accuracy comparable to non-time critical product (median RMSE difference of about 22.2 cm across 1655 virtual stations; Jiang et al. 2023a, b). Similarly, Sikder et al. (2021) showed that radar altimetry with a revisit of 1–3 days is sufficient to capture global flood dynamics, though current products with 3–5 day latency remain limiting for small- to medium-size basins. Incorporating NRT datasets, for example, from the Tropical Rainfall Measuring Mission (TRMM), has also proven to improve both the accuracy and responsiveness of forecasts (Kuligowski et al. 2013).

4.2 Spatial/Temporal Resolution: Comparison of Model Needs and Satellite Capabilities

The current trend revolves around the provision of data on a global scale from EO products. However, this request can be hardly obtained for all the variables. By way of example, the river discharge, due to the hydrological complexity and its spatial and temporal variability (flows can fluctuate seasonally, daily and even hourly), needs space-based sensors with high spatial and temporal resolutions to capture its variations accurately across different regions and time scales. The daily resolution is not guaranteed because the temporal resolution of current satellite products is lower and the current multi-mission techniques can provide only up to 3 days of temporal resolution for medium basins. However, integration with SWOT data has still to be done; therefore, some improvements can be expected. Moreover, most of the methods need in situ data to calibrate the relationships between in situ discharge and satellite variables and to improve the accuracy of satellite-based estimates. The problem is exacerbated by the limited in situ stations, especially in remote or inaccessible regions where the coverage can be scarce.

Furthermore, flash floods, characterized by their rapid onset and short duration, pose significant challenges for satellite-based monitoring. Due to the swift development of these events, they often occur before satellite data can capture the changes in affected areas. Flash floods require very high temporal and spatial resolution to track their localized and transient nature, but current satellite capabilities are limited in providing data at such fine resolutions, especially for short time frames. This limitation underscores the difficulty of accurately monitoring flash floods with existing space-based systems, highlighting a gap that requires further technological advancements to improve the effectiveness of flood forecasting models.

4.3 Uncertainties and Reliability: Accuracy Limits and Variations Between Sensors

Uncertainty is a pervasive factor in flood forecasting, arising from a confluence of limitations inherent in EO data and the inherent complexities of hydrological and hydraulic modeling. The accuracy of EO-derived hydrological variables, such as precipitation, soil moisture, and water surface elevation, is fundamentally constrained by the technical specifications of the sensors themselves. Spatial resolution, for instance, dictates the level of detail captured, while temporal resolution determines the frequency of observations. Coarse spatial resolution may obscure localized flood events, and infrequent temporal sampling can miss critical periods of rapid hydrological change. Atmospheric conditions, such as cloud cover and aerosol presence, can also attenuate or distort sensor signals, leading to inaccuracies in retrieved data. Additionally, sensor calibration and algorithmic processing

introduce their own sources of uncertainty, as these processes rely on assumptions and approximations that may not perfectly reflect real-world conditions.

Furthermore, the diversity of EO missions and sensor technologies contributes to significant variations in data quality and interpretation. Different satellite platforms, such as optical, radar, and gravity missions, employ distinct measurement principles and spectral bands, each with its own strengths and limitations. Optical sensors, for example, are highly sensitive to cloud cover, while radar sensors can penetrate clouds but are affected by surface roughness and vegetation. Gravity missions provide valuable information on large-scale water storage changes but have limited spatial and temporal resolution. Consequently, data from different EO sources may exhibit systematic biases or inconsistencies, making it challenging to integrate them seamlessly into flood forecasting models. These discrepancies can propagate through the modeling process, amplifying uncertainties in flood predictions.

Uncertainties in EO data play a crucial role also in data assimilation, as they directly influence the reliability and impact of the corrections applied to the model. For effective data assimilation, uncertainties must be accurately estimated, which is not always the case with EO data. Moreover, the weight given to an observation in the assimilation process depends on its uncertainty: If the uncertainty of the observation is greater than that of the model, the data will have little to no impact on the correction. Additionally, systematic biases in EO data can propagate into the assimilation process, potentially introducing biases in the model's corrected state. This highlights the need for careful uncertainty quantification and bias correction strategies to ensure meaningful improvements in model performance (Bonavita 2011; Fowler and Van Leeuwen 2013).

The cumulative effect of these uncertainties necessitates a comprehensive approach to uncertainty quantification in flood forecasting. This involves not only characterizing the accuracy limits of individual EO sensors but also assessing the propagation of errors through the modeling chain. Techniques such as ensemble forecasting, data assimilation, and sensitivity analysis, and, more recently, significant advances in AI and ML, can help quantify the impact of uncertainties on flood predictions. Additionally, rigorous validation and intercomparison of EO-derived products are essential for identifying and mitigating systematic biases. Ultimately, a thorough understanding of sensor-specific uncertainties and intersensor variations is paramount for developing robust and reliable flood forecasting systems that can support informed decision-making in flood risk management.

5 Future Prospects

5.1 New Satellite Missions: SWOT, Sentinel-6MF, NISAR, SMASH, HydroGNSS, etc.

Several satellite missions, both recently launched and upcoming, could revolutionize our understanding of Earth's water resources and hydrological processes. These missions employ advanced technologies to observe and measure key parameters crucial for hydrology, such as water surface elevation, soil moisture, and inundation extent.

One of the most notable examples is the SWOT mission, a joint effort by NASA, CNES, Canada, and the UK launched in December 2022. SWOT carries a Ka-band radar interferometer (KaRIn), enabling it to measure both water surface height and extent for millions of lakes, wetlands, and rivers worldwide. For the first time, it provides global water surface elevation at high spatial resolution (~ 50 – 100 m) with a revisit time of

about 21 days. This unprecedented capability opens new opportunities for discharge estimation and model calibration in ungauged basins and provides valuable insights into freshwater availability, flood forecasting, and climate prediction models (Fu et al. 2024). However, the current latency of data processing limits its near-real-time applicability and the large data volumes pose technical challenges. Future developments are expected to reduce latency and improve integration of SWOT products into operational flood forecasting chains.

Complementing SWOT's unique surface water capabilities, other upcoming missions will address specific gaps in radar coverage and continuity. Another significant mission is the NASA-ISRO Synthetic Aperture Radar (NISAR), a collaboration between NASA and the Indian Space Research Organisation (ISRO) (Jones and Raio 2021). Launched in July 2025, NISAR will use dual-frequency radar to map Earth's land, ice, and coastal regions. Its L- and S-band SAR will improve flood mapping especially in vegetated regions, enhancing the detection of inundation beneath forest canopies, a major limitation of current C-band systems. Its data will also support monitoring of soil moisture, snow cover, and glacier dynamics, all critical for hydrological studies.

In parallel, ensuring continuity of operational services is equally critical, a role taken by Sentinel-1 next-generation constellation. It will maintain the C-band SAR time series while improving revisit frequency, consolidating the role of Copernicus services in operational flood monitoring.

Sentinel-6MF, launched in November 2020, with Sentinel-6B being planned for November 2025, is another Key European mission. While primarily focused on oceanography, Sentinel-6 complements hydrology by monitoring rivers and lakes and by improving our understanding of coastal processes, including storm surges and erosion (Domingo et al. 2025). Its high-precision altimetry continues the long data record initiated in 1992 with TOPEX/Poseidon, providing an invaluable dataset for climate research and modeling. Despite these strengths, its operativity for flood forecasting remains limited if not integrated with other altimetry missions.

To address the coarse time sampling of classical altimetry, the Small Altimetry Satellites for Hydrology (SMASH) constellation is being developed with the support of CNES. SMASH aims to provide daily water level observations using a network of ~10 compact nadir altimeters, capable of capturing small water bodies (> 100 m × 100 m and rivers as narrow as 50 m) and extreme hydrological events with a short latency (from a few hours to one day).

In addition to these prominent missions, several other initiatives are worth mentioning. The upcoming HydroGNSS mission from ESA will use GNSS reflectometry (White et al. 2022) to measure soil moisture, inundation, and vegetation density. By leveraging signals from existing navigation satellites, HydroGNSS offers a cost-effective and innovative approach to hydrological monitoring.

Recent innovations have looked at Global Navigation Satellite System-Reflectometry (GNSS-R), particularly using data from the CYGNSS satellite constellation, as a powerful and indispensable tool for flood mapping and disaster response. The technology's primary strength lies in its ability to overcome the major limitations of conventional remote sensing systems: poor temporal resolution and the inability of optical sensors to see through the heavy cloud cover that often accompanies major flood events. Its high temporal resolution enables more detailed quantification of both the inundated area and the flood's duration, as successfully shown during the catastrophic 2021 Henan, China flood (<https://www.mdpi.com/2072-4292/13/22/4561>), where GNSS-R observations accurately tracked changes in surface reflectivity.

A key technical challenge being addressed is improving the spatial resolution of the raw GNSS-R measurements, which are inherently sparse and pseudo-random. Researchers are tackling this by developing hybrid models that integrate the dynamic water-sensing signal with static topographical data. By combining the GNSS-R reflectivity with terrain metrics like height above nearest drainage (HAND) and slope of nearest drainage (SND), which define flood-prone areas, continuous, large-scale inundation maps can be generated with much higher confidence (<https://www.mdpi.com/2072-4292/12/18/3026>). Although this integration introduces complexities that require careful refinement to reduce mapping over-estimation, it represents a crucial step toward operational high-resolution flood products. Furthermore, comparative studies have established the superior performance of the GNSS-R method, which has been shown to detect significantly more surface water than both optical sensors (like MODIS) and even synthetic aperture radar (SAR) products, confirming its reliability as a foundational dataset for flood assessment (<https://ieeexplore.ieee.org/abstract/document/10018248>).

Beyond spaceborne applications, innovations are also fostering rapid, localized response. The development of dedicated systems, such as the Flood Assessment Spatial Triage (FAST), demonstrates the use of low-latency airborne GNSS-R data collected from routine commercial aircraft (<https://ieeexplore.ieee.org/abstract/document/10641457>). This innovative framework allows for the rapid processing of reflected signals combined with terrain data immediately upon landing, providing near real-time flood detection. This capability is vital for emergency managers, as it enables them to quickly assess the extent of a flood and guide other high-value assets (like imaging drones or rescue teams) to the most affected areas, dramatically shortening the critical window between disaster onset and effective humanitarian response.

Geo-stationary platforms such as the Meteosat Third Generation (MTG) with its Infrared Sounder and Lightning Imager, represent an important advance for flood forecasting, as they provide continuous, high-frequency coverage of precipitation systems over Europe and Africa. Compared to polar-orbiting sensors, these missions can capture the rapid evolution of convective storms and thus enhance nowcasting capabilities. Although spatial resolution remains coarser than low-Earth-orbit satellites, their ability to monitor the life cycle of precipitation events in near-real-time makes them a valuable complement to existing datasets.

The emergence of CubeSats and commercial SAR constellations (e.g., PlanetScope, ICEYE, Capella) offers unprecedented flexibility for rapid flood mapping. Their high spatial resolution and short tasking time enable targeted acquisitions during flood emergencies, filling gaps left by systematic missions such as Sentinel-1. However, limitations remain in terms of global coverage, data continuity, and cost, which may constrain their widespread use in operational forecasting chains unless integrated into open-data frameworks.

Looking ahead, the real potential of these missions lies in their integration within broader initiatives such as the Copernicus Emergency Management Service, the Global Flood Monitoring system, and emerging digital twin approaches. The combination of systematic missions (e.g., Sentinel series), high-resolution tasking systems (CubeSats), and geostationary precipitation monitoring will provide a multi-sensor ecosystem. This integration trend is essential to ensure both the continuity and the reliability required for operational flood forecasting, while also addressing user needs for actionable, near-real-time information.

Taken together, these missions are not only advancing hydrological science, but also paving the way for more reliable and timely flood forecasting capabilities, thereby reducing risks to societies increasingly exposed to climate-driven extremes.

5.2 Machine Learning and Data Ingestion: Use to Improve Satellite Data Integration

AI and ML approaches, briefly introduced in Sect. 4, are expected to expand their role in flood forecasting over the coming years. AI models derive knowledge of system dynamics directly from sets of input and output data without any explicit process rules, as instead required by physics-based or conceptual models. Moreover, AI models can process multiple data source and types at once, making them highly suited for ingestion of satellite data. In hydrology, Artificial Neural Networks (ANN), e.g., Long Short-Term Memory (LSTM) networks have proven useful for streamflow predictions and flood forecasting. Convolutional neural networks (CNNs) learn spatial relationships from images, which may be useful to describe the link between runoff dynamics and the hydrological memory of a catchment (Oddo et al. 2024). Despite their potential, transferring ANN-based models from gauged to ungauged catchments remains a major challenge and is often prone to the same limitations faced by physical model transfer (Kratzert et al. 2019). Nonetheless, leveraging global and publicly available EO-based datasets, these methods provide promising avenues for improved predictions. In this context, Google's Flood Hub operationalizes a ML-based flood forecasting system, leveraging open tools and global EO datasets to deliver predictions, even in ungauged catchments, and has shown skill comparable to, and sometimes exceeding, conventional numerical models (Nearing et al. 2024). This approach illustrated both the opportunities and the challenges of AI in advancing globally accessible flood forecasting solution.

While AI models typically achieve a lower error score than traditional physics-based models (e.g., Frame et al. 2022a, b; Nearing et al. 2024; Kratzert et al. 2019), it is important to note that the performance is strongly linked to the quantity and quality of available training data. One limitation is typically the heterogeneity in data availability as the model must be trained against the variable it is designed to predict. Thus, model performance tends to decrease proportionally with the extremity of the predicted event. While purely data-driven hydrological predictions are becoming increasingly available, they are trained on existing observations and may struggle to predict unprecedented extremes, particularly in ungauged catchments. This limitation is critical under a more variable future climate, with important implications for hydrological modeling and flood and drought prediction. It should also be acknowledged, however, that such challenges are not unique to data-driven approaches: physically based models can similarly face difficulties in capturing unprecedented extremes, especially when observational data are sparse or unavailable.

Improving forecasts is an essential step in understanding, predicting and mitigating extreme floods and droughts, particularly in ungauged watersheds. A hybrid approach as presented in Kraft et al. (2020) can help more efficiently simulating hydrological extremes through data-driven processes. In a hybrid approach, the deep learning model (e.g., LSTM) learns the mapping of the input data—meteorological features—to target variables (e.g., evapotranspiration, discharge or total water storage). Hybrid approaches, still constrained by physical laws, can improve interpretability of results and gain better process understanding and forecasting capabilities of hydrological systems—and of the value of relevant global data streams, including EO (Kraft et al. 2022). Hybrid models expand the use of EO in hydrological models, where uncertain parameters and processes are replaced by the AI model rather than parametrized directly from EO, while maintaining physical consistency (Kraft et al. 2022). The advantage is indeed twofold:

interpretability compared to a black-box data-driven approach and improved predictability by incorporating more information than is usually possible in traditional models.

6 Discussion

EO technologies offer broad spatial and temporal coverage, bridging critical gaps in flood monitoring and providing unprecedented opportunities to observe flood dynamics in near real-time even in remote or inaccessible areas. Recent advancements, such as high-resolution imaging and rapid revisit capabilities, have significantly enhanced their potential for flood prediction and management. These innovations underscore the growing importance of integrating EO data into hydrological and meteorological models to improve the accuracy, reliability, and lead time of flood forecasts. While the integration of satellite data into operational forecasting systems remains limited, harnessing the full capabilities of EO technologies can greatly strengthen global efforts in flood preparedness, response, and disaster risk reduction.

6.1 Reflections on How Satellite Data can Change the Future of Flood Forecasting

Critical components essential for flood forecasting systems are represented by the input data such as river discharge, soil moisture, and precipitation necessary for running flood prediction models. The integration with EO data has a high chance to enhance forecast accuracy and expand flood forecasting capabilities globally. However, the latency of satellite data poses a challenge, and therefore, future efforts shall be focused on the development of integrated systems leveraging ground-based and remote observations, particularly in real time, that will revolutionize flood monitoring and forecasting.

By harnessing the capabilities of satellite technology and optimizing existing forecasting systems, we can improve our ability to predict and mitigate the impacts of floods, ultimately improving disaster resilience and community safety on a global scale. The integration of EO products within flood forecasting systems has four main purposes:

- (1) *As data forcing*: the integration of in situ and satellite observations offer substantial potential for enhancing flood forecasting reliability with continuous improvements in spatial and temporal resolution bolstering their utility for operational physics-based and data-driven hydrological modeling.
- (2) *For setting initial conditions*: recent studies highlight the benefits of incorporating satellite-derived products, such as satellite soil moisture or proxies such as river discharge and precipitation indices as alternatives, especially where extended warm-up phases are not feasible (Kim et al. 2018; Massari et al. 2014). Moreover, knowing reservoir water levels improves model representation, especially for flood events.
- (3) *For model calibration*: While traditional calibration methods rely on in situ discharge, recent literature emphasizes the advantages of using remote sensing data for rainfall-runoff and hydrodynamic model calibration (Hossain et al. 2014; Sutanudjaja et al. 2014; Zink et al. 2018; Falck et al. 2021; Eini et al. 2023). Satellite data, including water level, river discharge estimations, snow-covered area, land surface temperature, and soil moisture, offer valuable insights for improving model accuracy.
- (4) *Within a data assimilation framework*: data assimilation techniques help mitigate uncertainties arising from input data, model schemes, and meteorological forecasts (De Lan-

noy et al. 2022). Data assimilation involves sequentially updating hydrological models to align forecasts with current observations. The assimilation can help to correct the models' state and/or parameters and contemplate one or more hydrological variables under consideration in the model (e.g., water level, discharge, groundwater, etc.).

In summary, flood forecasting systems are already operational even at a global level, but they are driven by only ground data and their uncertainty is still high. The ingestion of satellite data would provide a quick and rapid advancement for the benefit of the community, especially in the Global South countries. The monitoring of river flood conditions, the calibration/validation of hydrological/hydraulic models, and the assimilation of satellite data have already been covered extensively in the scientific literature. It is time to invest in the development of the integration of all these systems to provide timely and accurate products for flood forecasting activities, by maximizing the use of available observations from ground-based and remote instruments into available models.

In today's era of rapid technological advancement, satellite products offer unprecedented levels of accuracy and coverage, providing invaluable insights into environmental conditions. However, despite their immense potential, these satellite products have yet to be fully integrated into operational flood forecasting systems. Our proposal seeks to bridge this gap by conducting testing and evaluation of the most advanced satellite products available. Through rigorous analysis, we have identified key areas for improvement and develop advanced approaches and techniques to enhance their usability within early warning systems.

7 Conclusion and Outlook

Flood forecasting requires diverse and integrated approaches that combine ground-based and satellite observations, robust hydrological and hydraulic models, and advanced data assimilation techniques, including ML. A balanced integration of these elements can enhance prediction accuracy and support decision-making at various scales, including input to European and international future Water Directives. However, achieving effective flood forecasting also demands collaboration among researchers, policymakers, and operational agencies across disciplines and governance levels to improve risk management strategies globally (as also emphasized in Kundzewicz et al. 2018).

A promising avenue for improving flood forecasting is the development of hybrid approaches that merge physics-based hydrological models with AI-driven techniques. Such models can leverage real-time data and historical hydrological records while incorporating advanced algorithms to enhance predictive accuracy and computational efficiency. By integrating multiple data sources and modeling techniques, these approaches aim to capture the complexity of hydrological processes under diverse climatic and environmental conditions.

Uncertainty remains a critical challenge in flood forecasting, arising from various sources such as data limitations, model assumptions, and natural variability. A probabilistic approach to predictive uncertainty (PU), which quantifies the likelihood of future discharge events based on observational data and model outputs, can improve reliability. Statistical frameworks, such as the model conditional processor (MCP, Todini et al. 2008), enable a more refined interpretation of forecasts by integrating multiple models probabilistically. These forecasts can then be used to inform hydraulic models, which account for river dynamics at different spatial scales. Employing multiple models allows

for a better understanding of how hydrological and geomorphological factors influence flood propagation, improving flood risk assessments and preparedness strategies.

A major limitation in flood forecasting is the availability of reliable and continuous in situ data, particularly in regions with sparse monitoring networks. This issue is especially pronounced in many developing countries, where data scarcity hinders model calibration and validation. Regionalization techniques offer a potential solution by extrapolating information from data-rich areas to ungauged basins, allowing for broader model applicability. Satellite-based estimates of river discharge and other hydrological variables can provide essential inputs for these models, extending their usability in regions with limited ground observations. By leveraging regionalization methods and remote sensing technologies, flood forecasting capabilities can be enhanced in data-scarce environments, improving risk assessment and management efforts.

As forecasting models and EO datasets become more sophisticated, the transition toward NRT applications becomes increasingly relevant. Shifting from non-time-critical datasets used for calibration to NRT datasets is essential for assessing the operational feasibility of satellite-based flood forecasting. While real-time data may initially introduce additional uncertainties, testing these datasets under operational conditions is crucial for evaluating their performance in dynamic flood events. The integration of NRT data into forecasting systems will help identify challenges and opportunities associated with the use of satellite observations for real-time streamflow prediction.

Looking ahead, future advancements in flood forecasting will likely involve a combination of emerging technologies and methodological innovations. These include the assimilation of multi-sensor datasets to improve hydrological variable estimation, further refinement of regionalization techniques for ungauged basins, hybrid modeling approaches that combine physical and data-driven methods, and enhanced integration of satellite data into operational flood forecasting frameworks. Additionally, comparative studies across different modeling approaches can help optimize forecast accuracy and applicability in diverse environmental conditions.

By advancing these strategies, flood forecasting systems can become more reliable and adaptive, improving early warning capabilities and supporting more effective flood risk mitigation on a global scale.

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Declarations

Conflicts of interest The authors declare no conflict of interest.

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